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INTENTION TO ADOPT A NEW M-COMMERCE APPLICATION BY BUYERS AND SELLERS IN NANJING, CHINA

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ABSTRACT

Data from the National Bureau of Statistics of China indicates that flow accessed using mobile internet experienced a 200 percent growth from 2014 to 2015. This opens the possibility of accessing new markets in China through mobile commerce. Then it becomes important to identify significant factors that could promote the adoption of mobile commerce applications. Identification of successful factors for the adoption of m-commerce applications are likely to vary depending on the products and the target market. Then, different separate studies are needed to identify significant factors for the adoption of m-commerce in each market sector.The objective of this research is to develop a model to determine significant factors influencing the intention to adopt a new mobile commerce application in Nanjing, China, by a group of buyers and sellers. The application studied in this research is already being used by some customers in Beijing, China. A formative structural equation model (SEM) is developed to assess the intention to adopt this new m-commerce application by a group of 98 buyers and sellers. A set of 12 indicators are used to build the final construct intention to adopt this new m-commerce application. It is found that when these groups are studied together issues of collinearity arise. Then, a modified research model determines the following as significant factors influencing the adoption of a new mobile commerce application for the sample studied in Nanjing, China: Age group, Perceived Benefits, Innovativeness, Perceived Cost and Perceived Enjoyment. These results extend previouslyavailable results but obtained with smaller samples

Keywords:
Formative model, Mobile Commerce, Structural equation model (SEM), Technology adoption.
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INTRODUCTION

Data from the National Bureau of Statistics of China [1] indicates that flow accessed using mobile internet experienced a 200 percent growth from 2014 to 2015. During the same period mobile internet subscribers experienced a 10 percent growth. These aspects are relevant since they open the possibility of accessing new markets in China through mobile commerce [2-4]. Then it becomes important to identify significant factors that could promote the adoption of mobile commerce applications [5]. The identification of such factors could guide marketing strategies and the design of m-commerce applications to attract more buyers and sellers. Identification of successful factors for the adoption of m-commerce applications are likely to vary depending on the products and the target market [5].Then, different separate studies are needed to identify significant factors for the adoption of m-commerce in each market sector. Results from previous studies identified significant factors influencing the adoption of the m-commerce application studied in this paper for each group of buyers and sellers when they are studied independently [6, 7]. In this sense, the research presented here differs from [6, 7] since in this study buyers and sellers are studied together using the same model and not separately. The objective of the present research is to propose a model to identify significant factors affecting the intention to adopt a new mobile commerce application by a group of buyers and sellers in Nanjing, China. Then, the contribution of the present research is to propose a model based on a set of 12 indicators to identify significant factors influencing the decision to adopt this new m-commerce app by a group of buyers and sellers. These indicators are: age group, gender and identification as a seller or as a buyer, perceived benefits, innovativeness, perceived security, perceived ease of use, perceived cost, perceived enjoyment, perceived compatibility, perceived lack of critical mass or perceived subjective norm and perceived intention to adopt mobile commerce [5, 2, 8].It is found that when the two groups are studied together issues of collinearity arise, requiring reformulating the model.

Mobile commerce involves more than using mobile devices for buying and selling goods, service and entertainment [5, 9]. It also involves the creation of a sharing platformwhere users interact at various levels.M-commerce offers the possibility of reaching new markets that could produce significant social and economic benefits [7]. Identifying factors affecting mobile commerce adoption is also relevant in several other different countries such as Bangladesh [10], India [8], Iran [11], Malaysia [2], Spain [12] and the U.S. [3, 4, 13]. The research presented here differs from some of the available studies about m-commerce [2-4, 8, 10, 12]since it researches the intention to adopt a new existing m-commerce application by buyers and sellersin a new market in Nanjing, China. Since there are more studiesabout m-commerce that focuses on the buyers alone [2-4, 8, 10, 12] this study adds to creating literature about m-commerce for the two groups together. The present paper extends the research presented in [6, 7] by analyzing together the intention to adopt the same new existing m-commerce application but by a group of buyers and sellers in Nanjing, China. As indicated in [9] a limitation of some of the research studies about m-commerce is that they tend to focus on promoting the positive side of the technology to increase the number of users while ignoring the negative side of the technology. In the analysis presented here to overcome this limitation potential m-commerce adopters are introduced the new features of the m-commerce application. This allows potential adopters to compare the positive and negative features of this new app against the features of leading m-commerce apps in the Chinese market.

In this research significant factors influencing the intention to adopt m-commerce are determined using aformative Structural Equation Model (SEM) variance based Partial Least Squares (PLS) technique [14-17]. The contribution of the present research is to propose a SEM-PLS model based on a set of 12 indicators to identify significant factors influencing the decision to adopt the new m-commerce app. Formative models build the final construct from a set of indicators representing different dimensions of the final construct. They are different from reflective models in that the indicators in a reflective model are made up of a set of highly correlated items representing the same dimension of the construct. Therefore, constructs in a formative model cannot be dropped from the model without affecting the meaning of the final construct [15, 16]. Indicators in a formative model are likely to be unrelated to each other [15,16]. Therefore, traditional reliability indicators such as Cronbach Alpha [15, 18, 19] may not be appropriate to use, despite its use in similar studies [2, 3, 8] in which there are multiple items measuring the same indicator. Highly correlated items in a formative model are likely to be indicators of the same aspect. In the study presented herethere are no duplicate items measuring the same indicator, therefore it is expected correlation among indicators not to be high. Formative SEM models remain controversial as oppose to reflective models specially in terms of defining standard reliability criterion [15, 17, 20-22].

The company JiuYaoPintuan developed the mobile commerce application studied in this research. This application is used in other cities in China but it is still a new entrant inthe Chinese m-commerce sector dominated by well-known companies as Taobao and Pinduoduo. The m-commerce application developed by JiuYaoPintuan is based on a novel concept of group buying in which unrelated buyers put together orders for the same product benefiting on the economies of scale that produce buying a larger quantity of the same product. As indicated by [23] mobile commerce applications that promote group buying present issues of trust and security. Organizers of group buying may not be known by all members of the group. Group members only share the common interest of buying the same product at a cheaper price. Mutual authentication could be used to increase the security of group buying transactions [23]. The mobile commerce application studied in this paper adds additional features that increase the security of the group buying transactions by not releasing the financial incentive to the group organizer until all participants in the group have confirmed they have received their complete orders. After this confirmation is received, payments are released automatically. The application is also promoting the creation of communities of buyers and sellers to make transactions more secure. In these virtual communities' sellerscould use live feeds to promote products in real time. Buyers could buy directly from the live feeds. Resellers could also be part of these virtual communities extending the reach of the m-commerce application.

Study presented here differs from [6] since the focus of [6] is only on the buyers whereas the focus of the present research is on the buyers and sellers. Reference [6] presents a formative model to determine the intention to adopt a mobile commerce application in China based on a set of 13 indicators. It is found that Education level and Perceived Lack of Critical Mass or Perceived Subjective Norm are significant factors determining the intention to adopt a new m-commerce application by buyers. These results are similar to previously available results for buyers in China [3, 6] but are different to those indicating the intention to adopt

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the same m-commerce application but by sellers. Present study differs from [7]since the focus of [7] is only on the buyers whereas the focus of the present research is on the buyers and sellers, as mentioned before. A set of 9 indicators are used in [7] to build the final construct intention to adopt this new m-commerce application by using a formative SEM-PLS model. It is found that perceived benefits, innovativeness and perceived enjoyment are significant factors influencing the adoption of a new mobile commerce application by sellers.

The results from the present research indicate that Age group, Perceived Benefits, Innovativeness, Perceived Cost and Perceived Enjoyment are significant factors influencing the intention by the buyers and sellers to adopt a new mobile commerce application. Previous results published in 2012 [2] for a similar study in China indicated that trust, social influence, and cost have a significant relationship with the decision to adopt mobile commerce.Earlier results published in 2009 [3] identified perceived usefulness, perceived ease of use, perceived cost and subjective norm as significant factors influencing the decision to adopt mobile commerce. Differences in the results from different studies may be due to the increase familiarity of Chinese users with m-commerce applications, therefore they have higher expectations about new applications entering the market.

MATERIALS AND METHODS.

SEM-PLS model

The formative Structural Equation Model Partial Least Squares (SEM-PLS) [14-16, 21]modelused in this research is presented in Fig. 1. This model determines the intention to adopt a new m-commerce application in Nanjing, China, by using a set of 12 indicators. Similarly, with most of the studies on mobile commerce adoption, the study presented is this research is basedon the Technology Acceptance Model (TAM) [24]. The survey used in this research consists of 9 items described below[2, 3, 5-8, 24, 25]. However, a total of 12 indicators are used in the model. These additional three self-explanatory indicators are:Age group, gender and identification as a seller or as a buyer.

Perceived Benefits (Q1):Buyers and sellers are likely to use the new mobile commerce application if they perceive it would be beneficial to them by exposing them to bigger marketsoffering better products and prices.

Innovativeness (Q2): buyers and sellers in the m-commerce sector in China are aware of the capabilities of major m-commerce apps.Then, they would only switch to a new m-commerce app if they perceive this applicationoffers a great deal of innovation not only in the way to reach different markets but also in the user interface and compatibility with other applications.

Perceived security (Q3): Electronic commerce transactions as well as mobile commerce transactions need to be secure preserving the privacy of the users. Buyers and sellers need guarantees that transactions are secured and their privacy is protected at all times.

Perceived Ease of Use (Q4): Mobile commerce applications need to allow buyers and sellers to perform transactions in a fast an easy way. Sellers would be reluctant to adopt a mobile commerce application that is too complex to use since potential buyers will not use it. Spending too much time searching for products or completing the sale carries additional costs to consumers (i.e. consumers are using more megabytes of their data plan to complete transactions).

Perceived Cost (Q5): Transaction costs, maintenance costs and any other costs associated to use an m-commerce platform have to be kept to a minimum. Potential sellers are willing to assume theses costs if in the long run the benefits are more. Sellers would be more likely toswitch to a new platform that offers no costs for them and their clients. Buyers would prefer to use a free m-commerce application, free to use with no transaction fees.

Perceived Enjoyment (Q6): Mobile commerce has to offer users a pleasant experience either to post products for sale or to search for items to buy. Potential users are looking for an application that provides entertainment with possibilities to share content and interact with other social media applications.

Perceived Compatibility (Q7): Mobile commerce applications to stay in the market need to keep up with constant technological changes. Potential users need to be reassured that any new m-commerce application will have the technical support and infrastructure to keep up or even stay ahead of such changes and trends.

Perceived Lack of Critical Mass or Perceived Subjective Norm (Q8): m-commerce users understand that m-commerce is an activity that involves more than buying and selling products. In an era characterized by social networks, users do not want to commit to a mobile platform that is not a trend setting platform and that it has become obsolete.

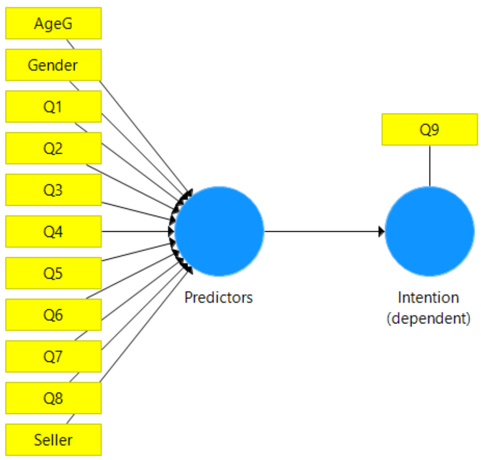

Fig. 1: Research Model

Perceived Intention to adopt m-commerce due to overall advantages (Q9):Intention to adopt the new mobile platform is estimated as a proxyvia this question in a similar fashion as in [3].

Survey Questionnaire.

A survey questionnaire was designed [6, 7]based on the items described in the previous section, to assess the intention to adopt this new mobile commerce application by potential buyers and sellerslocated in Xianlin, Nanjing, China. Students enrolled in the Corporate Challenge program at the School of Management, New York Institute of Technology, Nanjing, China, distributed the survey questionnaire to sellers. Potential buyers answered the survey in paper format. Respondents received information about the features of the new mobile application and they have the opportunity to use the application prior to completing the survey questionnaire. A total of 98 surveys are included in the present study.There are 49 respondents in each group. 55 percent of the respondents are females. 65 % are younger than 30, 34% are between 31 and 50 years old. Sample is skewed towards younger respondents. This may indicate that this age group is more likely to use mobile applications. However, there is no data available characterizing the target population of this m-commerce application as to conclude the representativeness of the sample to the population.

RESULTS

Results presented in this section are obtained using the program SmartPLS 3 [26]. The formative model introduced in Fig. 1 is evaluated in this sectionto determine significant indicators influencing the decision to adopt a new mobile commerce application. Consistent Partial Least Squares (PLSc) [16, 27] is used to identify significant factors. PLSc is a variance-based Structural Equation Modelling Partial Least Squares (SEM-PLS) technique. Variance-based SEM-PLS techniques offer advantages over other covariance-based SEM techniques [16, 21, 27-29]in the ability to handle small samples and requiring fewer assumptions about the distribution of the data [29]. PLSc [16, 27] is employed to evaluate the relationship between the indicators and the final construct "Intention" (Q9) which is used as proxy [3] to indicate the intention to adopt a new mobile commerce application. PLSc offers advantages over Partial Least Squares (PLS) [22, 27, 30, 31] since it produces asymptotically consistent estimators and it gives the possibility of derived goodness of fit estimators. This last aspect is still controversial in SEM-PLS formative models as the one used in this research [15, 20, 22].
According to the coefficient of determination R^2 presented in Fig 2. 37.2% of the target endogenous variable "Intention" variance is explained by the predictors used in the model. Values for R^2 greater than 0.67 are considered substantial, values between 0.67 and 0.33 are considered moderate and values between 0.19 and 0.33 are considered weak [15]. According to these cutoff values the research presented here has moderate explanatory power. Then, sample-based results presented here have to be considered with caution and moderation.Reference [16] proposes higher cutoff values for the coefficient of determination R^2. Model developed in [3] for China presents a higher explanatory value since R^2 is 0.523. However [3], uses a larger sample size with multiple items for the same indicator. Similarly, model presented in [6] for the same application studied here presents a higher explanatory value since R^2 is 0.446. Then, increasing the sample size

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and/or studying the two groups together is not increasing the explanatory power to improve the understanding of the factors influencing the intention to adopt a new m-commerce app.
Consistent PLSc Bootstrapping [26] is used to determine statistical significance of inner model path coefficientsand outer model weights. Bootstrapping method consist of drawing a large number of random subsamples with replacement to estimate the parameters. Therefore, this technique could produce results with small variations each time the algorithm is run for the same problem [15]. Consistent PLSc Bootstrapping technique estimates parameters using the PLSc procedure. Consistent PLSc Bootstrapping algorithm for the study conducted here uses 500 random samples considering individual sign changes, basic bootstrapping and Bias-Corrected and Accelerated (BCa) Bootstrap to determine the confidence intervals.Significant factors for values presented in Fig. 3 are those whose t-statistic is larger than 1.96 considering a significant level of 5% in a two tailed test. Therefore, the inner model path coefficient linking the predictors with the intention to adopt m-commerce is not significant. This aspect requires re-evaluating the model. This would be done in the following paragraphs presenting a modified research model. Furthermore, none of the predictors used in the model presented in Figure 3 are significant. Outer model weights are considered an estimator of the relevant contribution of an indicator to build the final construct.Outer Weights for all the indicators are not significant with p-values in the range of 0.290 and 0.770. Outer loadings for all the indicators are not significant with p-values in the range of 0.286 and 0.407.

Table 1: Variance Inflation Factor

	VIF		VIF
Age	1.162	Q5	2.051
Gender	1.162	Q6	1.154
Q1	1.687	Q7	5.352
Q2	1.367	Q8	7.913
Q3	8.582	Q9	1.000
Q4	8.540	Seller	2.858

Table 1 reports values for the Variance Inflation Factor (VIF) indicating problems with collinearity. Collinearity is considered to happen when the variance inflation factor (VIF) exceeds a value of 5 and tolerance values are less than 0.2 [15]. Tolerance can be obtained by subtracting 1 from R^2. In general, these two measurements are considered to provide the same information [15]. However, in this initial model tolerance equals 0.628 (i.e. tolerance = 1-0.372). This value is greater than 0.2 but there are problems with collinearity as reflected by VIF.In the model presented here the following indicators have VIF greater than 5: Perceived security (Q3), Perceived Ease of Use (Q4), Perceived Compatibility (Q7) and Perceived Lack of Critical Mass or Perceived Subjective Norm (Q8). Collinearity has not been a problem when buyers and sellers have been analyzed separately in previous research [6, 7]. Collinearity is more likely to happen in reflective models since there are several indicators representing the same construct. Therefore, these reflective indicators are expected to be highly correlated. However, in formative models each indicator represents a different dimension of the construct. Then, it is expected these formative indicators would have low correlation. Table 2 gives correlation values for highly correlated indicators: Q3, Q4, Q7 and Q8. These indicators are removed from the original model as given in Figure 4, representing a modified research model.

Table 2. Correlation Values for Q3, Q4, Q7 and Q8 indicators.

Correlation (Q3, Q4)= 0.913	Correlation (Q4, Q7)= 0.854
Correlation (Q3, Q7)= 0.858	Correlation (Q4, Q8)= 0.889
Correlation (Q3, Q8)= 0.874	Correlation (Q7, Q8)= 0.872

The modified research model presented in figure 4 includes only 7 indicators. These indicators are: Age group, Gender, Perceived Benefits (Q1), Innovativeness (Q2), Perceived Cost (Q5), Perceived Enjoyment (Q6) and

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identification of the respondent as a seller or as a buyer. Figure 5 gives outer model weights, inner model path coefficient and R^2 values. The proposed modified research model explains 36.5% of the target endogenous variable "Intention" variance. This modified research model has moderate explanatory power, according to the cutoff values presented above and given in [15]. Statistical significance of inner model path coefficients [22] and outer model weights is determined by using consistent PLSc Bootstrapping [26]. Significant factors for values presented in Fig. 6 are those whose t-statistic is larger than 1.96 considering a significant level of 5% in a two tailed test. Therefore, the inner model path coefficient linking the predictors with the intention to adopt m-commerce is significant (t= 8.328).Similarly, age group (t=2.059) and Q6 perceived enjoyment (t= 3.906) are significant. P-values for outer weights are: Age group (p-value =0.032), Gender (p-value = 0.062), Perceived Benefits (Q1) (p-value = 0.104), Innovativeness (Q2) (p-value = 0.201), Perceived Cost (Q5) (p-value = 0.065), Perceived Enjoyment (Q6) (p-value =0.000) and seller (p-value =0.466). Then, significant indicators considering outer weights at the significant level of 5% are: age group and perceived enjoyment (Q6).Before dropping not significant indicators [16] in a formative model based solely on Outer Model Weights Significance it is important to check Outer Loadings significance before removing the indicator. According to this criterion only indicators that have no significant Outer Model Weights and Outer Loadings should be removed. P-values for outer loading are: Age group (p-value =0.030), Gender (p-value = 0.256), Perceived Benefits (Q1) (p-value = 0.000), Innovativeness (Q2) (p-value = 0.001), Perceived Cost (Q5) (p-value = 0.000), Perceived Enjoyment (Q6) (p-value =0.000) and seller (p-value =0.000). The only non-significant factor based on p-values for outer loads is gender. This factor can be removed from the model since it also has non-significant outer weight. All other factors are not removed from the modified model. Then final modified research model includes: Age group, Perceived Benefits (Q1), Innovativeness (Q2), Perceived Cost (Q5) and Perceived Enjoyment (Q6).

In this paper convergent validity is assessed via redundancy analysis [16, 17] using indicator Q9 presented in Fig 5. According to this criterion the path coefficient linking predictors to intention should be greater than or equal to 0.8 [16, 17]. In the analysis presented here this path coefficient equals 0.604 for the modified research model. However, convergent validity remains a controversial issue in formative models [21] since convergent validity tests the degree of correlation among indicators. Indicators in formative models are likely to be uncorrelated since they represent different dimensionsof the construct.Therefore, collinearity should not be a problem. However, in the original model presented in figure 1 collinearity is a problem as described earlier in the paper. Collinearity is considered to happen when the variance inflation factor (VIF) excess a value of 5 and tolerance values are less than 0.2 [15]. In the present case for the modified research model tolerance equals (1-0.365) =0.622. Tolerance values less than 0.20 signal issues with multicollinearity. In cases when the coefficient of determination is greater than 0.8, collinearity must be evaluated. According to these two criteria, the initial model presented in figure 1 did not require evaluation for collinearity. But VIF values for the initial model contradict this statement as shown earlier. VIF for all indicators used in the modified model are less than cutoff value of 5 as presented in Table 3. Corresponding Inner VIF from predictors to Intention corresponds to 1.Therefore, the modified model has no issues with collinearity as opposed to the initial research model presented in figure 1.

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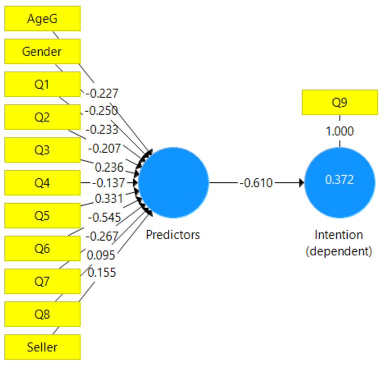

Fig.2: Outer Model Weights, inner model path coefficient and R^2 values.

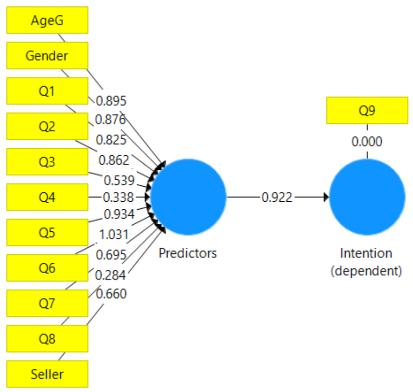

Fig.3: Inner Model and Outer Model Weights Significance.

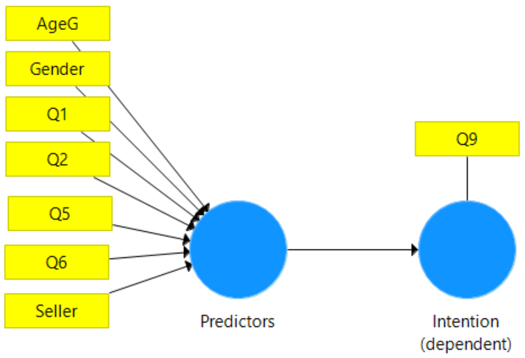

Fig. 4: Modified Research Model

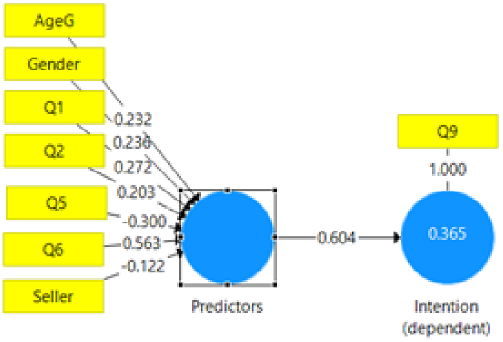

Fig.5:Outer Model Weights, Inner Model Path Coefficient and R^2 values.

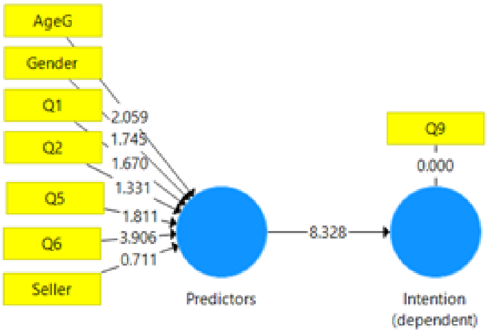

Fig.6: Inner Model and Outer Model Weights Significance.

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Table 3 Variance Inflation Factor (VIF) Modified Model

	VIF		VIF
Age	1.057	Q5	1.841
Gender	1.092	Q6	1.141
Q1	1.570	Q9	1.000
Q2	1.259	Seller	2.211

DISCUSSION

This research proposes to study significant factors influencing the decision to adopt a new mobile commerce application by a group of buyers and sellers from Nanjing, China. A formative model is developed using a set of 12 indicators. These indicators are: Perceived Benefits (Q1), Innovativeness (Q2), Perceived security (Q3), Perceived Ease of Use (Q4), Perceived Cost (Q5), Perceived Enjoyment (Q6), Perceived Compatibility (Q7), Perceived Lack of Critical Mass or Perceived Subjective Norm (Q8), Perceived Intention to adopt m-commerce due to overall advantages (Q9), age group, gender and identification as a seller or as a buyer.Consistent Partial Least Squares (PLSc) [17, 28] is used to determine significant factors influencing the intention to adopt the new mobile commerce application developed by JiuYaoPintuan.Results for this initial model indicate that theinner model path coefficient linking the predictors with the intention to adopt m-commerce is not significant. Furthermore, none of the predictors used in the model are significant. Variance Inflation Factors (VIF) indicate problems with collinearity for the following indicators: Perceived security (Q3), Perceived Ease of Use (Q4), Perceived Compatibility (Q7) and Perceived Lack of Critical Mass or Perceived Subjective Norm (Q8). Collinearity has not been a problem when buyers and sellers have been analyzed separately in previous research using formative models [6, 7]. Highly correlated indicators are consideredperhaps by some users as representing the same dimension of a desired super-construct that encompasses all of them together at the same time. Author is conducting additional research in a separate paper about this issue of collinearity. A modified research modelis presented by removing highly correlated indicators. The modified research model includes only 7 indicators: Age group, Gender, Perceived Benefits (Q1), Innovativeness (Q2), Perceived Cost (Q5), Perceived Enjoyment (Q6) and identification of the respondent as a seller or as a buyer. The proposed modified research model has moderate explanatory power since it explains 36.5% of the target endogenous variable “Intention” variance.The inner model path coefficient linking the predictors with the intention to adopt m-commerce is significant for the modified research model. The final modified research model includes the following indicators: Age group, Perceived Benefits (Q1), Innovativeness (Q2), Perceived Cost (Q5) and Perceived Enjoyment (Q6). In the present case for the modified research model tolerance equals 0.622. Since this value isgreater than 0.20 there are no problems with multicollinearity. Corresponding Inner VIF from predictors to Intention corresponds to 1. All of these indicates the modified model has no issues with collinearity as opposed to the initial research model.

Results from the analysis conducted here identified the following indicators as significantly influencing the decisions from buyers and sellers to adopt a new m-commerce app for the modified model: Age group, Perceived Benefits (Q1), Innovativeness (Q2), Perceived Cost (Q5) and Perceived Enjoyment (Q6).Results from [6] indicate that Education and Perceived Lack of Critical Mass or Perceived Subjective Norm (Q8) are the only two significant indicators for buyers to decide to adopt the m-commerce app developed by JiuYaoPintuan. Results from [7] indicate that perceived benefits (Q1), innovativeness (Q2) and perceived enjoyment (Q6) are significant factors influencing the intention by the sellers to adopt a new mobile commerce application. Significant factors identified in this research have more similarity with the factors identified for the sellers alone. Inclusion of the buyers and sellers in the same study creates some issues with collinearity requiring removal of highly correlated indicators. This issue is subject of additional research from the author in a separate study.Differences in the results presented here with earlier published results [3-4, 6-7] may be due to the increase familiarity of Chinese users with m-commerce applications, therefore they have higher expectations about new applications entering the market. It is important to remember that results about intention to adopt m-commerce applications are dependent on the application being studied and the sample size.Additional research studies are needed to determine whether or not some generalizations can be made to define guiding principles for the sector.

REFERENCES

[1] China Statistical Yearbook 2016. National Bureau of Statistics of China.
[2] Chong A.Y., Chan F.T.S., Ooi K. (2012). Predicting consumer decisions to adopt mobile commerce: Cross country empirical examination between China and Malaysia. *Decision Support Systems, 53(1), 34-43.*
[3] Dai, H., Palvia, P.C. (2009). Mobile Commerce Adoption in China and the United States: A Cross-Cultural Study *The DATA BASE for Advances in Information Systems, 40 (4),43-61.*
[4] Lu, J., Yu, C., Liu, Ch., Wei, J. (2017). Comparison of mobile shopping continuance intention between China and USA from an espoused cultural perspective. *Computers in Human Behavior, 75, 130-146.*
[5] Liébana-Cabanillas, F., Marinković, V., Kalinić, Z. (2017). A SEM-neural network approach for predicting antecedents of m-commerce acceptance. *International Journal of Information Management, 37(2), 14-24.*
[6] Cedeno, E. B. (2018). Formative Model to Determine Intention to Adopt Mobile Commerce. In Proceedings of the 2018 International Conference on E-business and Mobile Commerce (ICEMC '18). ACM, New York, NY, USA, 17-21. DOI: https://doi.org/10.1145/3230467.3230474
[7] Cedeno, E. B. (2018). An Exploratory Study on the Intention to Adopt a New Mobile Commerce Application in Nanjing, China. Forthcoming International Journal of e-Education, e-Business, e-Management and e-Learning (IJEEEE).
[8] Ahujaa, V., Khazanchib, D. (2016). Creation of a conceptual model for Adoption of Mobile Apps for shopping from E-Commerce sites-An Indian context. *Procedia Computer Science, 91,609 – 616.*
[9] O'Donnell, J., Jackson, M., Shelly, M., Ligertwood, J. (2007). Australian Case Studies in Mobile Commerce. *Journal of Theoretical and Applied Electronic Commerce Research, 2(2), 1-18.*
[10] Rahman, M.M. (2015).Opportunities and Challenges of M-commerce Adoption in Bangladesh: An Empirical Study. *Journal of Internet Banking and Commerce, 20(3), 2-23.*
[11] MortezaGhobakhloo, M., Tang, S.H. (2013).The role of owner/manager in adoption of electronic commerce in small businesses: The case of developing countries. *Journal of Small Business and Enterprise Development,20(4) 754-787.*
[12] Bigné, E., Ruiz, C., Sanz, S. (2007). Key Drivers of Mobile Commerce Adoption. An Exploratory Study of Spanish Mobile Users. *Journal of Theoretical and Applied Electronic Commerce Research*, 2(2),48-60.
[13] Hillman, S., Neustaedter, C. (2017). Trust and mobile commerce in North America. *Computers in Human Behavior, 70, 10-21.*
[14] Garson, G.D. (2016). *Partial Least Squares: Regression & Structural Equation Models*. StatisticalAssociates Publishing.
[15] Wong, K. K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS. *Marketing Bulletin, 24, Technical Note 1*.
[16] Dijkstra, T. K., Henseler, J. (2005). Consistent and asymptotically normal PLS-estimators for linear structural equations. *Computational Statistics & Data Analysis, 81 (1), 10-23.*
[17] Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y-M., Lauro, C. (2005). PLS Path Modeling. *Computational Statistics & Data Analysis*, 48 (1), 159-205.
[18] Starkweather, J. (2012). Step out of the past: Stop using coefficient alpha; there are better ways to calculate reliability. *Benchmarks, June.* Retrieved October 25, 2017 from http://it.unt.edu/benchmarks/issues/2012/06/news[4/28/16, 3:44:47 PM]
[19] Fornell, C., Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J Market Res*, 18(1), 39–50
[20] Andreev, P., Tsipi, H., Hanan, M., Nava, P. (2009). Validating Formative Partial Least Squares (PLS) Models: Methodological Review and Empirical Illustration. *ICIS 2009 Proceedings, 193.*
[21] Esposito Vinzi, V. et al. (2010). Handbook of Partial Least Squares. Springer HandbooksofComputationalStatistics.
[22] Henseler, J., Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *ComputationalStatistics*, 28, 565–580.
[23] Lee, J., Lin, K. (2013). An innovative electronic group-buying system for mobile commerce. *Electronic Commerce Research and Applications, 12(1), 1-13.*
[24] Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13(3), 319-340.*
[25] Mall at, N., Tuunainen, V. K. (2008). Exploring Merchant Adoption of Mobile Payment Systems: An Empirical Study. *e-Service Journal,6(2),24-57.*

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International Journal of Engineering Technology Research & Management

[26] Ringle, C. M., Wende, S., Becker, J. M. (2015). SmartPLS 3. Boenningstedt: SmartPLS GmbH, http://www.smartpls.com.
[27] Chin, W.W. (1998). Issues and opinion on structural equation modeling (Review). *MIS Quarterly: Management Information Systems*, 22 (1), vii-xvi
[28] Chin, W., Newsted, P. (1999). Structural Equation Modeling Analysis with Small Samples Using Partial Least Square. Statistical Strategies for Small Sample Research. Sage Publications.
[29] Reinartz, W.J., Haenlein, M., Henseler, J. (2009) An empirical comparison of the efficacy of covariance-based and variance-based SEM. *Int J Res Market*, 26(4), 332–344.
[30] Wold, H. O. A. (1982). Soft modelling: the basic design and some extensions. Joreskog, K. G., Wold, H. O. A. (Eds.), *Systems under Indirect Observation. Causality, Structure, Prediction*. Vol. II. North-Holland, Amsterdam, New York, Oxford, 1-54.
[31] Wold, H.O.A. (1973) Nonlinear iterative partial least squares (NIPALS) modelling. Some current developments. In:*Krishnaiah PR (ed) Proceedings of the 3rd International Symposium on Multivariate Analysis*,383–407.