

Extension of Information Technology in Increasing Marketing Products

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Abstract

The purpose of this study is to examine the predictive power of the technology acceptance model (TAM) on customer's intention to participate in the social customer relationship management (sCRM) program. Three additional constructs, perceived risk, user satisfaction, and perceived enjoyment were added to the original TAM. The collected data ($n=264$) were subject to statistical analysis of structural equation modeling, exploratory and confirmatory factor analysis. The study reveals that TAM by itself is not a robust model to predict customer's intention to participate in the sCRM program. Among the original constructs of TAM, attitude is the only determinant of intention. The impact of perceived usefulness and perceived ease of use was not significant on intention. Among the extended variables, perceived risk is the only variable that significantly influenced intention; perceived enjoyment and user satisfaction did not have any impact on intention. By applying the TAM to the sCRM, this study extends the overall body of the theoretical knowledge surrounding technology acceptance.

1. Introduction

The goal of every enterprise is to acquire, retain, and increase the number of customers. Until the 1980s, most enterprises focused their marketing strategies on acquiring and retaining customers by developing an efficient marketing mix of the four Ps (product, price, place, and promotion). Generalized marketing messages were sent to all potential customers through mass media. In the early 1990s, companies started to realize the need for customized messages and the importance of customer retention. Therefore, companies began shifting their focus from acquisition of new customers to maintenance, enhancement, and retention of existing customers through numerous strategies and tactics called Customer Relationship Management (CRM) (Baran et al., 2008). CRM is an emerging concept and it is a kind of e-business strategy that empowers the organization to better manage relationships with their customers using social technologies (Chen & Vargo, 2014). The underlying premise of CRM is that firms create customer knowledge in order to (1) effectively segment customers, (2) develop and maintain long-term relationships with profitable customers, (3) determine how to handle unprofitable customers, and (4) customize market offerings and promotional efforts (Sirivastava, Shervani, & Fahey, 1999). A CRM strategy aims to create a comprehensive customer-centric strategy that contributes to durable relationships with customers and makes a profit for owners (Soltani & Navimipour, 2016).

The paradigm shift from focusing on attracting new customers to retaining current ones is at the backbone of CRM (Winer, 2001). Studies revealed that small increases in customer retention rates greatly increased profits, proving that long term customers can be more valuable and more revenue on average is generated from repeat-purchase customers when compared to one-time buyers (Reichheld, 1996). Company must focus on building unique, one

to one relationships with customers based on individual needs and wants; thus, implementing customer relationship management is critical to the growth and future success of firms. The better relationships the company has with the customer, the more opportunities it will avail to learn about the customer's behavior.

The growth of social media technology has considerably changed relationships between companies and their customers (Harrigan, Soutar, Choudhury, & Lowe, 2015). The mixing of social media technology inside a CRM strategy is a rising circumstance, leading to an innovative efficient model which can be explained as social CRM (Harrigan & Miles, 2014). Social CRM is the process of converting content into conversations, extending those conversations into collaborative experiences, and then transforming those experiences into meaningful relationships (Walsh, 2010). Even though CRM stands for customer relationship management, in the social CRM environment, the company no longer controls the relationship; the control has shifted to the customer. Social CRM puts the customer at the core of the company's strategy. The basic premise of social CRM is that the firm is able to interact with its customers based on customers' needs, not the firm's predefined rules, thus opening the door to a permission-based dialogue between a firm and its current and potential customers. Therefore, social CRM is a dialogue-based marketing solution supported by information system tools that help firms not only to sell but also to know what happens in customers' minds, why customers are dissatisfied, why customers like a firm's products, what problems customers have, and how firms can make customers satisfied again (Bago, 2011). Social CRM creates a two-way interaction between parties and gives customers ownership over the conversation with the firm (Shimp, 2010; Greenberg, 2009).

2. Gaps in Research

The usage of CRM continues to grow in the industry at an astounding rate. Since 2011 each year around 70% of businesses have stated they plan to increase spending on CRM in a consistent basis (CosmosCRM, 2016). According to market research firm Gartner, worldwide CRM implementation totaled \$23.2 billion in 2014, up 13.3 percent from 20.4 billion in 2013; the CRM usage increased from 56% to 74% in 2015 (Gartner, 2015). Forecasts from Gartner anticipate that the CRM market will be worth \$36.4 billion worldwide by 2017 (CosmosCRM, 2016). Despite the consistent growth and continuous investment on CRM implementation at a staggering rate, little research has been undertaken to explore the behavioral aspect of consumers in the CRM domain.

The CRM implementation success rate is disappointing. CRM initiatives currently have a 63% fail rate and 53% of this failure is primarily due to the lack of clear understanding of customer insight (Direct Marketing News, 2013). Between 25% and 60% of CRM projects fail to meet expectations in the last decade (CosmosCRM, 2016). One of the requirements of CRM success is to make the marketing strategy customer-centric. Most companies fail to achieve their desired benefits of CRM because of the failure to put the customers in the center of their marketing strategy. Companies are developing product-centric strategy without conducting adequate customer-centric research.

The technology acceptance model (TAM) has been applied in a variety of studies testing user acceptance of information technology that includes green IT (Yoon, 2018), mobile app (McLean, 2018), digital library (Xu & Du, 2018), Social media usage (Hansen, Saridakis, & Benson, 2018), Virtual learning (Belletier, Robert, Motak, & Izaute, 2018), work processing (Davis et al., 1989), spreadsheet application (Mathieson, 1991), web browser (Dillon & Morris, 1996), telemedicine (Hu et al., 1999), e-mail (Szajna, 1996), wallet phone (Swilley,

2010), blackboard (Landry, Griffeth, & Harthman, 2006), m-commerce (Snowden et al., 2006), communication technologies (Zaremohzzabieth et al., 2015), online purchase (Chiu et al., 2005), e-collaboration (Dasgupta, Granger & McGarry, 2002), and websites (Koufaris, 2002). Since social CRM is relatively a newer field of study, TAM has not been examined in this new domain of social CRM. Therefore, the predictive power of TAM is still unknown in social CRM. This study will fulfil this research gap.

Although numerous studies have been undertaken on CRM, little effort has been made to explore the customers' intention to participate in the social CRM program. The majority of CRM research studies focuses on the organizational and management-related factors to explore the causes of high failure in CRM implementation. Therefore, customer behavior remains an under-focused area for marketing researchers in the CRM world. As customer participation is one of the key factors for social CRM success, it is imperative for marketers to identify what factors influence customers' decision to participate in social CRM programs.

3. Purpose of the Study

Customer participation is a prerequisite for the success of any IT application and CRM is not an exception. Previous research studies found that user acceptance of CRM is an essential factor for its success (Corner & Rogers, 2005; Wu & Wu, 2005). In a controlled environment, customer's intention is the immediate and direct antecedent of behavior. Although extant literature provides helpful insight into the company's point of view, researchers have shown little concern about the potential gap between CRM activities and customer's willingness to participate in the CRM program (Kim, Park, Dubinsky, & Cha, 2012). The majority of the existing CRM research has focused only on the company side of CRM implementation (Jallat & Ancarani, 2008). Therefore, marketing academicians have overlooked customer's perceptions towards participating the CRM program. To fill this gap, this study attempts to investigate the factors that influence customer's intention to participate in the social CRM program. One of the most widely used models to predict consumer technology acceptance is the TAM and it has been considered the most validated model for explaining the acceptance of IT and information systems in recent decades (Lu, Yu, Liu, & Yao, 2003). The main reason for its popularity is its parsimony and the empirical support for it (Agarwal & Prasad, 1997; Adams et al., 1992). Therefore, the objective of this study is to examine the predictive power of the TAM on customer's intention to participate in the social CRM program. In order to achieve this goal, this study will investigate the factors that influence the customer's intention to participate in the social CRM program by employing the TAM as the research framework. This will help increase the current understanding of customer's acceptance of social CRM.

4. Research Model

TAM is an intention-based model derived from the Theory of Reasoned Action (TRA) but tailored to meet the broad needs of information technology research (Davis et al., 1989). It was introduced by Davis (1989) to explain an end-user's computer acceptance using a parsimonious and theoretically justified model. TAM proposes that an attitude towards technology acceptance and subsequent use is comprised of the belief component (usefulness) and perception that the belief is attainable with the targeted behavior (ease of use) (Davis, Bagozzi, & Warshaw, 1989). Previous research has continuously reported that the TAM was very useful in predicting and explaining technology use in various situations (Dillon & Morris, 1996).

TAM has evolved in the last two decades, and many researchers have developed new models by adding variables to the TAM in order to increase its explanatory power. Davis (1989) also

argued that research should explore other variables that could affect perceived usefulness, perceived ease of use, and actual usage. Dishaw and Strong (1999) noted that one of the weaknesses of the TAM is its lack of explicit inclusion of external variables. As an extension of the TAM, Dishaw and Strong (1999) added new variables that include the relation between task-technology fit to the existing TAM and their new extended TAM model explained the variance of the dependent variable better than the original TAM. In a study to explain the participants' usage behavior on the World Wide Web, Moon and Kim (2001) added a new variable "perceived playfulness" to the existing TAM. In another study of bulletin board systems, Mathieson and Chin (2001) developed a new model by adding the variable of "perceived user resources" to TAM. In testing consumers' intention to adopt e-commerce, Pavlou (2002) developed a new model by incorporating two additional factors: trust and perceived risk. Similarly, numerous extended variables with specific contexts have been added to TAM: Teo, Lim, and Lai (1999) introduced the variable "perceived enjoyment" in a study of Internet usage, and Luo and Strong (2000) proposed the variable "perceived critical mass" in their study of groupware usage. Recent important additions to the TAM include the constructs of "perceived risks," "perceived enjoyment," "internet usage," and "previous online shopping experience" (Jarvenpaa & Todd, 1997; Bhatnagar, Misra, & Rao, 2000; Childers et al., 2001; Park & Jun, 2003).

In addition to TAM's original variables, attitude, perceived usefulness, perceived ease of use, and intention, current study added three new variables, perceived risk, perceived enjoyment, and user satisfaction in order to predict the participants' intention to participate in social CRM. The reasons that these constructs were picked will be explained in the next section.

5. Hypothesis Development

Based on the theoretical model of TAM with three additional variables, this study develops a research model (Figure 1) and proposes the following constructs and corresponding hypotheses with regard to intention to participate in the social CRM program.

5.1 Attitude Towards Participating in Social CRM (ATCRM)

Attitude has been one of the central concepts for research in psychology and behavioral science for many years. Fishbein and Ajzen (1975) defined attitude as "a person's favorable or unfavorable evaluation of an object." Attitude has long been identified as a cause of intention (June, Chun-Seng, Chang, & James, 2003). A positive relationship between attitude and usage intention has been supported in a variety of research contexts (Sheppard et al., 1988; Yousafzai, Foxall, & Pallister, 2007). Taylor and Todd (1995) found attitudes to be predictive of the intention to use IT. In a research study on e-commerce, Pavlou (2002) found that the consumer's attitude towards using online services is a predictor of the consumer's behavioral intention. The relationship between attitude and intention in a technology-based context has also been confirmed by Shin (2007). This current research study defines ATCRM as the degree of an individual's positive or negative feelings about participating in social CRM. Users who participate in social networking sites can develop effective ties with other participants (Gruen et al., 2006). These relationships may have a positive impact on participants' intention to engage in social CRM programs. Similarly, negative comments from other users in the social media may have negative influence on participants' intention to engage in social CRM programs. Since attitude has previously been identified as a cause of intention (June, Chun-Seng, Chang, & James, 2003), this study constructed the following hypothesis.

H1: Attitude towards social CRM significantly affects the intention to engage in social CRM programs.

5.2 Perceived Usefulness (PU)

Davis (1989) defined PU as the “degree to which a person believes that using a particular system would enhance his or her job performance.” The TAM’s PU was based on previous motivation, expectancy theory, and information systems research performed by Askool and Nakata (2010); Choudhury and Harrigan (2014). Prior studies have documented the importance of PU in information system adoption (Chiu, Lin, & Tang, 2005; Cheong & Park, 2005; Pikkarainen, Pikkarainen, Karjaluoto, & Pahlila, 2004). Chiu et al. (2005) found that PU positively influences online purchase intentions. The result of this study indicates that consumers are likely to consider the online purchase when they find online environment is useful for making purchases. Pikkarainen et al. (2004) found that PU was positively correlated with online banking use. The current research study defines PU as the degree to which a person believes that participating in the social CRM would increase his or her satisfaction as a customer.

There has been wide support for the hypothesis that PU positively relates to computer and technology adoption research. Thus, this study incorporated the following two hypotheses with regard to PU of social CRM programs.

H2a: Perceived usefulness positively affects intention to engage in social CRM programs.

H2b: Perceived usefulness positively affects attitude towards social network.

5.3 Perceived Ease of Use (PEU)

PEU is defined as the degree to which an individual believes that using a particular system would be free of physical and mental effort (Davis, 1989). Adams, Nelson, and Todd (1992) found that system usage relied on both PU and PEU determinants. The easier a technology is to interact with, the greater should be the user’s sense of efficacy; efficacy is thought to operate autonomously from instrumental determinants of behavior (Chung, 2005). The current research study defines PEU as the degree to which a person believes that participating the social CRM would be free of effort. Empirical studies in applying the TAM have verified that PEU has a strong effect on user acceptance of an application (Askool and Nakata, 2010; Harrigan and Choudhury, 2014; Ramayah, 2006). Therefore, this study incorporated the following hypothesis with regard to PEU of social CRM programs.

H3a: Perceived ease of use positively affects attitude towards social network.

H3b: Perceived ease of use positively affects perceived usefulness.

5.4 Perceived Enjoyment (PE)

Enjoyment is a major factor that drives users to use a new technology (Bruner & Kumar, 2005; Davis, Bagozzi, & Warshaw, 1992). When someone enjoys spending time with any technology or software or application, it is obvious that the person’s intention to participate in or use the technology will be high. Individuals engage in activities because these activities lead to enjoyment and pleasure (Teo & Lim, 1997). PE is defined as the extent to which the activity of using a technology is perceived to be enjoyable in its own right, aside from any performance consequences resulting from technology use (Venkatesh, 2000). PE as an intrinsic motivation has been found to have a significant impact on a user’s technology acceptance, especially for hedonic systems (Davis, Bagozzi, & Warshaw, 1992); Teo et al.,

1999; Igbaria, Iivari, & Maragahh, 1995; Pikkarainen et al., 2004; Davis, Bagozzi, & Warshaw, 1992; Nysveen, Pedersen, & Thorbjørnsen, 2005; Amin, Baba, & Muhammad, 2007). Teo et al. (1999) found that PE has a positive effect on frequency of Internet usage because of the fun, excitement, flexibility, and pleasure associated with it. Nysveen et al. (2005) reported a strong correlation between PE and usage intention of mobile chatting. The current research study defines PE as the extent to which spending time in social media is perceived enjoyable. This study incorporated the following hypothesis about PE.

H4: Perceived enjoyment positively affects intention to engage in social CRM programs.

5.5 User Satisfaction (US)

US is a widely studied construct as a predictor for future system usage of similar products. Satisfaction can be defined as the degree to which the user of the system believes the system performs satisfactorily for its intended use (Seddon, 1997). Homberg et al. (2002) defined customer satisfaction as positive disconfirmation of expectations, which means that perceived performance is equal to or better than the expected outcome. According to the expectation-confirmation theory (Oliver, 1980), a customer has expectations of a good or service prior to its consumption. If any good or service meets the customer's expectation, it can be expected that

previous usage experience and satisfaction will have a positive impact on the customer's intention for future purchases. In the current research study, US with social media was measured to examine the effect on the user's intention to participate in social CRM programs. Prior research has suggested that satisfaction plays an important role in affecting customers' decisions regarding the purchase of goods and services (Yi, 1989). Therefore, this study incorporated the following hypothesis with regard to US.

H5: User satisfaction positively affects intention to engage in social CRM programs.

5.6 Perceived Risk (PR)

PR has been studied in the field of marketing for almost half a century, and researchers have found this construct as an essential element of consumer behavior. Perception of risk is a pivotal aspect of consumer behavior because it often produces anxiety that consumers must deal with (Taylor, 1974). PR refers to the degree to which psychological risks are attributed to a product (Gatignon & Robertson, 1985; Herbig & Day, 1992). PR is the expected negative utility associated with the purchase of a particular product or brand (Dunn, Murphy, & Skelly, 1986). The current research study defines PR as the degree to which a person believes the potential threat of losing his or her personal and financial data associated with participating a social CRM program. Previous studies have suggested that PR is an important factor for consumer technology usage. For example, studies found a negative relationship between PR and intention to shop online (Bhatnagar et al., 2000; Park, Lennon, & Stoel, 2005). A similar relationship was found in online auctions (Pavlou & Gefen, 2004), Internet banking (Kim & Prabhakar, 2000), and online shopping (Bhatnagar et al., 2000; Forsythe & Shi, 2003). Therefore, this study incorporated the following hypothesis with regard to PR

H6: Perceived risk negatively affects intention to engage in social CRM programs.

5.7 Intention to Participate in Social CRM (INT)

Behavioral intentions can be defined as an individual's anticipated or planned future behavior (Swan, 1981). When the person has complete control over the behavior in question and when the behavior is completely voluntary, intentions alone should adequately predict behavior

(Ajzen & Fishbein, 1980). In other words, intention can be assumed to be the immediate antecedent of behavior. Results of numerous studies have supported the notion that behavioral intentions affect behavior positively (Hung et al., 2003; Tung, 2004; Nysveen et al., 2005). The current research study defines intention to engage in social CRM as the probability that an individual will participate in the social CRM program. In the current research model, intention to engage in social CRM was considered a dependent variable.

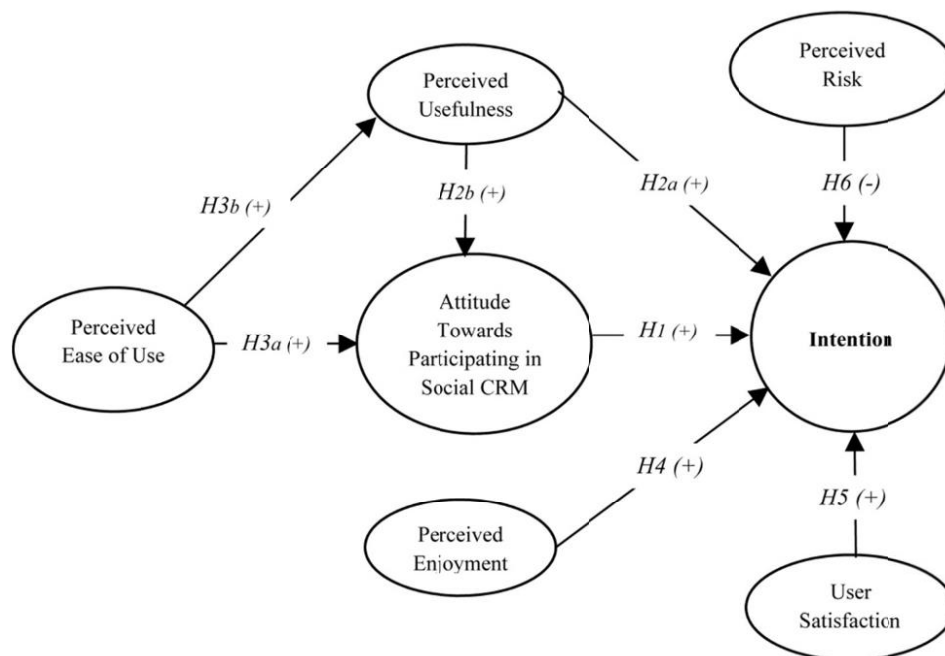


Figure 1. Research model

6. Research Methodology

6.1 Instrument Development

This research study utilized a survey instrument that featured closed-ended questions. The scales adapted in this survey instrument have been used in previous TAM related researches (e.g., Pan, 2003; Siegel, 2008) and have been modified to fit in the current study in the social CRM context. The demographic questions included gender, age, income, ethnic background, educational background, preferred social networking site, and social media usage. All items were measured on a 7-point Likert-type scale.

6.2 Data Collection

The participants of this study were the adults living in USA who were active in social media. Data for this study were collected from January to March 2018 through a self-administered web-based survey instrument using Qualtrics using multiple sources. The survey link was posted in numerous online forums for students, researchers, social community groups, professional forums, general discussion forums, question-and-answer forums, blogs, and social networking sites such as Facebook, Twitter, and Google+. Additionally, an e-mail message with a link to the web survey was distributed to potential participants.

6.3 Pilot Study

A pilot study that included 30 participants was conducted for two weeks. The feedback from the participants of the pilot study helped the researcher make changes to the questionnaire so that the final participants could understand and reply to all questions without difficulty.

6.4 Demographic Profile

There were 921 people participated in this study; only 305 of them successfully completed the survey. Out of 305 participants, 155 (51%) were female and 150 (49%) were male. The largest (50.2%) age group was in 19-30 years old, followed by the group of 31-40 years old with 25.9%. Thirty seven percent of the participants has master's degree, 25% has bachelor's degree, and 14% has doctoral degree. This distribution demonstrates that the majority of the participants (76%) are educated, holding bachelor's degree or higher. Approximately, 22% of the participants has annual income less than \$40,000, 12.8% has income between \$40,000 and \$60,000, and 12% earns more than \$80,000. The largest segment (59%) of the participants is Caucasian, followed by Asian (22%). The most popular social media site is Facebook, followed by LinkedIn, Twitter, and Google Plus. Majority of them use more than three sites, accounting for one-third of the total participants, 90% use Facebook, 57% use LinkedIn, 44% use Twitter, and 41% use Google Plus.

6.5 Data Screening

The assumptions for factor analysis are the existence of linear relationships, the absence of outliers, the lack of high multicollinearity, and the presence of multivariate normality. Before proceeding with the data analysis, all variables were screened for possible code and statistical assumption violations. Additionally, data were screened for finding missing values and outliers using SPSS frequencies, explore, plot, and regression procedures.

6.5.1 Linearity

The result of the linearity test through examining scatterplots and R^2 linear value shows that all R^2 linear values are between 0.022 and 0.418. This result demonstrates the existence of linear relationships in the sample data.

6.5.2 Outliers

Univariate outliers were examined by computing the standardized scores (z) of each variable. Hair et al. (1998, p. 99) recommended considering cases with z scores exceeding ± 2.5 to be outliers and thus deleting them. In this study, outliers exceeding this recommended value of ± 2.5 were deleted. Multivariate outliers were examined by computing the Mahalanobis distance. Cases with a Mahalanobis distance of more than 22.46 ($p < .001$) were considered multivariate outliers and deleted from the dataset. By following the guidelines of univariate and multivariate outliers, 41 cases were removed as outliers. After removing these data as outliers, the final count for data analysis was 264.

6.5.3 Multicollinearity

In order to examine the multicollinearity in the data, a series of multiple regressions were conducted. In this series of tests, each independent variable was treated as a dependent variable, and all other remaining independent variables were considered independent variables. A tolerance value less than .10 or a variance inflation factor (VIF) above 10 indicates high collinearity (Hair et al., 1998, p. 746). The result of the multicollinearity test shows that all the tolerance values are between .679 and .986 and the VIF values are

between 1.014 and 1.444. Thus, the values of tolerance and the VIF values are within the acceptable limits. This result demonstrates that the sample data do not have the presence of high multicollinearity.

6.5.4 Normality

The distribution of the data was examined using skewness and kurtosis for confirming the normality. The skewness and kurtosis values of all variables used in this study were within ± 2 . The results of all of these tests confirmed the normality distribution of the dataset.

Although the constructs of this study were adapted from previous studies with acceptable validity and reliability, the validity and reliability of those constructs were retested in this study. In order to verify how closely the survey measurements met the objectives of this study, a reliability test was performed to test the proposed model. Construct validity was established in this study by proving the measures provide reliability, content validity, convergent validity, unidimensionality, and discriminant validity.

6.5.5 Reliability

A measure to test how well a set of constructs measures an underlying construct, Cronbach's alpha is widely used to measure the reliability of the constructs. Therefore, Cronbach's alpha was employed for testing the consistency between multiple measurements of the research variables of the current study. A Cronbach's alpha value of 0.70 or more is generally considered to be acceptable reliability (Creswell & Miller, 2000; Chau, 2001; Wu, Chang, & Guo, 2008). In this study, internal consistency of the construct ranged from .702 for US to .915 for ATCRM. These values for Cronbach's alpha are a significant indication of high reliability. Reliability coefficients are presented in Table 1.

Table 1. Reliability coefficients

Variable	Cronbach's Alpha
Perceived Usefulness (PU)	0.915
Attitude Towards Participating in Social CRM (ATCRM)	0.844
Perceived Ease of Use (PEU)	0.810
Intention (INT)	0.849
Perceived Enjoyment (PE)	0.762
User Satisfaction (US)	0.702
Perceived Risk (PR)	0.780

6.5.6 Discriminant Validity

The square root of average variance extracted (AVE) for each variable should be higher than the values of all correlated variables to meet the requirement of discriminant validity. As illustrated in Table 2, all variables meet this condition. Similarly, for all variables, AVE is higher than maximum shared variance (MSV) and average shared variance (ASV). All constructs meet the minimum threshold of discriminant validity.

6.5.7 Convergent Validity

Convergent validity is the extent to which a measure correlates highly with other measures designed to measure the same construct. Having acceptable construct validity means that each construct actually measures what it originally intended to measure (Churchill, 1979). Evidence of convergent validity can be found by checking the AVE of each construct. Fornell and Larcker (1981) suggested that the AVE value for a construct should be minimum 0.50. As the statistics show in Table 2, the AVE values for all constructs exceed 0.5, which confirm the convergent validity. The CRs of all constructs meet the minimum requirement of 0.70 to establish the reliability of the constructs.

There is an alternative way of measuring validity and reliability in addition to the previously discussed methods. This method utilizes composite reliability (CR), AVE, MSV, and ASV to calculate discriminant validity, convergent validity, and reliability. The advantage of this method is all aforementioned validity and reliability measures can be determined by viewing the results of a single table. Table 2 shows the calculated values of CR, AVE, MSV, ASV, and the squared root of the AVE for all variables (shown in bold). Here are the threshold values for validity and reliability: for reliability: $CR > 0.7$; for convergent validity: $CR > AVE$ and $AVE > 0.5$; for discriminant validity: $MSV < AVE$ and $ASV < AVE$. This alternative method also confirms the validity and reliability of the constructs used in this study.

Table 2. Calculation of validity and reliability

	CR	AVE	MSV	ASV	PEU	PU	INT	ATCRM	PR
PEU	0.800	0.572	0.284	0.147	0.756				
PU	0.916	0.645	0.454	0.242	0.533	0.803			
INT	0.875	0.590	0.454	0.211	0.393	0.674	0.768		
ATCRM	0.837	0.569	0.213	0.125	0.387	0.462	0.355	0.754	
PR	0.813	0.593	0.111	0.035	-0.033	-0.129	-0.333	-0.109	0.770

Note. CR = Composite Reliability; AVE = Average Variable Extracted; MSV = Maximum Shared Variance; ASV = Average Shared Variance.

6.6 Data Analysis

This research study utilized quantitative data analysis methodologies to test its hypotheses. The efficacy of the research model was analyzed using SPSS (v 21), and Analysis of Moment Structures (AMOS) (v 20). Data analysis was conducted in multiple phases. In the initial phase, demographic analysis was conducted to investigate the demographics of the participants. In the second phase, data screening was performed. In the third phase, exploratory factor analysis (EFA), was performed to identify the number of factors to extract for the research model. EFA also helped detect the variables that were not suitable for the model. In the fourth phase, structural equation modeling (SEM) was conducted, which was the combination of confirmatory factor analysis (CFA) and path analysis. In this phase, CFA was performed to determine whether the measured variables reliably derived from the EFA reflected the hypothesized latent variables. The path analysis was conducted to finalize the structural model derived from the CFA. All hypotheses were tested in this phase. Finally, in the fifth phase, reliability and validity testing were conducted. The reliability test was

performed to verify how closely the survey measurements met the objectives of this study, and the validity test was performed to measure the degree to which the measurement instruments truly measure the constructs they intended to measure.

6.6.1 Exploratory Factor Analysis (EFA)

EFA with varimax rotation and maximum likelihood analysis factoring method was performed in order to obtain the optimum model structure, and the result was compared with that of the principal component analysis. Both results demonstrated similar findings. The process of removing items and performing the factor extraction was repetitive in nature and was done until a desired factor structure was achieved.

In the final round of EFA, PE and US constructs were dropped because of the low factor loading and Kaiser-Guttman retention criteria of eigenvalues less than 1.0, thus these two constructs have been excluded from subsequent data analysis. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.890, indicating that the present data were suitable for principal component analysis. Similarly, Bartlett's test of sphericity was significant ($p < .001$), indicating sufficient correlation between the variables to proceed with the analysis. Using the Kaiser-Guttman retention criteria of eigenvalues greater than 1.0, a five-factor solution provided the clearest extraction. These five factors accounted for 66.288% of the total variance. Table 3 presents the factor loading of all constructs.

Factor 1, PU (eigenvalue = 8.407) accounted for 33.628% of the variance and had six items; Factor 2, INT (eigenvalue = 2.792) accounted for 11.168% of the variance and had four items; Factor 3, ATCRM (eigenvalue = 2.227) accounted for 8.909% of the variance and had four items; Factor 4, PEU (eigenvalue = 1.777) accounted for 7.110% of the variance and had four items; and Factor 5, PR (eigenvalue = 1.368) accounted for 5.473% of the variance and had three items.

Table 3. Factor loading

Constructs and Scale Items	Factor Loading				
	PU	INT	ATCRM	PEU	PR
Perceived Usefulness (PU)					
PU4: Participating in the social CRM program would allow me to compare several purchasing options and choose the best one.	.894				
PU3: Participating in the social CRM program would be more rewarding than a non-CRM environment.	.877				
PU2: Participating in the social CRM program would increase my customer satisfaction.	.827				
PU5: Participating in the social CRM program would enable me to save time.	.797				
PU6: Participating in the social CRM program would allow me to save money.	.689				
PU1: I think participating in the social CRM program is useful.	.668				

Intention of Participate in Social CRM (INT)	
INT3: I am willing to update my profile (personal information) whenever requested.	.962
INT2: I am willing to provide personal information (e.g., name, age, address, phone number, interests, and hobbies) when registering for the social CRM program.	.866
INT1: I am willing to participate in the registration for the social CRM program.	.552
INT5: If requested, I am willing to allow a firm's representative to participate in the conversation with my social friends about its products and services.	.493
INT4: I am willing to provide feedback on products and services if requested by a firm's representative.	.475
Attitude Towards Participating in Social CRM (ATCRM)	
ATCRM4: I like the idea of participating in the social CRM program.	.866
ATCRM 1: Participating in the social CRM program would be a good idea.	.837
ATCRM 3: Participating in the social CRM program would be a wise idea.	.747
ATCRM 2: Participating in the social CRM program would be a pleasant experience.	.620
Perceived Ease of Use (PEU)	
PEU1: Learning how to participate in the social CRM program would be easy for me.	.862
PEU2: Participating in the social CRM program would be easy for me.	.779
PEU3: I would find the Social Networking sites easy to use for participating in the social CRM program.	.655
Perceived Risk (PR)	
PR1: I am worried that my financial information could be stolen.	.815
PR2: I am worried that my personal information collected could be misused.	.750
PR3: The security systems built into the social CRM program would not be strong enough to protect my privacy.	.698

As Hair et al. (1998, p. 797) suggested, items exhibiting low factor loading ($<.40$), high cross-loading ($>.40$), or low commonalities ($<.50$) have been deleted. After removing the items that do not contain these minimum required values, EFA was performed again on the remaining items. Additionally, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were performed to test the adequacy of the distribution of the

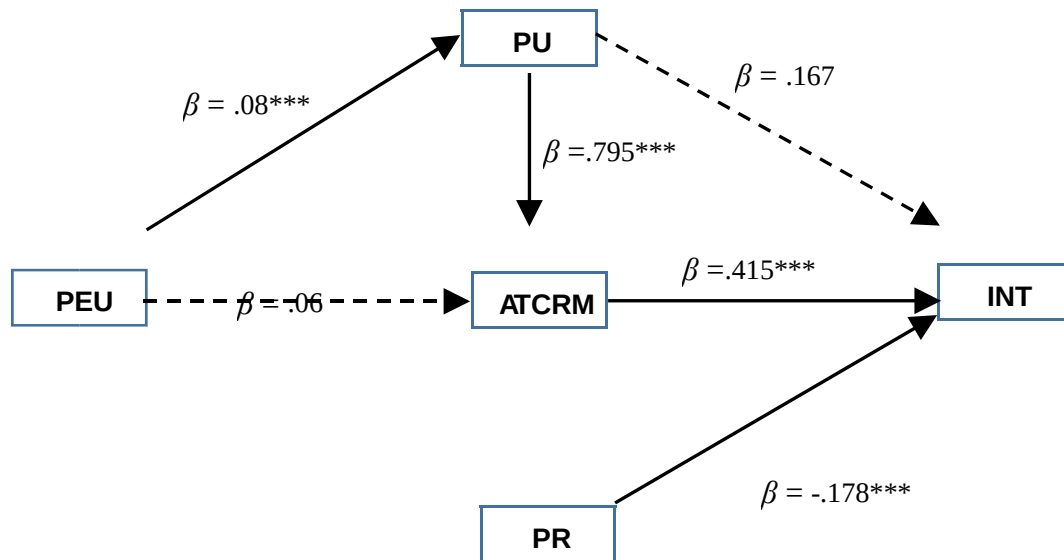
values for conducting the factor analysis. The KMO value should be higher than 0.60, while a value of 0.90 or higher is considered excellent (George & Mallery, 2007). The KMO measure of sampling adequacy indicated a practical level of common variance with a value of 0.886. This indicates that the factor analysis was appropriate.

6.6.2 Confirmatory Factor Analysis (CFA)

The CFA was performed multiple rounds until the model reached the satisfactory fit. The hypothesized model was assessed by maximum likelihood analysis in AMOS. This model was evaluated by eight fit measures: (a) χ^2/df , (b) CFI, (c) GFI, (d) AGFI, (e) NFI, (f) IFI, (g) TLI, and (h) RMSEA. Table 4 summarizes the goodness-of-fit results of all three rounds. Among those three rounds, the third model demonstrates the best results in terms of model-fit indices. It has the lowest ratio of chi-square to the degree of freedom ($\chi^2/df = 1.274$) and the lowest RMSEA value (.032) among all rounds. It also shows the highest values of the CFI, GFI, AGFI, NFI, IFI, and PCLOSE among these three rounds. The AGFI and NFI values are slightly less than the minimum threshold of 0.9; however, the GFI, CFI, IFI, and PCLOSE values are above this threshold. The path diagram of the research model test is shown in Figure 2.

Table 4. Results for model fit indices

Model Fit Indices	Recommended Values	Obtained Values		
		1 st Round	2 nd Round	3 rd Round
χ^2/df	<2	1.778	1.362	1.274
GFI	>0.9	.885	.919	.925
AGFI	>0.9	.851	.886	.893
CFI	>0.9	.715	.878	.909
IFI	>0.9	.732	.888	.917
NFI	> 0.9	.544	.678	.703
PCLOSE	>0.9	.224	.967	.992
RMSEA	<0.1	.054	.037	.032



Note. *** indicates a p value that is statistically significant at 0.001 level.

Solid lines demonstrate statistically significant path at 0.001 level and dotted lines demonstrate statistically non-significant path.

Figure 2. Path diagram of research model

6.7 Hypothesis Testing

The structural model revealed an acceptable fit with the data: $\chi^2 = 207.662$, $df = 163$, $\chi^2/df = 1.274$, GFI = .925, AGFI = .893, CFI = .909, IFI = .917, and RMSEA = .032. The hypotheses were examined by performing a structural equation model analysis that tested the statistical significance of the standardized path coefficients between constructs of the model. The CFA and the path analysis illustrate that the overall model fit of the study was good. However, some paths between variables were not supported by the data. The standardized path coefficients between variables with corresponding statistical significance and critical ratio are reported in Table 5.

The first hypothesis examined the positive effect of ATCRM on INT. The standardized path coefficient ($\beta = .415$, $p < .001$) between ATCRM and INT was 0.415 with a critical ratio of 4.989, which is significant at the .001 level. Thus, $H1$ was supported.

The standardized path coefficient ($\beta = .167$, $p = .046$) between PU and INT was .167 with a critical ratio of 1.995, which is not significant at the .001 level. Thus $H2a$ was rejected.

PU shows to have positive effect on ATCRM, supporting hypothesis $H2b$. The standardized path coefficient ($\beta = .795$, $p < .001$) between PU and ATCRM was .795 with a critical ratio of 18.365, which is significant at the .001 level.

As Table 5 indicates, the standardized path coefficient ($\beta = .059$, $p = .170$) between PEU and ATCRM was 0.059 with a critical ratio of 1.372, which is not significant at the .001 level. Thus, $H3a$ was rejected.

PEU shows to have positive effect on PU, supporting hypothesis *H3b*. The standardized path coefficient ($\beta = .080$, $p < .001$) between PEU and PU was .080 with a critical ratio of 1.694, which is significant at the .001 level.

In the final round of EFA, the constructs PE and US were dropped off the research model and data analysis because of the low factor loading. Thus, hypotheses *H4* and *H5* were rejected.

PR shows to have negative effect on INT, supporting hypothesis *H6*. The standardized path coefficient ($\beta = -.178$, $p < .001$) between PR and INT was -.178 with a critical ratio of -3.487, which is significant at the .001 level.

8. Conclusions

It has been empirically proven that intention is the predictor of actual use (Sheppard et al., 1988; Shim et al., 2001; Pavlou, 2002; Pikkarainen et al., 2004; Chiu et al., 2005; Cheong & Park, 2005; Yousafzai et al., 2007; Shin, 2007). Therefore, this study attempted to understand customer usage behavior through identifying the factors that influence customer intention. If a company fails to identify the factors that influence customer's intention, then the company will reasonably fail to understand and predict customer's usage behavior. This study not only identified and analyzed the factors that directly influence customers' intention to participate in social CRM but also examined other factors that had indirect effects on the model. The data analysis examined the direct and indirect effects to determine the total causal effect in the model.

The foundation of CRM was built on the concept of relationship marketing; therefore, the customer relationship is one of the founding pillars of a successful CRM program. In order to build strong customer relationships, companies need to predict customer behavior as accurate as possible. Predicting customer behavior is one of the most challenging parts of every business. Moreover, predicting how and why customers make their purchase decisions is not as clear as it was in the past, especially since the emergence of social media. With the evolvement of social media, customer's purchase decisions have been significantly influenced by peer opinions. A customer can cause a significant impact on a company's reputation because the customer shares his or her experience in the uncensored environment of the social network, and that experience can influence thousands of other viewers' purchase decisions. This is how marketers can utilize customers as a powerful marketing vehicle. At the same time, marketers need to keep in mind that this powerful marketing vehicle may work against the company if the customer had a bad experience with the company, product, or service.

Companies are spending billions of dollars in research to predict customers' behavior, needs, preferences, likings and disliking, and the factors that influence their decisions. Marketing research has even gone to the extent of neuromarketing research where customer's brain is scanned through functional magnetic resonance imaging (fMRI) to identify the "buy button" in the brain. All these efforts are dedicated to achieving one common goal: predicting customer's behavior. If a company fails to predict customers, all efforts and resources will be in vain regardless of how good quality of products it produces. This research study is one step towards exploring the world of customer behavior.

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