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ORIGINAL ARTICLE

Customer relationship management technology: bridging the gap between marketing education and practice

Dana E. Harrison[1] · **Haya Ajjan**[2]

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Abstract

The recent machine learning and analytics advances in customer relationship management (CRM) technologies place new demands on marketing education and practitioners to develop the skills needed to use the technology. Compounding the issue, research on the use of technology in sales curriculum is underdeveloped. In a comprehensive review of the sales education literature, one study identified that only six articles on sales technology were published in major marketing education journals from 1979 to 2013. In an effort to bridge the gap between critical industry competencies and marketing curriculum, understanding the impact of technology use and training is important for educational planning and student development. Using a survey of 82 salespeople in the United States, the current study empirically evaluates how use of technologically advanced CRM features influences self-perception of CRM knowledge, the perception that additional technology training would be beneficial, and adaptive selling performance of sales practitioners. A majority of survey respondents in the current study cited a need for college students to receive increased exposure to advanced CRM technology training and skill development. We propose an experiential learning approach to teach marketing college students advanced CRM features to help them bolster their effectiveness and value in the workplace.

Keywords Customer relationship management · Adaptive selling · Machine learning · Marketing education · Frequency of CRM use

Introduction

Digital transformation through technological advancements enhances a company's ability to develop and harness information assets, engage in customer relationships, and gain subsequent insights. Technological advancements permit the collection, integration, management, storage, and processing of data. These data are the bedrock of a company's ability to develop a coherent understanding of its customers' preferences, needs, and perceptions (Breur 2015).

Data management requires companies to invest heavily in customer-oriented technology applications. Therefore, it is no surprise that customer relationship management (CRM) technology is the fastest-growing business application market, with a growth rate of 16% (Davies et al. 2017; Gartner 2018) and valued at almost $40 billion in 2017 (Thompson et al. 2018). A recent study also noted that 61% of organizations identified machine learning and artificial intelligence (AI) as their most significant initiative for 2019 (Columbus 2018; Lewandowski 2018). The technology market surrounding these advanced initiatives is expected to grow to $57.6B by 2021 (Columbus 2018). Although CRM and AI solutions can be considered independently of one another, CRM is currently undergoing transformation with the advent of AI add-ons. For example, the Salesforce CRM application has an AI add-on that uses a company's historical lead and account data to make suggestions in real time, which help salespeople predict which customers are most likely to close a deal. Companies expect technology purchases to synthesize processes and add capabilities that improve understanding of customers and manage relationships.

As CRM solutions become more advanced, adopting the embedded technologies becomes more challenging. In

✉ Dana E. Harrison
harrisondl@etsu.edu

Haya Ajjan
hajjan@elon.edu

[1] College of Business and Technology, East Tennessee State University, Johnson City, TN, USA

[2] Martha and Spencer Love School of Business, Elon University, Elon, NC, USA

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fact, when surveying senior executives, 38% cited employees' lack of required skills as the main barrier to digital information integration (DeNisco-Rayome 2017). Another study found that of 581 CMOs, 78% of them believed that marketing functions will fundamentally change in coming years due to infusions of digital, analytic, and mobile technologies (Shah et al. 2014). According to Burning Glass, knowledge of CRM software and analytics are of the top ten digital skills that boost marketing careers (Tenorio 2018). It is evident that a demand exists for college graduates to be prepared with a marketing education where they can gain experience with the kinds of technology that are transforming marketing and sales functions (McCorkle et al. 2001; Schlee and Karns 2017).

Research on the use of technology in sales curriculum is underdevelope there is a lack of study on the teaching of advanced analytics in the marketing curriculum (Liu and Levin 2018). In a comprehensive review of sales education literature, only six articles focused on sales technology were published in major marketing education journals from 1979 to 2013 Cummins et al. (2013) and Gray et al. (2012) identified that very few articles were published on sales education in the Journal of Marketing Education since it commenced publishing. However, marketing education research in general has indicated that, due to pervasive changes in practice, marketing programs are struggling to keep pace and align skills with those necessary to prepare students for marketing careers (Rohm et al. 2018).

How can academia collectively integrate marketing education and salesperson research to improve coursework that provides students access to a necessary set of skills? One way to address this question is through mapping key skills needed in practice to an effective and intentional marketing learning environment. This study parallels results from salespeople in an academic setting.

The purpose of this study was to uncover the importance of exposure to advanced CRM technology and necessary advanced technology skills for marketing students entering the workforce. Using a post-adoption theoretical framework (Shih and Venkatesh 2004; Venkatesh et al. 2016), we explored the use of advanced CRM technology among salespeople. Specifically, to gauge the impact of CRM technology experience, we addressed three research questions surrounding post-adoption. First, what is the impact of advanced CRM technology features and frequency of CRM use on salespeople perceptions of whether they possess high levels of CRM knowledge? Second, do self-perceived knowledge of CRM technology and the frequency of CRM technology use improve adaptive selling skills? Third, how can academia collectively integrate marketing education and salesperson research to improve marketing/sales course instructions and provide students access to advanced CRM analytics skills? In an effort to bridge the gap between critical industry competencies and marketing curriculum, understanding the impact of technology use and training is important for educational planning and student development. Due to the pervasive use of technology in sales, we propose integrating technological skills into the classroom curriculum using experiential learning approaches. Knowledge and skills developed within an applied context provide students with a competitive advantage in the early stages of their careers (Rohm et al. 2018).

Literature review

Customer relationship management

CRM is a crossfunctional process (Day 2001) or business strategy (Zikmund et al. 2003) that provides individuals in an organization with a comprehensive view of its customers. CRM has been described as an approach for acquiring new customers, retaining existing customers, and enhancing customer relationships (Payne and Frow 2005). Companies use technology to support CRM and efficiently manage information for marketing and sales purposes. CRM technology integrates information and adds value to an organization by accumulating unique, detailed information about each customer. Recently, advanced features have been added to CRM software to enable coaching during customer engagement and use of predictive and machine learning analytics to evaluate future leads and past sales performance. These advanced features help salespeople identify sales opportunities and improve decision making (Farquad et al. 2014; Syam and Sharma 2018). They also change the way the CRM system is used and is navigated (Antonio 2018)

As a supportive organizational resource and information system, CRM technology enables the efficient and effective management of customer interactions (Zablah et al. 2004), allowing people throughout an organization to sense and respond to customer needs through relationship management. Although some debate exists regarding the impact of CRM technology on a company's performance (Day and Van den Bulte 2002; Reinartz et al. 2003), many studies indicate its crucial role in building long-term and profitable customer relationships (Hunter and Perreault 2007; Shoemaker 2001; Zablah et al. 2004). However, before any value is reaped from CRM technology, its adoption by salespeople within the organization must be well-established.

Technology adoption and use

Individuals' acceptance and use of technology is one of the most mature research streams in the information systems literature (Venkatesh et al. 2007). This research typically uses a framework based on innovation diffusion theory (Rogers

1995), focusing on three high-level stages: pre-adoption activities, the adoption decision, and post-adoption activities (Rogers 1995). Compared to research on the first two adoption stages of technology, relatively few studies have examined behaviors and outcomes following technology adoption (Venkatesh et al. 2007, 2016). Shih and Venkatesh (2004) conceptualized technology usage based on two distinct measures. The first, variety of use, measures the extent to which different features of a technology system are used, and the second, frequency of use, measures the amount time a person spends using the technology. According to Shih and Venkatesh (2004), variety and frequency of use influence satisfaction with technology and interest in acquiring future technology.

We develop a theoretical model from a post-adoption lens. Post-adoption behavior can be defined as "the myriad feature adoption decisions, feature use behaviors, and feature extension behaviors made by an individual user after an IT application has been installed, made accessible to the user, and applied by the user in accomplishing his/her work activities" (p. 531) (Jasperson et al. 2005). The features offered by a technology, also referred to as its "building blocks," are designed to support user tasks (Griffith 1999; Jasperson et al. 2005). The extent to which users exploit the building blocks to perform tasks is thought to drive individual performance outcomes (Burton-Jones and Gallivan 2007). That is, user performance is expected to improve as users exploit more of a system's features and infuse the technology into routines (Venkatesh et al. 2016). The post-adoption theoretical perspective suggests that the frequency of use and features of the technology are drivers to support user tasks and performance outcomes. However, research examining the mediating or moderating links between feature-level use and individual perception that additional technology training would be beneficial and subsequent outcomes is scarce (Venkatesh et al. 2007). Therefore, we extend this theory to focus on advanced CRM technology features and their level of use to address this gap.

Conceptual model and hypotheses

The current study forms a nomological network of post CRM adoption. Specifically, we examined behavior and behavioral outcomes for two types of usage patterns related to the level of CRM technology features used and their frequency of use. We hypothesized a direct relationship between these factors and a salespersons' self-perception of their knowledge of the CRM technology and with their own perceived benefit toward additional technology training. We predicted that individuals with higher perceived knowledge of CRM technology and higher frequency of use will have more effective adaptive selling capabilities compared to those with lower levels of both. Figure 1 depicts expected direct and indirect effects of each construct.

The impact of CRM variety and frequency of use

Since companies invest heavily in CRM technology and it is heralded as a pivotal factor in improving sales performance, it is important to consider factors that influence successful outcomes (e.g., Ko et al. 2008). Unfortunately, refusal to use the CRM technology can have detrimental effects on salesperson performance and organizational outcomes. Rejecting the use of CRM technology, however, can be prevented since research shows that salespeople forgo using CRM technology due to insufficient training (Zablah et al. 2004). The efficient and effective outcomes of technology use are contingent upon proper training (Ahearne et al. 2005) and adequate knowledge of the features.

Technology features that are in use at any point in time influence and determine work outcomes (Jasperson et al. 2005). Features, such as analytics and machine learning add-ons, represent fundamental ingredients of the technology and a variety of features reflects the potential of the technology to improve work tasks. Following adoption of the technology, users have an opportunity to become aware of available features and can actively acquire information about the presence of useful features. Recognizing that technology possesses a variety of features could prompt users with a desire to learn more about the capabilities in an effort to extract additional value from the technology. We predict that CRM technology advanced features (e.g., machine learning, predictive analytics, and visualization) of CRM system use will have a positive effect on salespeople's perception of their CRM system knowledge and their perception that additional technology training would be beneficial.

H1 Variety of advanced feature use affects a) how knowledgeable salespeople feel they are about a CRM system and b) the salesperson's perception that they would benefit from additional technology training.

Salespeople who infuse system use in regular activities should possess more confidence in their understanding of the available features and also value opportunities to attain a higher level of expertise. If salespeople frequently spend time relying on the system to complete work tasks, it's likely that they will feel somewhat knowledgeable of system features and capabilities. Similar to this point, salespeople that exhibit higher levels of system use to complete work tasks will likely feel there is more to potentially learn and seek additional expertise. Training improves self-efficacy (e.g., Speier and Venkatesh 2002) and user beliefs in his/her ability to operate the technology system (e.g., Davis et al. 1989). When salespeople possess the knowledge to engage with the

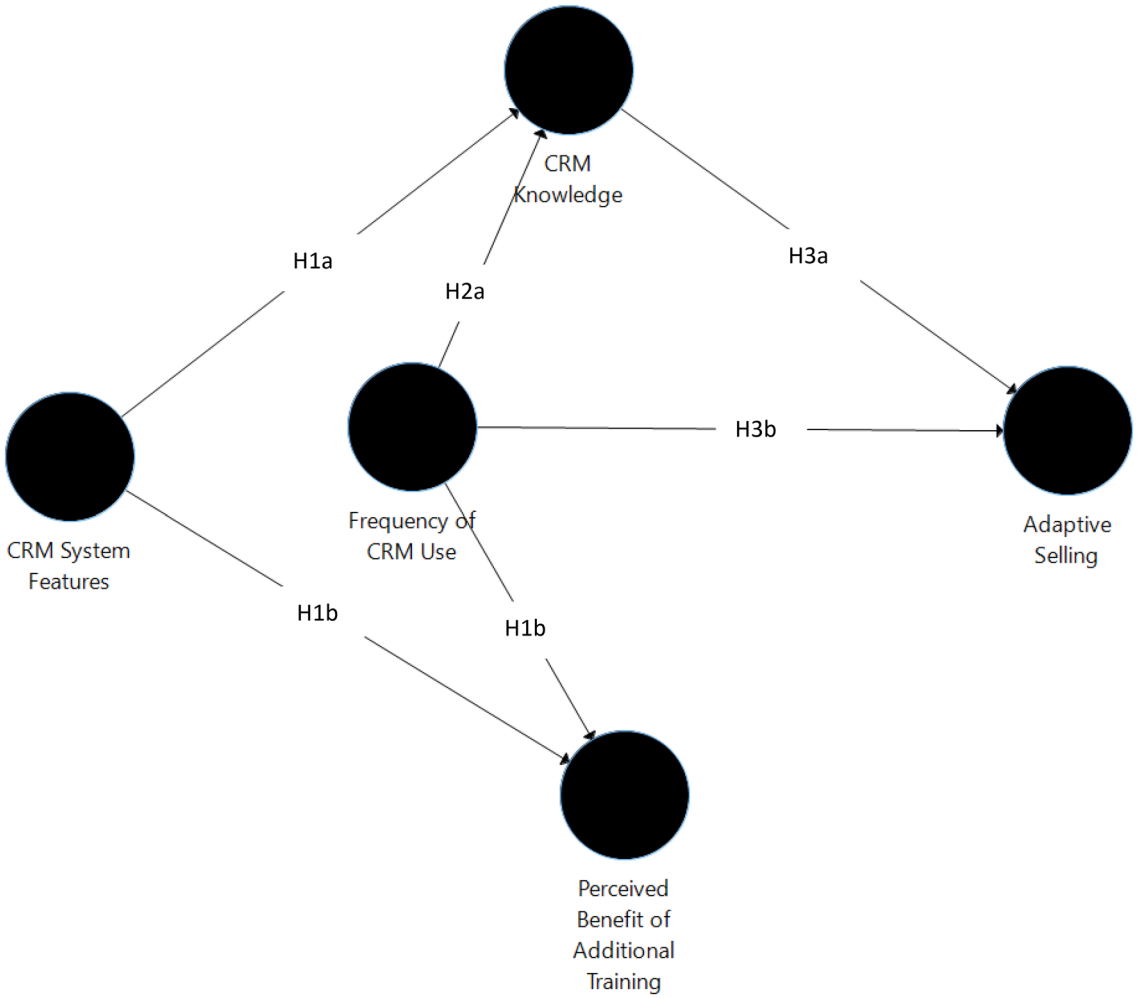

Fig. 1 Conceptual model

CRM technology to its full capacity, the company should reap ensuing maximum performance benefits. Therefore, it is imperative that companies offer technology support and training in post-adoption stages of CRM technology to properly address customer needs and wants. We predict that CRM system frequency of use will have a positive effect on salespeople's perception of their CRM system knowledge and their perception that additional technology training would be beneficial.

H2 Frequency of use affects (a) how knowledgeable salespeople feel they are about a CRM system and (b) the salesperson's perception that they would benefit from additional technology training.

Adaptive selling abilities

Salespeople rely and thrive on information (Hunter and Perreault 2006). Information is shared by salespeople and customers in the relationship building process (Day 1994) and CRM technology enables salespeople to quickly access, analyze, and interpret intelligence gathered about customers. Salespeople can use digitally organized and stored data to prepare for, enhance the strategic focus of, and adapt their sales calls and presentations so that sales communications are aligned with and customized for customer needs and wants. In other words, they can use adaptive selling, which refers to the ability to "determine the suitability of sales behaviors and activities that will be undertaken, the capacity to engage in a wide range of selling behaviors and activities, and the alteration of sales behaviors and activities in keeping with situational considerations" (Sujan et al. 1994, p. 40). Research indicates that CRM technology use has a positive effect on adaptive selling (Ahearne et al. 2008; Rapp et al. 2008), but research on factors that mediate this relationship is lacking. Since adaptive selling has a positive impact on customer satisfaction and salesperson performance (Boorom et al. 1998; Franke and Park 2006; Spiro and Weitz

1990; Weitz et al. 1986), it is important to investigate circumstances that modulate technology use and adaptive selling behavior. Users who are knowledgeable of the features of a CRM system should have an advantage for improving adaptive selling behavior through accessible information, compared to less knowledgeable colleagues. Salespeople use the information to communicate effectively and develop long-term relationships by anticipating, understanding, and creating value for customers.

We predict that individuals with higher levels of perceived knowledge of CRM technology and experience with CRM systems through higher levels of use will be more adept at adaptive selling than those with lower levels.

H3 (a) The knowledge of CRM system features and (b) the frequency of CRM technology use impacts adaptive selling abilities.

Methods

Measures

The measures used in this study were based on existing scales. A composite index-scale for Level of CRM technology features was used in the study (Choudhury and Harrigan 2014; Ryall and Sampson 2009). Single-item, likert-type scales for knowledge of the CRM technology (Saini et al. 2010) and frequency of the CRM technology use (Sundaram et al. 2007; Taylor and Todd 1995) were adapted to fit the context of the study. For example, with knowledge of the CRM technology, rather than survey respondents on their knowledge of IT in general, we asked specifically about their knowledge of the CRM technology in use. Existing literature (e.g., Ahearne et al. 2005; Avlonitis and Panagopoulos 2005; Barksdale et al. 2003; Goodhue and Thompson 1995) focuses mainly on perception of training that occurred prior to technology adoption and the number of hours of training that were received. Therefore, we developed a new likert scale based upon established literature that asked participants about the extent to which they would benefit from additional technology training. Single-item measures are common in exploratory research with small sample sizes, and when multiscale items representing the respective constructs are expected to be highly homogenous (Hair et al. 2017a, b). In addition, when constructs are easily understood, single-item measures can be reasonable alternatives (Petrescu 2013). The salesperson's perception of their knowledge of CRM technology was measured using a 7-point scale, where frequency of the CRM technology use and the perception that they would benefit from more training in a formal setting were measured on 5-point scales. Four items were adopted from an existing adaptive selling measure (Robinson et al. 2002), which salespeople rated on a 7-point scale where 1 was strongly disagree and 7 was strongly agree. According to the recommended threshold (Hair et al. 2017a, b), the sample size needed to achieve a statistical power of 80% for detecting R^2 value of at least 0.25 (with a 1% probability of error) is 53.

Data collection and sampling

Eighty-two salespeople (32 [39%] female) in the United States, representing a variety of industries, completed an online questionnaire through a Qualtrics panel. As shown in Table 1, the three most represented industries were manufacturing (22%), professional, scientific or technical services (15.9%), and retail (11%). The ages of respondents were diverse and included 13.4% between the ages of 21–29, 28% between the ages of 30–39, 34.1% between the ages of 40–49, and 24.4% greater than 50 years of age. Over 87% of respondents had more than a 10-year tenure with their company, and 52.4% held a full-time sales role for over 10 years.

Self-report measures were collected via the questionnaire referred to earlier following the guidelines of Podsakoff et al. (2003) to reduce the likelihood of common methods variance (CMV). Following prior literature to examine CMV (Babin et al. 2016; Fuller et al. 2016), we applied Harman's single factor method which indicated no presence of common method bias.

Data analysis

We used SmartPLS 3 (Ringle et al. 2015) to execute variance-based structural equation modeling (PLS-SEM). This method of modeling is appropriate for this study because the theory of post-adoption use of technology is underdeveloped and our intent was to predict and explain exogenous constructs (Hair et al. 2011, 2017a, b, 2018a, b). PLS-SEM

Table 1 Respondents by industry

Industry	Percent
Accommodation or food services	1.2
Arts, entertainment, or recreation	2.4
Education	1.2
Health care	7.3
Information	2.4
Management of companies or enterprises	6.1
Manufacturing	20.7
Professional, scientific, or technical services	15.9
Retail	11.0
Transportation/logistics	1.2
Wholesale/distribution	8.5
Other	22.0

is increasingly applied across social sciences disciplines including studies in marketing (Hair et al. 2012a, b), family business (Hair et al. 2014), and management (Hair et al. 2012a, b).

Measurement and structural models were examined for the multi-item-adaptive selling scales (Table 2). Outer loadings for all items were significant, exceeding .70, and met the recommended statistical guidelines (Hair et al. 2017a, b). Guidelines for composite reliability and average variance extracted also surpassed recommended thresholds (Hair et al. 2017a, b). Thus, convergent validity was established (Henseler et al. 2015).

Recommended PLS-SEM guidelines were followed when evaluating discriminant validity (Hair et al. 2017a, b). The square roots of the AVEs for constructs were greater than the interconstruct correlations, thus meeting the Fornell and Larcker (1981) established AVEs criteria. We applied the HTMT approach to examine discriminant validity and all construct correlations were below .85 (Hair et al. 2017a, b; Henseler et al. 2015), providing further evidence of discriminant validity.

Results

Table 3 and Fig. 2 show statistics for model relationships. All hypotheses were supported with the exception of h3b.

The level variety of feature use of the CRM system had a significant impact on both the salespeople's self-perception of CRM technology knowledge ($\beta = 0.22$, $p < .01$), and their perception that they would benefit from additional technology training ($\beta = 0.21$, $p < .05$). Therefore, both h1a and h1b were supported. As the level of CRM system feature-level use increased, so did self-perception of CRM knowledge and the acknowledgment that additional technology training would be valuable. This indicates that using an increased number of a CRM technology's features enhances confidence in system knowledge while also motivating the user to sharpen their skills.

Over 85% of respondents reported that their company required employees to use the adopted CRM technology. The frequency of CRM technology use significantly impacted self-perception of CRM knowledge ($\beta = .50$, $p < .01$) and salespersons' perception that additional training would be beneficial ($\beta = .252$, $p < .05$). Thus, h2a and h2b were also supported. Frequency of use offers salespersons experience with the technology and allows for integration into regular tasks, increasing their perceived level of knowledge, but also motivating them to undertake additional training.

H3a was supported since self-perceived knowledge of CRM technology had a significant impact on adaptive selling ($\beta = 0.38$, $p < .01$). However, h2b was not supported. The frequency of CRM technology use did not have an impact on adaptive selling ($\beta = 0.03$, $p > .10$). Although not formally hypothesized, the relationship between how frequently the system was used and adaptive selling was fully mediated (Baron and Kenny 1986) by how knowledgeable the salesperson felt regarding their CRM technology expertise. That is, frequency with which CRM technology was used increased self-perceived technology knowledge of the system, which in turn led to improved adaptive selling capabilities.

Coefficients of determination (R^2 values) indicated the impact of exogenous constructs on endogenous constructs.

Table 2 Reliability and validity indices for the measurement model (single-measure items excluded)

Measurement items	Outer loadings	*t* value for loading	Cronbach's Alpha	Composite reliability	Average variance extracted
Adaptive selling			0.863	0.907	0.710
I like to experiment with different sales approaches	0.771	11.571			
I am very flexible in the selling approach I use	0.886	24.406			
I can easily use a wide variety of selling approaches	0.896	32.890			
I try to understand how one customer differs from another	0.812	13.517			

Table 3 Structural model relationships including path coefficients, *t* values

Independent variables	Dependent variables		
	CRM knowledge	Desire for training	Adaptive selling
CRM system feature-level use	0.221***/2.89	0.209**/1.99	0.083*/1.88
CRM knowledge			0.377***/3.37
Frequency of CRM use	0.498***/5.03	0.252**/2.13	0.025/0.173

*$p < .10$; **$p < .05$; ***$p < .01$ (all two-tailed)

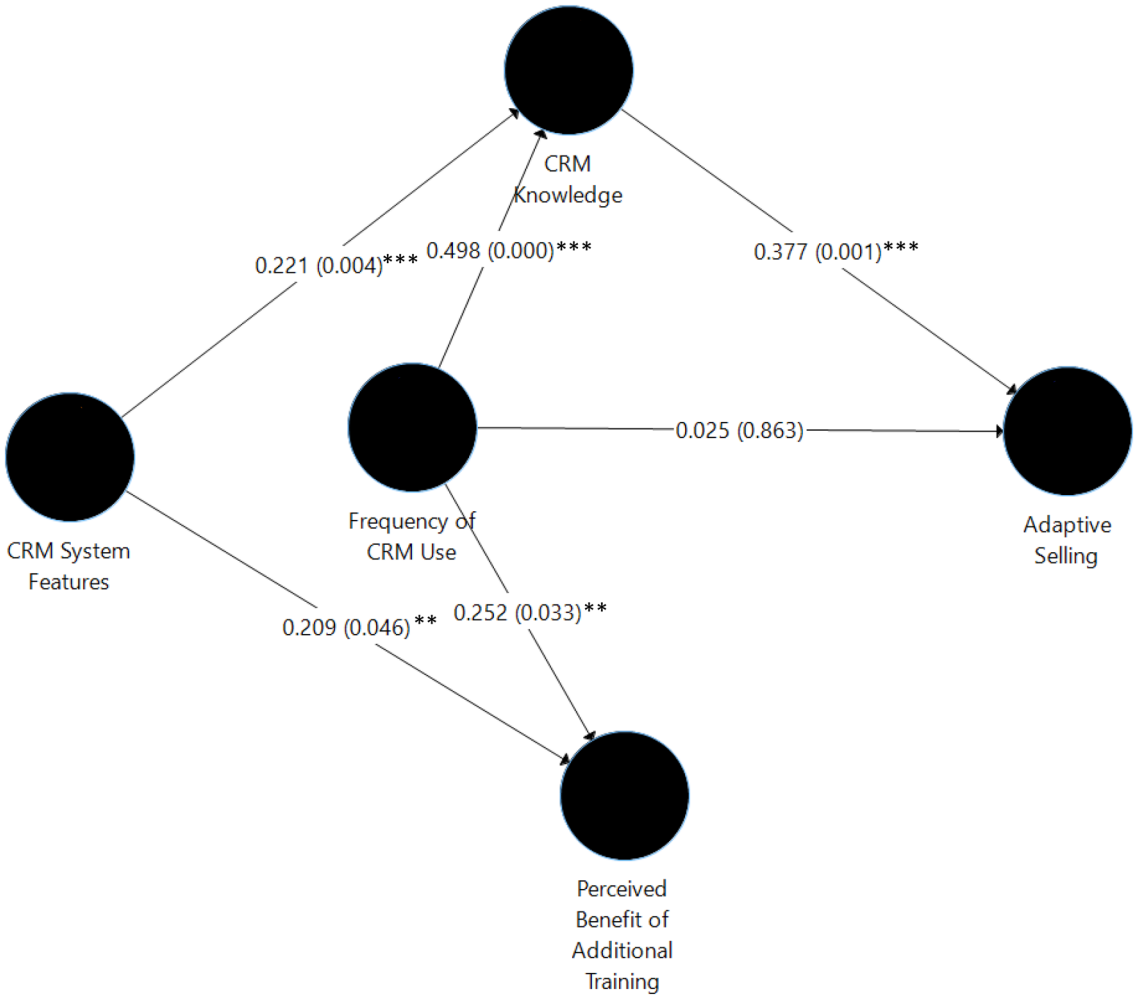

Fig. 2 Model results

Combined, the variety of CRM technology feature use and frequency of CRM use explained 36% of the self-perceived knowledge of the CRM technology and 14% of a salesperson's perception that they could benefit from additional training. Combined frequency of CRM use and self-perceived knowledge of the CRM technology explained 15% of adaptive selling capability.

Effect size analyses revealed that system features had a small effect on self-perception of CRM technology knowledge ($f^2 = 0.07$) and the perception that additional training would be beneficial ($f^2 = 0.05$). The frequency of CRM usage had a large effect on self-perception of CRM technology knowledge ($f^2 = 0.36$) and a small effect on the perception that additional training would be beneficial ($f^2 = 0.07$). Lastly, self-perception of CRM knowledge effected adaptive selling capabilities only moderately ($f^2 = 0.12$).

To assess the model's predictive relevance, we calculated Q^2 for each endogenous construct. Values for all the three variables (self-perceived CRM technology knowledge, desire for more training, and adaptive selling capability) were above 0, indicating a meaningful impact for each predictor variable. Self-perceived CRM technology knowledge had the highest Q^2 value (0.323), followed by the perception that more training would be useful (0.093) and adaptive selling behavior (0.093).

Discussion

Although this study extends the literature on CRM use and post-adoption of CRM technology (Alshawi et al. 2011; Harrison and Hair 2017; Jaber and Simkin 2017; Ko et al. 2008; Rodriguez et al. 2015), the fundamental motive was to enhance marketing education by understanding skills that could potentially offer an early advantage for students before entering the workforce. Through focusing on post-adoption perceptions and performance outcomes of salespeople, we examined the impact of advanced features offered by CRM

solutions and the frequency with which salespeople use CRM solutions. Specifically, we observed how the sophistication of advanced features and frequency of using the CRM technology not only influenced their perceived knowledge of the system and perception that additional formal training would be helpful, but that these were also beneficial to enhance adaptive selling capabilities.

Taking into consideration changes in marketing practice and the value of CRM technology use and understanding, we believe that the impact of CRM technology on salesperson performance warrants increased emphasis in the amount of technology exposure that college students receive in the classroom (e.g., CRM). Bridging the skills gap between practice and education could include student training in advanced functionality of innovative technologies (e.g., machine learning and analytics), data interpretation, and the application to business needs. Understanding the effects of CRM technology use in practice is critical to incorporating necessary technological and analytic training in marketing education.

Developing academic frameworks that produce cogent technology skills for students brings distinct benefits. If students experience technology prior to entering the workforce, they are better prepared, leading to increased performance at an accelerated rate. These enhanced skill sets yield work-ready graduates who distinguish themselves from their peers and escalate their desirability among employers. Concurrently developing a student's aptitude for technology and analytics helps meet industry expectations and enhances students' career success.

Instructors have a responsibility to develop teaching methodologies, learn new instruction techniques, and improve upon existing approaches to train students in advanced technological competencies (Sledgianowski et al. 2017; Grewal et al. 2018). Current students might be digital natives (Buzzard et al. 2011), but being technology savvy does not automatically equate to advanced technological competencies. Understanding how to improve proficiency and motivate a desire to hone advanced technology and analytic skills can enhance practices at an academic level prior to entering the workforce (Schlee and Karns 2017).

Theoretical and practical implications

Theoretical implications

Our results have several implications for marketing education and post-technology-adoption literature. First, we demonstrate the impact of advanced CRM technology features and frequency of use on salesperson perceptions of their knowledge of the system and acknowledgement of the potential benefits regarding additional training. The level of advanced features and the frequency that CRM technology systems are used to perform work tasks are meaningful drivers of a salesperson's system understanding. With our focus on salespeople, rather than current students, we capture meaningful skills that are essential to possess when entering the workforce.

Second, our research contributes to post-technology-adoption literature to recognize CRM technology's influence on adaptive selling skills among salespeople. This is an important finding for both marketing education and technology literature. It is evident that CRM technology plays an important role to enhance salesperson capabilities. A 2015 study by LinkedIn and HubSpot revealed that with the rise of big data, the marketing field is changing at a rate faster than any other business field (Linkedin and Hubspot 2015). In fact, a Forbes article reported on results from Trilogy Education that data analytics is the most in-demand skill among today's employers (Kauflin 2017). This trend is further confirmed by numerous marketing articles. For example, Zoltners et al. (2018) stated "More companies and industries are taking on the challenge of orchestrating marketing and sales outreach to align with modern customer buying needs. As the volume, variety, and velocity of business data escalate, analytics (including artificial intelligence) will play an even bigger role in the effort to improve the customer buying experience" (p. 2). The customer experience can be improved using predictive analytics of customer transactions and interactions in the CRM software (e.g., Salesforce, Microsoft, Zoho, Hubspot, and others) using AI plugins (Antonio 2018). In a survey of indeed.com, Table 4 shows a sample of current job titles with basic functions and facilitating technologies required for marketing-related positions specifying CRM and analytics software such as Salesforce, Tableau, Einstein, Google AdWords, and others. Marketing education literature should also recognize the potential value in understanding skillsets in practice. Employers are expecting graduates to meet new requirements where they understand marketing, as well as, possess analytic and technology skills (Grewal et al. 2015). Thus, it is necessary for marketing education to equip students with advanced technology skills to perform important tasks following graduation.

Practical implications

Finally, "an overhaul of the marketing curriculum is due" (Rohm et al. 2018, p. 1). It is important that deficiencies between marketing education and practice are addressed (Rohm et al. 2018). Based upon marketing education research (Knight et al. 2014), developing experiential exercises that introduce CRM technology can increase students' confidence in their understanding of the technology, how it functions within organizations and inspire them to continue

Table 4 Examples of job titles, basic job functions, and facilitating technology extracted from Indeed.com for marketing-related positions

Position	Basic job function: critical domain knowledge and required skills	Example of facilitating technology
Customer insights analyst	Track and understand customer behavior: social network analysis; analyze brand strategy, evaluate customer behaviors, profile customers, and develop customer-centric marketing strategy	Tableau, NodeXL, Qualtrics, IBM Watson, Hadoop
Digital marketing consultant	Monitor, evaluate, and improve digital activity: conduct web and mobile marketing analytics; develop search engine optimization (SEO) and pay-per-click (PPC) strategy; analyze customer experience to improve engagement and interactivity; and convert data into a concise and meaningful format	Tableau, Google Analytics, Google AdWords, HTML, Adobe Experience Cloud
Marketing analyst	Identify questions, interpret data, and communicate business insights: understand machine learning, implement statistical analysis and predictive analytics, undertake competitive data analysis, and understand the systematic approach to problem solving	Tableau, SPSS, RapidMiner, R, DataRobot
Salesperson	Acquire and maintain customer and supplier relationships: identify and qualify sales prospects, maintain extensive contact with customers and suppliers, and collect and use market information to understand the needs of the customer	Tableau, Salesforce Einstein, Hoovers, Data.com

learning. Students that frequently use advanced CRM technology in an academic setting could subsequently witness career performance at a faster pace when entering the job market in comparison with others.

There has been a growing demand in the number of sales positions across all industries, and many marketing graduates are selecting to pursue careers in sales (Ahearne 2017; Carnevale et al. 2011). Unfortunately, sales education has been slow in responding to industry demands in teaching technology systems (Gray et al. 2012) such as CRM that are important for practitioners (Mallin et al. 2010). Technology-based marketing education courses (including CRM and internet marketing) have been taught in marketing curricula for over a decade now (Hannaford et al. 2005). However, the addition of advanced CRM analytics features is changing the ways that technology can be used and managed (Antonio 2018). In a qualitative in-depth interview with senior marketing managers, Harrigan and Hulbert (2011) found that CRM and data analytics seemed to be in short supply among marketing graduates. Duffy and Ney (2015) state a need to integrate digital technology systematically and purposefully into the marketing classroom. Although a few universities are offering courses or degree programs related to marketing analytics (Petrescu and Krishen 2017), there is room for substantial growth.

In an effort to parallel results in an academic setting, there are several considerations from marketing education research and the current study that warrant acknowledgement. The empirical results with sales practitioners presented earlier show that advanced features (e.g., automated recommendations, sentiment detection, and predictive analytics to analyze why the sale was won or lost) and frequency of CRM software use influence knowledge of the system, the need for additional training, and improve adaptive selling capabilities.

Our empirical results show how the increase in those features is leading to a desire for more training among sales practitioners with 56.1% of this study's survey respondents wanting additional formal training of CRM technology and skills for themselves (e.g., analytics). This is also placing pressure on marketing academics to prepare students for digital changes in market expectations and industry requirements (Duffy and Ney 2015). Marketing education research has raised the alarm for the need to develop students' capabilities of managing "big data" analytics (LeClair 2018; Erevelles et al. 2016; Wedel and Kannan 2016). Davis et al. (2002) found that alumni felt underprepared for technical software skills in a marketing context. Frederiksen (2015) noted that universities are not preparing students with key software skills sought by employers such as CRM, marketing automation, and content management systems. A majority of the current study's respondents (91.5%) (e.g., somewhat to strongly agree) also affirmed that college students should receive a higher level of exposure to technology and subsequent skills training. A national survey found that while marketing students felt they are gaining adequate exposure to key skills such as computer skills and analytic problem-solving skills, employers' feedback was that the new marketing graduates are underqualified (Hartley et al. 2018).

The use of CRM software in marketing and sales curriculum provides students with a skill set valued by employers, brings relevance to the curriculum, and enhances students' education to stimulate engagement (Wang et al. 2013). Due to the high demand for marketing analytics talent, Schlee and Karns (2017) found that the number of analytic and technology skills (such as dashboard design) listed in a job ad also has a significant relationship to the advertised salary. According to Michaels and Marshall (2002), the best way to effectively teach CRM systems is by simulating the system in a course, using a vendor package. In order to increase student comfort with advanced technologies, it's important to develop a variety of suitable educational resources and strategies.

There are many strategies to guide student learning, beyond the traditional lecture. Marketing faculty can enhance the learning process by supplementing their lectures with experiential analytics-related examples and cases (Mintu-Wimsatt and Lozada 2018). The goal of these experiential strategies is to develop students' skills while improving student engagement. Experiential learners drive their own learning as they practice using technology. They sometimes fail while using it, but they continuously and gradually learn how to tackle unfamiliar challenges. Students can build their skills through practice, formative assessment, and reflection (Rohm et al. 2018). Experiential learning improves critical thinking (Warren 1997), intellectual development (Granitz and Hugstad 2004; Hollenbeck et al. 2011; Neill and Etheridge 2008; Roach et al. 1993; Peterson 2001), and application of knowledge beyond the classroom (Smith and Van Doren 2004).

Results from workforce and education research indicate that hands-on experience in practice and education play an important role in skills development. Marketing education can combine the most effective methods of how students learn with results indicating the necessary skills needed to function as expected upon entry into the workforce and be successful. By learning to fuse techniques with prior concepts and reflecting on performance and instructor feedback, students can more successfully apply learned knowledge to real life, complex situations (Rohm et al. 2018). Research indicates that experiential learning has the potential to "spark curiosity and motivation" (Rohm et al. 2018, p. 3), enhance inquisitive behavior and equip students with necessary skills to perform important tasks when entering the workforce (Rohm et al. 2018). Moreover, students prefer experiential learning (e.g., hands-on technology projects) to methods of instruction limited to lectures and exams to achieve advanced learning outcomes (Ackerman and Hu 2011).

Learning by doing or hands-on learning in conjunction with the opportunity for reflection and analysis can make for a powerful knowledge building technique (e.g., Cummins et al. 2013; Healy et al. 2011; Knight et al. 2014). Experiential learning can be very effective in a computer-mediated classroom environment (Knight et al. 2014). In fact, Knight et al. (2014) found that experiential learning had a positive impact on sales knowledge among university students. There is a similar connection to behavior in practice since based upon results of the current study, salespeople with higher levels of experience or use with CRM technology feel more confident in their knowledge of CRM technology but also feel they could benefit through additional training. Furthermore, increased use of CRM technology and perceived knowledge of the system improved the salesperson's adaptive selling capability. This is an important finding since adaptive selling capabilities have been known to increase salesperson's performance and induce customer satisfaction toward the product and salesperson (Román and Iacobucci 2010). Thus, we build upon the results of our study among sales practitioners to present an in-depth, experiential learning approach to CRM technology to address the current skills gap. This proposed three phases CRM experiential learning approach can be introduced to sales/marketing students in a senior-level course:

Phase 1 The objective of phase 1 (runs from Week 2 to 4) is to introduce students to the fundamentals of analytics in a sales practice. Students are introduced to analytics techniques, processes, and concepts in an active-learning environment within a computer lab using IBM Watson Analytics on the cloud access. The students are presented with sales wins and losses dataset from the IBM Community (IBM Community 2018). Using the dataset the students will learn how to run a predictive model to identify what leads to wins and what leads to losses in a sales process. This active-learning case approach engages students in the application of the analytics techniques, processes, and concepts while learning the sales process.

Phase 2 The objective of phase 2 (runs from Week 4 to Week 8) is to allow students to experience a CRM sales training mirroring how salespeople in a real business setting are learning. Students have access to a computer lab with Salesforce on the cloud using the Salesforce Academic Alliance (Salesforce Academic Alliance 2018), the Trailhead portal (TrailHead 2018) and a preloaded curriculum dataset. The focus in this step is to introduce students to different CRM sales processes on how to access customer information, document new interactions, review leads, and decide on the best strategy to approach the customer. Students will be able to make use of actual lead and interaction transactions provided by the CRM system, which provides a good sense of what a CRM sales person would experience in the workplace. The students here are building their knowledge with the system processes and sales processes in an engaged and active-learning environment. Corporate sales training is normally delivered through on-the-job training, sales online

training, and formal classes. The students will have access to online training and in-class formal training sessions to simulate a real-work environment.

Phase 3 The objective of phase 3 (runs from Week 9 to Week 13) is to give the students the opportunity to interact with advanced analytics features in the CRM system as they work in teams. In this phase, optional advanced analytics feature training is made available for students. It is our expectation from prior research on experiential learning and the current empirical study that the higher the variety of the advanced features introduced, the higher the desire for training.

Students in-class will be assigned into one of two groups: customers or sales teams. The sales team will identify potential customers for a product of their choice based on customer demographic information assigned by the instructor. Students will apply the analytics capabilities in the CRM system to visualize and validate the sales approach with their current customers using automated insights. Advanced machine learning tools can also be utilized, for example based on hypothetical home addresses the professor has assigned to the customer groups. The sales students can run an image recognition machine learning algorithm available in the CRM system to decide if they should send a customer an offer for solar panels. Solar panels typically require flatter roofs, the machine learning algorithm using satellite images can classify the rooftop of a house for a given address to identify the pitch and size of the roof. Based on the machine learning algorithm results, the students will decide if the customer should receive a cold call and a special offer for a solar roof. The students in the customer group are responding to the sales personnel-targeted messages and deciding whether to buy or not buy the product offered to them based on their needs and demographics as assigned by their instructor. The sales and customer teams switch roles and repeat the process. This approach enables learning by generating a dynamic environment and allowing students to focus on analytics and decision making; giving them an opportunity to translate their sales approaches into actionable insights using a CRM system and its advanced analytics features.

The purpose of this learning approach is to provide students with a sense of a real-world CRM sales training. Students can develop an understanding of technology by applying best sales practices and linking them to a results-driven approach in a 13-week period. This simulation is likely to lead to a better understanding of adaptive selling behavior, and most importantly it will help students achieve good employment opportunities given the high demand for these skills.

As the role of marketers within an organization is evolving (Ferrell et al. 2015) to incorporate more quantitative and technological skills (Grewal et al. 2015; Harrigan and Hulbert 2011), academia must understand how to integrate these areas with discipline knowledge (Hair et al. 2018a). Marketing education has an existing advantage in that the unique factor that distinguishes marketers from pure quantitatively focused analysts is marketers' training in translating information into actionable marketing insights. Business students who are able to bridge the gap between business needs and technology offerings are highly desirable in the current analytic environment (Henke et al. 2018). Due to continued investment in CRM technology and its pervasive use throughout many organizations, exposures to the most current, evolving features and application of CRM technology and accompanying analytic skills are crucial for college students to acquire, which are even found to be associated with higher wages (Schlee and Karns 2017). Furthermore, recruiters indicate that students' technical fluency to solve marketing problems and the attainment of personal selling skills were highly valuable competencies (Steenkamp 2018; Hopkins et al. 2011).

Instructors need to act cautiously when introducing complex technology or advanced skills. Technology has the potential to overwhelm students and reduce engagement. However, when students grasp the association between classroom experiences and practical marketing situations in business environments, they are likely to become engrossed in their education (D'Aloisio 2006; Buzzard et al. 2011). Thus, instructors should emphasize the strategic value of becoming adept at both functional knowledge and technological fluency.

Limitations and future research

As a result of wanting to align marketing curriculum with skills that are beneficial in practice, data for this study were collected from experienced salespeople. As such, it does not assess outcomes of technology learning that occurred inside the marketing classroom. It would be advantageous for future research to examine the impact of experiential learning assignments as they are introduced during the semester and how students augment this knowledge in other courses.

In addition, quantitative proficiency is critically important for marketing graduates, as evidenced by the significance recruiters are placing on such skills (Steenkamp 2018). As CRM technology is being enhanced through greater AI and machine learning technologies, insights into the appropriate level of quantitative skills training and other technology solutions that correspond with marketing roles are needed. Future research could compare outcomes for professionals early in their career that had experience through experiential learning assignments to those students with no hands-on training to examine the potential benefits of CRM technology exposure. Longitudinal research designs that follow

students into their first year of employment can determine if exposure to technology and analytic skill acquisition provided graduates with a competitive advantage and removed barriers to employment.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there are no conflicts of interest to disclose.

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Dana E. Harrison has over 10 years of experience in the technology industry and is currently an Assistant Professor of Marketing at East Tennessee State University. She teaches undergraduate and graduate level courses focused on marketing analytics, research and strategy. She is leading the development of a marketing analytics undergraduate concentration at her university. She co-developed a Marketing Analytics certificate offered at the Academy of Marketing Science Conference. She has also consulted with other universities on the development of marketing analytics courses and programs and is currently involved with several academic and corporate research projects in the area of advanced marketing analytics. She is a co-author on the 5th edition of Essentials of Marketing Research, McGraw-Hill and 1st edition of Essentials of Marketing Analytics, McGraw-Hill. Her research has appeared in leading journals including Journal of Business Research, Journal of Marketing Channels, and Journal of Product and Brand Management.

Haya Ajjan is Associate Professor of Management Information Systems, and teaches data analytics and information systems courses in Elon's undergraduate business and MBA programs. She started the Center for Organizational Analytics at Elon University and has been instrumental in developing the undergraduate and graduate curriculum for Business Analytics at Elon. She is involved in several analytics consulting and corporate research projects involving data mining, text mining, and visualization. Her research has appeared in journals such as European Journal of Operations Research, Journal of Business Research, Journal of Marketing Theory and Practice, and Journal of Enterprise Information Management. She is a co-author on the 1st edition of Essentials of Marketing Analytics, McGraw-Hill.