International Journal of Business and Economics
ISSN: 1607-0704
Vol. 26, No. 1, 2026
DOI: https://doie.org/10.10399/IJBE.2026525279

A DEEP EMPIRICAL ANALYSIS OF RELATIONSHIPS AMONG THE OPERATIONAL PARAMETERS IN THE M-COMMERCE SUCCESS MODEL

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Abstract
M-commerce is a maturing area with high levels of consumer adoption in many markets. Services including mobile shopping apps, mobile payments systems and even social commerce on mobile devices may be considered under the umbrella of m-commerce and further extended to the future virtual reality spectra in VR-commerce context. This research first examines current research in the broad areas of innovation adoption and more specifically adoption of new technologies in information systems, marketing and psychology literature. Next, it explores the relationships among several antecedent and outcome variables in a parsimonious model of consumer's preference to use M-commerce applications using prior peer reviewed literature in several fields such as information systems, management, marketing and psychology. Relationships among specific variables such as consumer innovativeness, quality perceptions, trustworthiness, and perceived value on consumers' intention to use mobile technology applications are examined for mediation, moderation, and other effects using structural equations modeling and suited multivariate analytical techniques per the empirical formulations. The results of the data analyses and their findings explicated from viewpoints of statistical and substantive significance showed that the relationship of consumers' intention to use mobile technology applications with antecedents such as their innovativeness, quality perceptions, trustworthiness, and perceived value of mobile technology is far more complex and nuanced than shown in prior research.

Keywords: *M-Commerce, User Intention, Trustworthiness, Perceived Value, Innovativeness*

Introduction
M-commerce focuses on hand-held mobile technology devices using which consumers perform a range of applications and purchase transactions over a wireless telecommunication network (Barnes, 2002; Coursaris and Hassanein, 2002; Gunesaekaran and Ngai, 2003). Considering the many applications of wireless technologies, providers of M-commerce services must understand what the generalized mobile user might value and desire (Malladi and Agrawal, 2002). Past research has focused on issues in mobile commerce use, adoption, and satisfaction from the user's perspective (Sarkar and Wells, 2003). Clarke (2008) discuss the value M-commerce provides over traditional E-commerce including ubiquity, convenience, localization, and personalization. E-commerce models are limited to fixed or stationery users with wired infrastructure, such as a browser on a personal computer connected to the Internet (Varshney and Vetter, 2002) while M-commerce thrives on their being 'always on' and 'always available' (Mahatanankoon, Wen and Lim, 2004). Social commerce using social media platforms for transactions and relationship-building may be seen as extending past M-commerce research and provides further potential for determining users' intentions to engage in other mobile technology applications beyond social media to include 'mixed-media' platforms such as augmented and virtual reality.

This paper views the M-Commerce success model (Byramjee et al., 2009) and its variations in more depth from users' perspective by parsing out factors affecting consumers' intention to use mobile technology applications using varied statistical approaches. We reexamine the relationships in the original model such as impact of consumer innovativeness for mobile technology usage, consumers' quality perceptions of mobile technology, trustworthiness of the mobile technology system, and perceived value from mobile technology on consumers' intention to use mobile technology applications. The paper provides a parsimonious set of statistically justifiable relationships, and the results and discussions elaborate on the changing environment of 'mobile' technologies and related behaviors of consumers.

M-Commerce Adoption and Diffusion

Diffusion of innovative technologies in a general context finds its inspiration from Rogers' (1962) Diffusion of Innovation theory. The focus of Rogers' framework is at the systemic level applying to a market (a system of users) when information and opinions about a new technology "diffuses" among potential users. Rogers considers several outside factors (personal and systemic) that can lead to success or failure of an innovation. MacVaugh and Schiavone (2010) forwards an integrated model of factors limiting innovation adoption wherein they consider the impact of facets of technology (utility or usefulness; complexity; and complementarity), social structure (context, orientation, and contagion) and learning (capacity, capability, and cost). They posit that lack of usefulness/utility, greater complexity, lack of complementarity with existing systems, among other factors, will limit the acceptance of the innovation. Our focus is at the individual level – the innovativeness (innate or aspirational tendency toward acceptance of new products or processes). Consumer Innovativeness is broadly defined as a person's propensity to learn about, own or just being receptive to new ideas (Rogers and Shoemaker, 1971; Goldsmith et al., 2003; Midgley and Dowling, 1978; Hirschman, 1980); thereby affecting levels of technology adoption (Van Rijnsover and Donders, 2009). Consumer technological innovativeness was measured with a collection of cognitive and emotional attributes (such as creativity, involvement and expertise) by Bhagat and Garg (2008). Here, consumer innovativeness is viewed as an innate personality trait rather than the result of a communicated experience (Bhagat and Klein, 2016). We extend this definition to Consumer's Innovativeness for Mobile Technology, where (mobile) technology innovations refer to "new and different set of features, performance and price attributes relative to existing products and technologies" (Slater and Mohr, 2006). The operationalization of this construct includes phrases in the validated scale such as "curious about (new mobile phones)", "savvy", "quick to use newer models", "favorable attitude toward .." and "keep abreast of the latest mobile phones" (Byramjee et al., 2009). A more recent study of fitness apps found innovativeness (among other variables such as compatibility, performance expectancy, effort expectancy, social influence, and habit) to influence intention to use (Talukder et al., 2019).

Davis (1989) initiated the discussion (and research) on the acceptance of information technology which ultimately led to what is termed "TAM 3" model (Venkatesh and Bala, 2008) and its extensions. Davis' model was based on theories popular in marketing and other literature at that time including Bandura's (1986) Self-efficacy theory, the cost-benefit paradigm from behavioral decision theory (Beach and Mitchell, 1978), and Adoption of Innovations (Rogers and Shoemaker, 1971), among others. Davis sees "ease of use" as a self-efficacy judgement which may lead to or influence "usefulness", an outcome judgement based on Bandura's theory, which in turn leads to "intention to use". Davis, Bagozzi and Warshaw (1989) compared TAM with the other popular

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theory at that time – the Theory of Reasoned Action (Fishbein and Ajzen, 1975). The TAM model is in line with the stimulus-organism-response theory in environmental psychology forwarded by Mehrabian and Russell (1974). After reviewing intervening research studies, Venkatesh and Davis (2000) extend the TAM model by defining five external variables influencing Perceived Usefulness and two moderating variables. In the intervening period, Segars and Grover (1993) add Effectiveness as an antecedent; Straub (1994) consider Culture as a factor; Igbara (1995) include Organizational Factors such as user training; Gefen and Straub (1997) assess gender differences; and, Agarwal and Prasad (1999) introduce the influence of individual differences. Subsequent to TAM 2 (Venkatesh and Davis, 2000), Venkatesh et al. (2003) reconcile eight models prevalent in human-computer interface literature to arrive at the Unified Theory of Acceptance and Use of Technology (UTAUT) model and show it outperforms the eight individual models (theory of reasoned action; TAM; motivational model; theory of planned behavior; model combining TAM with TPB, model of PC utilization; the innovation diffusion theory; and the social cognitive theory). Venkatesh and Bala (2008) then go on to propose TAM 3 as a "complete nomological network of the determinants of individuals' IT adoption and use." Finally, Venkatesh, Thong and Xu (2012) extend the UTAUT to the "consumer use context" – the context relevant to and focus of the current paper. In addition to the original variables, the authors add "hedonic motivation", "price value", and "habit" as antecedents influencing behavioral intention and use behavior. They keep "experience" as a moderator from the TAM2 model and recognize age and gender as moderating covariates frequently considered in marketing studies.

Trust and Trustworthiness

The construct "trust" has been studied in marketing literature for over half a century. Trust is often captured in the context of interpersonal relationships as seen in its definition by eminent scholars: "trust existing when one party has confidence in an exchange partner's reliability and integrity" (Morgan and Hunt, 1994); ".. willingness to rely on an exchange partner in whom one has confidence" (Moorman et. al., 1993); or "a generalized expectancy held by an individual that the word of another can be relied on." (Rotter, 1967). A two-component model of generalized trust is seen to be attitudinal or behavioral (Yamagishi et al., 2015). Trust, as a verb, may be seen as an innate trait or a context-specific attitude. Trust may be specific to a transaction or general to a relationship. The object of focus may be human or a thing – trust in a person or in a technology. Here, we focus on "trustworthiness" of a technology – specifically mobile commerce technologies. Trustworthiness is a steady active pattern of behavior toward mobile commerce technologies. Trust building is critical for customers (Siau and Shen, 2003). Trustworthiness is seen to lead to active engagement of the individual user within the spectrum of m-commerce activities.

Consumers' Trustworthiness for Mobile Commerce Technology

Recent research extends the application to mobile technologies other than commerce. Octavius and Antonio (2021) found that initial trust is the most critical determinant of a patient's intention to adopt mobile health applications. Du and Li (2019) found trust correlates with service quality, system quality and information quality. Sim et al. (2021) integrated the core constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) with trust-building mechanisms and found they "play an important role in increasing consumers' confidence … in m-commerce adoption." Sun and Chi (2019) tested the relationship between trust and Innovativeness and found that while both have a statistically significant relationship with ease-of-use, the direct relationship

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between trust and innovativeness was not statistically significant. Finally, trust was found to be a moderator between the other three variables (ease-of-use, usefulness, and intention to use) in the TAM model (Ejdys and Gulc, 2020). Yeh and Li (2009) found satisfaction to mediate the relationship between quality and trust. Park and Yoo (2019) study the impact of newer technologies on the attitudes of consumers, a surrogate dimension for trust. They show that interactivity of a technology (Augmented Reality in their case) - captured as controllability and playfulness – and mental imagery – captured as elaboration and quality – impact the attitude toward the technology which, in turn, impacts behavioral intention.

Consumers' Perceived Value of Mobile Technology

The perceived value of any product or service depends on the extent to which the new mobile technology benefits the consumer regarding the total costs or sacrifices that he/she expends. Seybold (2006) considers "structural tension between lead users' current reality and their desired outcomes and experiences drives innovation" to result in perceived value of the new technology. Kim et al. (2007) propose a value-based model when adopting new technologies. They consider the classic determinants of value – benefits and costs (sacrifices, both monetary and non-monetary) with usefulness and enjoyment as the benefits and technicality and perceived fee/cost as the sacrifice as determinants of perceived value and intention to use. In the context of IoT smart home service adoption, Kim et al. (2017) extend the model to incorporate the Elaboration Likelihood Model (Petty and Cacioppo, 1986) which derives an outcome based on either the Central or the Peripheral route of persuasion based on the quality or valence of the benefits and costs. Kim et al. (2019) incorporate the Expectation-Confirmation Model, originally proposed by Oliver (1980), into the Value-based Adoption Model by including determinants of Satisfaction, Perceived Value, and Continual Purchase Intention.

Consumers' Intention to Use Mobile Technology Applications/Services

Behavioral intentions, behaviors, and actions are consequences several models consider with differing terminologies. Park and Jun (2003) propose a model of internet shopping that is driven by three factors: internet usage, innovativeness and perceived risk. Perceived risk is a cost in the value-based adoption model that takes away from the benefits perceived by the consumer. Wong and Hsu (2008) extend the technology acceptance model and propose a "confidence-based" framework for m-commerce adoption that considers the impact of psychological and behavioral factors on attitude, behavioral intention, and actual behavior. Kim et al. (2019) showed the statistically significant impact of perceived value and satisfaction on continuous (behavioral) intention. Pavlou and Fygenson (2006) extend Ajzen's model to e-commerce adoption and include external process and technology factors, attitude, controllability, and self-efficacy influencing behavioral intention.

Deeper Comprehension of the M-Commerce Success Model

The next section digs deeper into the M-Commerce Success Model first proposed by Byramjee et al. (2009) by empirically parsing out each relationship based on the theoretical foundations and nomological comprehension elaborated here using several statistical tools appropriate for a better understanding. A reader may contrast our research model variables with those in the TAM models. There are similarities and distinctions between the models. While our outcome variable remains "intention to use" similar to the TAM models, our model results apply to m-commerce domain alone and do not extend to other technologies. While our independent variables may overlap with those used in TAM-inspired models (consumer innovativeness, trustworthiness, quality perception and perceived value), our context is mainly applying to marketing alone. One might ask why we revisit this study on m-commerce. Du and Li (2019) provide a meta-analysis of research in the domain till date viewing it in this new era of the ubiquitous presence of m-commerce with applications in several commercial and industrial realms of mobile financial applications, advertising, inventory management, service management, entertainment, and distance education. They find that research in this domain has moved from a focus on technologies to marketing in the 2012 cluster of research they identified. They identify key dependent variables in their meta-analysis which include “purchase intention, trust, satisfaction, buying behavior, word of mouth, loyalty, value, user acceptance and m-commerce adoption” – all salient in marketing. Venkatesh et al. (2012) also extend their model to the “consumer use context” recognizing the impact on marketing is the ultimate goal.

Research Design for the Study

The empirical operationalization of our model’s variables and their suited measurement scales was conducted per the constructs’ respective domains. The empirical indicators which adequately reflected the domain of each respective construct, thereby serving to reliably measure the construct, were corroborated by experts to assess their face validity and thereby the constructs’ content validity (Nunnally, 1978). The Consumer Innovativeness (CI) construct comprises of personal characteristics of a consumer to engage in using mobile technology applications (like M-Commerce). These characteristics include measurable items like the consumer having favorable attitude toward it, being tech-savvy, being quick to use, being early adopter, being knowledgeable about such offerings in market, and wanting to know how they work. The Trustworthiness (T) construct pertains to information security and data integrity in M-Commerce. It measures aspects of consumers’ trust in the transactions, issues of privacy, misuse of personal information, and security of personal information when the consumer is engaged in mobile technology applications. The Perceived Value (PV) construct judges the value (supposed benefits) perceived from M-Commerce application. It measures consumers’ perception regarding whether the benefits of mobile technology applications outweigh its price, that ability being important to the consumer, appreciate for its positive aspects, willingness to learn how to use, believe that it is useful for online purchasing, and its efficiency and advantages. The Quality Perceptions (QP) construct measures consumers’ perception of what aspects seem desirable when needing to use M-Commerce. System/information-related aspects such as features, displays, functionality, user-friendliness, and operating ability of the mobile technology applications are measured herein. The Intention to Use (IU) construct is measured by items like consumers’ intent to use mobile technology, their desire to continue using it if favorable, their belief in its suitability and need, their keenness to use it, their having a favorable opinion of it, and their liking to purchase online using it.

All the empirical indicators, as assessable items in psychometric scaling, were measured as continuous variables. Each of these empirical indicators was semantically framed into a question in the survey instrument and measured via 1 through 7 likert-type balanced non-forced choice scale, with the anchors being ‘strongly disagree’ and ‘strongly agree’ respectively; the correspondence rule of the scale thereby reflecting respondents’ rising level of sentiment with respective facets of the M-Commerce variables via agreement expressed along higher response

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position on the scale. The surveys were administered online via a well-articulated user-friendly web browser format. The sampling frame constituted users of mobile commerce technologies (at seemingly varying levels, as evidenced by the variances in their empirical responses); thereby meeting the norms of our sample being random and indeed representative of the population intended for this inquiry. The final usable sample size, constituting a complete data set without any missing values or responses, comprised 225 respondents.

To test for non-response bias (per Armstrong and Overton, 1977), we compared the set of early respondents (those being the first one-third of the collected data) with the set of late respondents (those being the last one-third of the collected data) on certain key empirical indicators as well as on couple of the key modeled constructs. Since no statistically significant differences were found in these tests, it is noted that discernable issue of non-response bias does not appear in the data.

Since the data for all the predictor variables (CI, T, QP, PV) and the criterion dependent variable (IU) were naturally collected from the same sample using the same survey instrument and measures, a potential for common methods bias could arise. To assess the viability of this issue, we performed Harmon's one-factor test on the items in the dataset (per Podsakoff and Organ, 1986). The principal components type factor analysis revealed five factors with eigen values greater than 1.0 and these accounted for about 71% of the total variance. Seeing the fact that multiple factors emerged from the principal components analysis and that the first factor accounted for only about 38% of the total variance, it is noted that common methods bias does not appear to exist in the data.

From a marketing science perspective, user intention to utilize M-commerce (IU) as the research objective dependent variable constitutes our main explanandum which per our original M-Commerce Model was posited as being influenced by our key modeled explanans namely PV, CI, T, and QP serving as independent variables. Substantive reasoning from a stance of external validity pertinent to real-world consumer utilization dynamics within this matured mobile commerce spectrum now leads us to inductively reevaluate the originally modeled stance. Predictors like consumers' trustworthiness in mobile technology (T) and consumers' quality perceptions of mobile commerce (QP) realize to be more user-geared technical manifests as system-related factors and cognitive considerations toward user intention for M-Commerce applications (IU). The consumer innovativeness (CI) predictor is a more user-driven conative manifesting toward mobile commerce adoption and diffusion definitive of more behaviorally inclined user consideration and utilization. Thus, CI, QP, and T held together as an explanans' block defining user attitude and behavior in the mobile commerce scape will then collectively shape users' perceived value (PV) from M-Commerce application, and such value perceived by the user (PV) will in turn impact proclivity for mobile commerce adoption in terms of intention to use M-Commerce (IS). Thereby, our posited Modified M-Commerce Model [shown in Figure 1] inducts PV as a key mediator between explanans CI, QP, T and the key explanandum IU.

Figure 1: The 'Modified' M-Commerce Success Model

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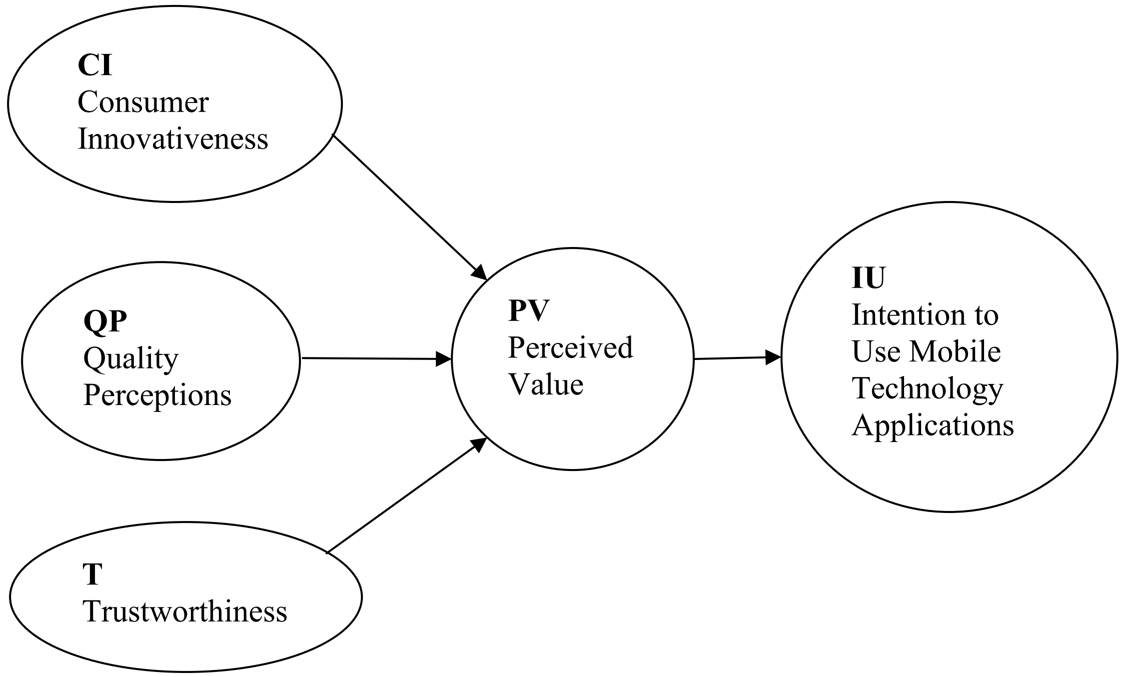

Steenkamp and Van Trijp's (1991) proposed method of employing exploratory factor analysis and then confirmatory factor analysis to validate marketing constructs was systematically followed here. We first used exploratory factor analysis techniques to establish the convergent and discriminant validity of the constructs in the proposed empirical model. The procedure respectively included within-factors type factor analysis as well as between-factors type factor analysis to judge and establish the unidimensionality of each of the constructs. Then, the measurement scales for all these constructs were tested for their internal consistency through reliability analysis. Thereafter, structural equations modeling was employed to assess model fit characteristics and to test the nomological relationships between the constructs by coding and analyzing the structural model.

Exploratory factor analysis was conducted for each of the five reflective constructs which comprise our model. The empirical indicators for each construct loaded strongly onto their respective construct. Thus, these items did adequately represent and measure the underlying conceptual domain of their respective construct, thereby establishing good convergent validity for each construct. Thereafter, Principal Axis Factoring with Direct Oblimin Rotation was conducted on the data set for the three key independent variables (namely constructs CI, T, QP) held together. The Kaizer-Meyer-Olkin (KMO) Measure of Sampling Adequacy values were considerably high in all cases, and the Bartlett's Test of Sphericity was also found significant in all cases, implying that factor analysis be performed on the data (Tabachnick and Fidell, 2001). Further, the sample size of 225 compared to the 29 measurable variables in the survey data yielded an approximate 8:1 ratio of sample size to number of variables, which justified the suitability of factor analytic procedures on the data (Tabachnick and Fidell, 2001). Loadings below 0.4 were suppressed throughout, to view a cleaner loadings' structure. The pattern matrix (as shown in Table I) for the factor analysis conducted between the three key independent variables resulted in a segregated loadings' structure wherein the indicators loaded mainly on their respective constructs and no noticeable cross-loadings emerged, thereby establishing substantive discriminant validity for the constructs.

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Table I: Pattern Matrix of the Factor Analysis among the Exogenous Constructs [CI, T, QP]

Measures (Empirical Indicators) of the Respective Constructs	Factor Loadings of the Empirical Indicators yielded per their respective Constructs		
	Factor 1 [“T”]	Factor 2 [“CI”]	Factor 3 [“QP”]
T2	.868		
T5	.859		
T4	.856		
T3	.814		
T1	.757		
T6	.637		
CI4		.886	
CI3		.857	
CI7		.804	
CI2		.724	
CI5		.657	
CI6		.527	
CI1		.480	
QP5			.871
QP3			.811
QP6			.805
QP4			.745
QP2			.699
QP1			.641

Reliability analysis was then performed on each of the five constructs to test for their respective scales’ internal consistency. Table II shows the Cronbach's Alpha reliability coefficients for each construct. The high Alpha values (greater than 0.7) for each of the five constructs (per Nunnally and Bernstein, 1994), along with the adequate item-total statistics’ values and corrected item-to-total correlations’ values of their respective measures, indicated good internal consistency of the factors. Thereby it was determined that all the items measuring their respective construct do homogeneously represent their respective measurement domains. Thus, the five constructs in the model represent strong measures.

Table II: Reliabilities of the Constructs

Constructs	Cronbach Alpha
“CI” Consumer Innovativeness [7 items’ scale]	0.885
“T” Trustworthiness [6 items’ scale]	0.929
“QP” Quality Perceptions [6 items’ scale]	0.894
“PV” Perceived Value [6 items’ scale]	0.867
“IU” Intention to Use M-Commerce [4 items’ scale]	0.900

After having established the validity and reliability of the measures, the goodness of fit parameters for the model (as shown in Table III) along with the posited relationships among the three

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exogenous variables (CI, T, QP) and the two endogenous variables (PV, IU) were tested using the structural equations modeling approach by coding and analyzing the structural model (Joreskog and Sorbom, 1996). This structural model was programmed in Lisrel 8.51 as an x-y and ξ-η model (x's being the empirical indicators measuring their respective latent constructs' ξ's as the three exogenous variables, and y's being the empirical indicators measuring their respective latent constructs' η's as the two endogenous variables) (Byrne, 1998). All the λx's loadings and λy's loadings were freely estimated, and the variances-covariances matrix standardized (Byrne, 1998). All the empirical indicators loaded strongly on their respective constructs as evidenced by their statistically significant standardized loading coefficients yielded with their resultant t- and sig-values. This further lent to the already ascertained convergent validity of the constructs/measures. The goodness of fit statistics section of the structural model output was scrutinized to evaluate the measures (Byrne, 1998). The comparative fit index (CFI) (Bentler, 1990), normed fit index (NFI), goodness of fit index (GFI), and incremental fit index (IFI) (Bollen, 1989) were 0.90, 0.83, 0.79, and 0.90 respectively; these high values suggested a good model fit. The root mean square error of approximation (RMSEA) value was 0.078; being lesser than 0.08, it showed medium to good fit for the model (MacCallum, Brown and Sugawara, 1996). While the hypothesized model's Chi-square statistic value of 828.7 was found statistically significant ($p<0.05$), which is not unusual with larger sample sizes, it was still way lower than the independence model's Chi-square of 4998.97. The expected cross-validation index (ECVI), Akaike information criterion (AIC), and Consistent version of AIC (CAIC) were also examined; the ECVI, AIC, and CAIC all suggested good fit, as their hypothesized model values being respectively 4.49, 1005.34, and 1296.81 were far lower than their independence model values which were respectively 22.58, 5056.97, and 5185.04 (Hu and Bentler, 1995), thereby signaling the greater extent to which parameter estimates from the original sample will cross-validate in future samples (Bandalos, 1993). Thus, these results altogether suggested that the data provides a good fit with the hypothesized model.

The structural equations modeling run also yielded the composite reliability (CR) values and the average variance extracted (AVE) values for each of the five constructs in our model (as shown in Table IV). The composite reliability values for each of the five constructs well exceed the 0.7 threshold (much like their respective counterparts i.e. the Cronbach Alpha coefficients), thereby confirming strong internal consistency for the constructs' measures. The average variance extracted values for each of the five constructs were well above the 0.5 threshold to further confirm the already ascertained convergent validity of the five constructs. Thereupon, the HTMT (hetero-trait mono-trait) ratio of correlations test (as shown in Table V) per Fornell-Larcker criterion (1981) indicated for each of the five constructs respectively that their computed square-roots of their AVE's were greater than their correlations with the other constructs, thereby further confirming the already ascertained discriminant validity of the five constructs.

Further, the standardized beta coefficients, t-values, and sig-values of respective Gamma-path estimates and Beta-path estimate yielded in the structural model output and path diagram were examined to ascertain the statistical significance of variables in the structural model representative of the hypothesized relationships, analogous to multiple regression wherein summed averages of respective item-measures used to represent their constructs (Hair, Black, Babin, Anderson and Tatham, 2006). As shown in Table III, variables CI, T, and QP were all found to bear statistically significant impact on PV. T exerted the highest effect on PV, followed by QP and CI. PV was found to bear statistically significant impact on IU. Alongside, the Variance Inflation Factor values for CI, T, and QP as parallelly generated by their multivariate regression run on PV (as shown in

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ISSN: 1607-0704
Vol. 26, No. 1, 2026
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Table VI), were all lower than the threshold of 4.0, thereby lending further to the already ascertained discriminant validity of the constructs/measures.

Table III: Results of the Structural Equations Model Testing
(coefficients'/estimates' effects statistically significant at *5% and **10% levels of significance)

Path ; SEM Coefficient	Predictor	Stdzd. β	t - value
CI → PV ; Gamma	CI [Zi]	0.24 *	4.47
T → PV ; Gamma	T [Zi]	0.46 *	6.77
QP → PV ; Gamma	QP [Zi]	0.32 *	5.24
PV → IU ; Beta	PV [Eta]	0.87 *	10.24
Model Chi-square 828.70 (sig 0.0)			
CFI 0.90; IFI 0.90; NFI 0.83			
RMSEA 0.078			
Standardized RMR 0.071			
Model ECVI 4.49			
Model AIC 1005.34; Model CAIC 1296.81			

Table IV: Composite Reliabilities and Average Variance Extracted Values of the Constructs

Constructs	Composite Reliability (CR)	Average Variance Extracted (AVE)
"CI" – Exogenous Construct	0.887	0.540
"T" – Exogenous Construct	0.930	0.694
"QP" – Exogenous Construct	0.896	0.592
"PV" – Endogenous Construct	0.885	0.515
"IU" – Endogenous Construct	0.900	0.705

Table V: HTMT (hetero-trait mono-trait) Matrix showing Square-Roots of the AVE's of the Constructs along the diagonal and Correlations among the Constructs along the lower off-diagonal

	CI	QP	T	PV	IU
CI	0.735				
QP	0.346	0.769			
T	0.481	0.579	0.833		
PV	0.553	0.607	0.680	0.718	
IU	0.540	0.699	0.737	0.778	0.839

Our posited Modified M-Commerce Model [shown in Figure 1] demands a comparison of the direct and indirect effects' pathways posed by the explanans CI, T, and QP on PV and on IU

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ISSN: 1607-0704
Vol. 26, No. 1, 2026
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respectively. As shown in Table VI, CI, T, and QP bear statistically significant impact on PV, and PV in turn very significantly affects IU. As shown in Table VII, CI, T, and QP bear statistically significant effect on IU as well when tested as an explanans' set. These tests' implications are indeed thought inducing for PV functioning as the key mediator in this posited model in light of the explanans' significant direct effects on PV along with PV's own substantial impact on IU. In all the above regressions, the VIF values being far lesser than the strictest threshold of 4.0 points to lack of multicollinearity issues whereby the discerning roles of each of the independent covariates manifest in drawing unique variance in their measurement and explanatory content.

Table VI: Results of the Direct Effects' Testing
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Multiple Regression – Dependent Variable "PV"				
Independent Variables	Stdzd. β	t - value	Sig.	VIF
CI	0.197 *	4.034	.000	1.269
T	0.445 *	8.145	.000	1.583
QP	0.299 *	5.819	.000	1.404
Model: R-square 0.584; F-value 103.286 *				
Regression – Dependent Variable "IU"				
Independent Variable	Stdzd. β	t - value	Sig.	
PV	0.719 *	15.437	.000	
Model: R-square 0.517; F-value 238.313 *				

Table VII: Results of the Indirect Effects' Testing
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Multiple Regression – Dependent Variable "IU"				
Independent Variables	Stdzd. β	t - value	Sig.	VIF
CI	0.259 *	4.848	.001	1.269
T	0.355 *	5.945	.001	1.583
QP	0.277 *	4.923	.001	1.404
Model: R-square 0.502; F-value 74.359 *				

The testing initiative now extends our deductive nomological objective along a deeper exploration of the diagnostics of these M-Commerce explanans (CI, T, QP, PV) in critical terms of how they interact with each other toward manifesting user effects appropriated as the explanandum IU. We systematically subject every pair of explanans to the mediation method toward statistically examining the presence and extent of mediating effect posed by the concerted variables. Adopting the Baron and Kenny (1986) approach for mediators' testing wherein a certain explanan is declared as the mediator between the other explanan and the dependent variable, each variable in this explanans' pair is tested for its main effect on the dependent, followed by the combined effect of both explanans on the dependent; thereupon, the increase or decrease in the magnitude of

International Journal of Business and Economics
ISSN: 1607-0704
Vol. 26, No. 1, 2026
DOI: https://doie.org/10.10399/IJBE.2026525279

statistically significant impact of the explanan on the dependent in presence of the mediator is gauged to determine the presence and extent of the mediation effect. Considering our four thematic explanans (CI, T, QP, PV) with all pair-wise combinations of respective main effects and mediator effects exerted on IU as the dependent variable, twelve such yielded pairs' mediation effects' tests are conducted as summarized in Table VIII.

Table VIII: Results of the Regressions for Mediators'/Mediation Effects' Testing
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Dependent Variable	Independent Variable/s	Stdzd. β	Implication toward "High" or "Low" Mediation Effect of the Mediator Variable along the Multiple Regression Tested Path
IU	PV	0.719 *	
IU	CI	0.507 *	
IU	PV	0.619 *	High Mediator Effect of PV along Tested Path: CI → PV → IU
	CI	0.202 *	Low Mediator Effect of CI along Tested Path: PV → CI → IU
IU	PV	0.719 *	
IU	QP	0.547 *	
IU	PV	0.609 *	High Mediator Effect of PV along Tested Path: QP → PV → IU
	QP	0.183 *	Low Mediator Effect of QP along Tested Path: PV → QP → IU
IU	T	0.618 *	
IU	CI	0.507 *	
IU	T	0.489 *	High Mediator Effect of T along Tested Path: CI → T → IU
	CI	0.287 *	Low Mediator Effect of CI along Tested Path: T → CI → IU
IU	PV	0.719 *	
IU	T	0.618 *	
IU	PV	0.558 *	High Mediator Effect of PV along Tested Path: T → PV → IU
	T	0.232 *	Low Mediator Effect of T along Tested Path: PV → T → IU
IU	QP	0.547 *	
IU	CI	0.507 *	
IU	QP	0.429 *	Low Mediator Effect of QP along Tested Path: CI → QP → IU
	CI	0.371 *	Low Mediator Effect of CI along Tested Path:

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ISSN: 1607-0704
Vol. 26, No. 1, 2026
DOI: https://doie.org/10.10399/IJBE.2026525279

			QP → CI → IU
IU	QP	0.547 *	
IU	T	0.618 *	
IU	QP	0.306 *	Low Mediator Effect of QP along Tested Path: T → QP → IU
	T	0.457 *	High Mediator Effect of T along Tested Path: QP → T → IU

Treating PV as the mediator between CI and the dependent IU, the multiple regression shows a substantial drop in CI's main effect (0.507 to 0.202) on IU in presence of PV's strong covariate influence (0.619); thereby pointing to the high mediation effect of PV between CI and IU. Treating CI as the mediator between PV and the dependent IU, the multiple regression shows a marginal drop in PV's main effect (0.719 to 0.619) on IU in presence of CI's relatively weaker covariate influence (0.202); thereby pointing to the low mediation effect of CI between PV and IU. Treating PV as the mediator between QP and the dependent IU, the multiple regression shows a substantial drop in QP's main effect (0.547 to 0.183) on IU in presence of PV's strong covariate influence (0.609); thereby pointing to the high mediation effect of PV between QP and IU. Treating QP as the mediator between PV and the dependent IU, the multiple regression shows a marginal drop in PV's main effect (0.719 to 0.609) on IU in presence of CI's relatively weaker covariate influence (0.183); thereby pointing to the low mediation effect of QP between PV and IU. Treating T as the mediator between CI and the dependent IU, the multiple regression shows a substantial drop in CI's main effect (0.507 to 0.287) on IU in presence of T's relatively stronger covariate influence (0.489); thereby pointing to the high mediation effect of T between CI and IU. Treating CI as the mediator between T and the dependent IU, the multiple regression shows a marginal drop in PV's main effect (0.618 to 0.489) on IU in presence of CI's relatively weaker covariate influence (0.287); thereby pointing to the low mediation effect of CI between T and IU. Treating PV as the mediator between T and the dependent IU, the multiple regression shows a substantial drop in T's main effect (0.618 to 0.232) on IU in presence of PV's strong covariate influence (0.558); thereby pointing to the high mediation effect of PV between T and IU. Treating T as the mediator between PV and the dependent IU, the multiple regression shows a marginal drop in PV's main effect (0.719 to 0.558) on IU in presence of T's relatively weaker covariate influence (0.232); thereby pointing to the low mediation effect of T between PV and IU. Treating QP as the mediator between CI and the dependent IU, the multiple regression shows a marginal drop in CI's main effect (0.507 to 0.371) on IU in presence of QP's relatively moderate covariate influence (0.429); thereby pointing to the low mediation effect of QP between CI and IU. Treating CI as the mediator between QP and the dependent IU, the multiple regression shows a marginal drop in QP's main effect (0.547 to 0.429) on IU in presence of CI's relatively moderate covariate influence (0.371); thereby pointing to the low mediation effect of CI between QP and IU. Treating QP as the mediator between T and the dependent IU, the multiple regression shows a marginal drop in T's main effect (0.618 to 0.457) on IU in presence of QP's relatively moderate covariate influence (0.306); thereby pointing to the low mediation effect of QP between T and IU. Treating T as the mediator between QP and the dependent IU, the multiple regression shows a substantive drop in QP's main effect (0.547 to 0.306) on IU in presence of T's relatively strong covariate influence (0.457); thereby pointing to the high mediation effect of T between QP and IU.

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ISSN: 1607-0704
Vol. 26, No. 1, 2026
DOI: https://doie.org/10.10399/IJBE.2026525279

These several mediation tests conducted among the four explanans' pair-wise combinations reveal statistically the fact that PV consistently bears high mediator effect, thereby substantively positing its key mediation role between the influences of CI, T, and QP on IU. Accordingly, PV stands reason to manifest itself as key mediator in the modeled pathways between each CI, T, and QP to IU as the consequent dependent. This further bolsters our rationale for having modeled PV as key mediator in the modified M-Commerce Model [shown in Figure 1].

Further inquiry from a deductive statistical bearing of marketing science leads us to explore the varied interaction dynamics among the four key explanans toward their segregated and collective influence borne on the explanandum. To begin with, the testing on IU looks at the full explanans (PV, CI, T, QP) set's main effects and all combinations of their first-order interaction effects represented by their first-order interaction terms computed throughout the model. All the main effects' and interaction terms' predictors as well as the criterion variable are standardized for appropriate statistical comparability. The multiple regression is then conducted to primarily focus on these interaction effects of the six multiplier terms on the dependent IU. The results are shown in Table IX. Beyond the significance of the four predictors' main effects, the only emergent statistically significant interaction (CI x QP) effect that influences the dependent IU is between CI and QP. While there is no issue of multicollinearity surfacing, even amidst these related variables and their interactions, none of the other five interaction effects bore any impact of the dependent IU.

Table IX: Regression Results of the full model with main effects and all first-order interaction effects among all the predictors
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Multiple Regression – Dependent Variable "IU"				
Independent Variables	Stdzd. β	t - value	Sig.	VIF
PV (main effect)	.466 *	6.533	.000	2.721
CI (main effect)	.202 *	3.822	.000	1.495
T (main effect)	.146 *	2.267	.024	2.219
QP (main effect)	.108 **	1.744	.083	2.059
PV x CI (Interaction Effect)	-.066	-.992	.322	2.331
QP x PV (Interaction Effect)	.054	.725	.469	2.961
CI x T (Interaction Effect)	.054	.845	.399	2.149
PV x T (Interaction Effect)	-.012	-.191	.849	2.207
CI x QP (Interaction Effect)	.148 *	2.093	.038	2.690
T x QP (Interaction Effect)	-.071	-.967	.335	2.862
Model: R-square 0.600; F-value 32.063 *				

Hence, a perspective of establishing theoretical grounding for these existential dynamics of interactions leads our inquiry toward configuring the relationships among these variables along a more confined pair-wise bases to ascertain specific moderation type impacts on the dependent term. Accordingly, a series of regressions are conducted on IU as the dependent as tested when being affected by pair-wise combinations of the four predictors via their main effects and the computed interaction terms' effects in each of the six runs. The Baron and Kenny (1986) approach for moderators' testing is adopted hereby to check for the statistical significance of the interaction terms in each run which would signal a potential interaction effect among those pairs of predictors. The results are shown in Table X. Beyond the consistent significance of the four predictors' main effects through their respective six runs, three statistically significant interaction effects emerged toward influencing the dependent IU, namely between QP and PV (QP x PV), between CI and T (CI x T), and between CI and QP (CI x QP). The other three interaction terms (PV x CI, PV x T, T x QP) did not bear any significant effect on IU.

Table X: Results of the Regressions for Moderators'/Interactions' Effects Testing
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Dependent Variable	Independent Variables	Stdzd. β	t - value	Sig.
IU	PV (main effect)	0.616 *	11.858	.000
	CI (main effect)	0.215 *	4.063	.000
	PV x CI (Interaction Effect)	0.057	1.235	.218
IU	QP (main effect)	0.192 *	3.388	.001
	PV (main effect)	0.613 *	10.835	.000
	QP x PV (Interaction Effect)	0.087 **	1.905	.058
IU	CI (main effect)	0.310 *	5.520	.000
	T (main effect)	0.480 *	8.650	.000
	CI x T (Interaction Effect)	0.117 *	2.331	.021
IU	PV (main effect)	0.562 *	8.940	.000
	T (main effect)	0.232 *	3.699	.000
	PV x T (Interaction Effect)	0.045	0.985	.326
IU	CI (main effect)	0.392 *	7.159	.000
	QP (main effect)	0.410 *	7.524	.000
	CI x QP (Interaction Effect)	0.096 **	1.828	.069
IU	T (main effect)	0.453 *	7.694	.000
	QP (main effect)	0.309 *	5.255	.000
	T x QP (Interaction Effect)	0.046	0.912	.363

This testing sequence confirmed indeed the presence of notable interactions among those respective explanans. Hence, the objective now progresses toward assessing the nature of the moderation nomologies among these emergent interaction effects in terms of which variable to what extent within each respective interaction pair serves as the worthy moderator to the other variable in its pair gauged to be playing the main effect. For this purpose, a series of follow-up conditional-sample regression analyses are performed utilizing as explanans each of the above three interaction effects' terms which turned out significant to begin with. For each pair, we declare one of the predictors as the main effect independent variable and the other predictor as the

International Journal of Business and Economics
ISSN: 1607-0704
Vol. 26, No. 1, 2026
DOI: https://doie.org/10.10399/IJBE.2026525279

moderator variable wherein we split the moderator at its mean to generate a high-level (values at and above its mean) and a low-level (values below its mean). Thereupon, we compare the impact of the main effect independent variable's resultant regression coefficient on the dependent variable IU across the moderator's high-level conditional-sample regression run and the moderator's low-level conditional-sample regression run to gauge the magnitude of their difference toward substantiating statistically the presence, directionality, and extent of the moderator's influence on its respective independent variable in affecting the dependent variable. The results are shown in Table XI.

Table XI: Results of the Regressions for 'further' Moderators' Effects Testing [for those resultant/yielded significant interactions]
(coefficients' effects statistically significant at *5% and **10% levels of significance)

Dependent Variable	Moderator Variable [split at its Mean to generate 'High' and 'Low' Levels]	Independent Variable's Main Effects at the 'High' and 'Low' levels of the Moderator	Stdzd. β	t - value	Sig.
IU	T [High]	CI	.496 *	6.014	.001
IU	T [Low]	CI	.269 *	2.930	.004
IU	CI [High]	T	.616 *	8.745	.001
IU	CI [Low]	T	.476 *	5.003	.001
IU	QP [High]	PV	.702 *	10.758	.001
IU	QP [Low]	PV	.588 *	7.333	.001
IU	PV [High]	QP	.402 *	4.608	.001
IU	PV [Low]	QP	.345 *	3.877	.001
IU	CI [High]	QP	.522 *	6.847	.001
IU	CI [Low]	QP	.472 *	5.249	.001
IU	QP [High]	CI	.569 *	7.556	.001
IU	QP [Low]	CI	.326 *	3.485	.001

When working on the CI x T interaction, treating CI as the independent main effect variable and T as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between CI and IU was greater in the high mean T level (.496) than in the low mean T level (.269). This statistically shows that T moderates that relationship between CI and IU. Further, working on the CI x T interaction, treating T as the independent main effect variable and CI as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between T and IU was greater in the high mean CI level (.616) than in the low mean CI level (.476). This statistically shows that CI moderates that relationship between T and IU. When working on the QP x PV interaction, treating PV as the independent main effect variable and QP as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between PV and IU was greater in the high mean QP level (.702) than in the low mean QP level (.588). This statistically shows that QP moderates that relationship between PV and IU. Further, working on the QP x PV interaction, treating QP as the independent main effect variable and PV as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between QP and IU was greater in the high mean PV level (.402) than in the low mean PV level (.345). This statistically shows that PV moderates that relationship between QP and IU. When working on the CI x QP interaction, treating QP as the independent main effect variable and CI as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between QP and IU was greater in the high mean CI level (.522) than in the low mean CI level (.472). This statistically shows that CI moderates that relationship between QP and IU. Further, working on the CI x QP interaction, treating CI as the independent main effect variable and QP as the moderator being split into high and low levels, the strength (regression β) of the positive relationship between CI and IU was greater in the high mean QP level (.569) than in the low mean QP level (.326). This statistically shows that QP moderates that relationship between CI and IU.

Considering the resultant findings for each pair-wise interaction effect (per Table XI), each variable lands up serving as moderator to the other for impacting IU. So, the decisive way to gauge each variable's extent of moderation effect within the pair is to compare its respective magnitudes exerted on the main effect variable in terms of the proportion of difference yielded in that main effect variable's regression strength (β coefficient) whereby strong or weak moderation be signaled. For the CI x T interaction, with T as the moderator the difference in CI's main effects on IU is 0.227 [.496 - .269], while with CI as the moderator the difference in T's main effects on IU is 0.140 [.616 - .476]. Thus, we determine that T exerts a stronger moderator effect between CI and IU, while CI exerts a weaker moderator effect between T and IU. For the QP x PV interaction, with QP as the moderator the difference in PV's main effects on IU is 0.114 [.702 - .588], while with PV as the moderator the difference in QP's main effects on IU is 0.057 [.402 - .345]. Thus, we determine that QP exerts a stronger moderator effect between PV and IU, while PV exerts a weaker moderator effect between QP and IU. For the CI x QP interaction, with CI as the moderator the difference in QP's main effects on IU is 0.05 [.522 - .472], while with QP as the moderator the difference in CI's main effects on IU is 0.243 [.569 - .326]. Thus, we determine that QP exerts a stronger moderator effect between CI and IU, while CI exerts a weaker moderator effect between QP and IU.

Lastly, a variation of the M-Commerce Model is tested toward the collective impacts of PV, CI, T, and QP on IU whereby the multiple regression (as shown in Table XII) retains PV and CI as the original continuous variables while controlling for the effects of T and QP both now coded as dummy variables. Considering the original 1-7 scale along which T and QP are measured, the dummy coding for each T and QP is generated by splitting them at the mid-point of the scale. Thereby, values for T lower than 3.5 on its scale are coded as 0 representing low trustworthiness while values for T higher than 3.5 on its scale are coded as 1 representing high trustworthiness. Similarly, values for QP lower than 3.5 on its scale are coded as 0 representing low quality perception while values for QP higher than 3.5 on its scale are coded as 1 representing high quality perception.

Table XII: Regression – Dependent Variable "IU"

(coefficients' effects statistically significant at *5% and **10% levels of significance)

Independent Variables	Beta Coefficient	t - value	Sig.
PV [continuous predictor]	0.670 *	8.344	.000
CI [continuous predictor]	0.241 *	3.717	.000
T [dummy: 0, 1]	0.502 *	2.980	.003
QP [dummy: 0, 1]	0.214	1.261	.209

As expected, both PV and CI significantly affect IU; noted that PV exerts way higher an impact on IU than CI. Anyhow, it is primarily the influence of T and QP in this test that is of consequence. Per the resulting statistically significant beta coefficient of dummy variable T, it gets interpreted that given same levels of CI and PV, consumers with high trustworthiness (T) exhibit markedly higher intention to use (IU) mobile commerce than consumers with low trustworthiness (T), regardless of whether their quality perception (QP) of mobile commerce is high or low. Since the beta coefficient of dummy variable QP is not statistically significant, it gets interpreted that given same levels of CI and PV, high or low levels of quality perception among consumers do not exert any differing effect on their intention to use (IU) mobile commerce, regardless of their trustworthiness (T) levels.

Conclusion and Future Research

M-commerce is no longer a nascent phenomenon; it has branched out over the past decade from e-commerce and coexists with it with a joint revenue of over $1 trillion. It sees new branches that emerge such as social commerce with which it will coexist as well. Into the foreseeable future, we see social commerce to branch out into the metaverse which does not yet have a label – meta-commerce, VR/AR-commerce, etc. While thematics of innovation, technology and consumer perceptions stay steady, future models will continue to extend existing operationalizations for evolving antecedents, consequences, and their relationships. M-commerce research opportunities will be evolving (Frolick and Chen 2004). The challenge remains to provide a generalized framework for this evolving topic while striving for parsimony in this conceptualization. Our model attempts to integrate existing variables with the parsimoniously conceptual model variables identified in this and related prior research. This is in line with recent trends in m-commerce research with current research focusing on mobile commerce consumer (Du and Li 2019).

Just as m-commerce is now an integrated channel in the overall marketing strategy, social commerce and meta-commerce will be in the future in the ever-evolving omni-channel marketing world. Park and Yoo (2019) extend and test the modified technology-acceptance model using AR technologies in a mobile commerce app to study the effects of perceived interactivity of augmented reality on consumer responses. Consistent with past literature, they found that high involvement shopping context resulted in greater influence of interactivity dimension of controllability and, in turn, mental imagery and attitude formation. There is much scope for such research using newer technologies like mixed reality headsets within the domain of m-commerce applications. Another study extending m-commerce application is by Sagnier et. al (2020) where the authors study the intention to use Virtual Reality (distinct from AR in that this application is a simulation of an interactive three-dimensional environment that users are immersed into and can interact with) using an extended TAM model by including dimensions of cybersickness and hedonic quality (as contrasted with rationally determined quality). They found that while consumers can get tired of technology (cybersickness) resulting in a lower intention to use VR, hedonic quality-stimulation and personal innovativeness can increase perceived usefulness and, in turn, user acceptance of VR. A logical extension of this research is to the domain of Social Commerce. Byramjee et al. (2021) propose a nomological model to analyze consumer's intention for value utility in social commerce by considering the variables of the m-commerce success model and adding two new variables – consumer's personal connectivity within the social network and consumer's social presence within the social channel.

There remains the issue of synthesizing models as well as operationalization of variables in past research. For instance, Venkatesh et al. (2003) provide an excellent approach to reconciling the eight models frequently studied in Information Technology acceptance research reconciling the diverse set of variables across the models and showing statistical relevance of key variables in each. While the resulting UTAUT model (fig. 3, table 16) summarizes the resulting integrated variables, some of the variables in competing models are not reconciled. During the same timeframe, Lee, Kozar and Larsen (2003) show twenty-five different variables used by various authors in models of TAM over the years. For instance, showing the convergence of the core constructs in Innovation Diffusion Theory with the UTAUT constructs (table 16) would be illustrative of synthesis. Similarly, Salloum et al. (2019) apply the TAM model in the context of e-learning to include constructs such as Enjoyment and Computer Playfulness which could be synthesized with the construct of Flow (see Csikszentmihalyi, Abuhamdeh and Nakamura 2014 for a collection). Such synthesis would lend a more parsimonious and generalized model applicable in fields not limited to Information Technology or M-Commerce but to the holistic realms of adoption, utilization, and diffusion of any marketplace innovation.

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