ATLANTIS PRESS

The Impacts of Online Comments and Bandwagon Effect on the Perceived Credibility of the Information in Social Commerce: The Moderating Role of Perceived Acceptance

Choon Ling Kwek*, Bi Lei, Lai Yan Leong, Michelle John A/P John Saggayam, Ying Xue Peh

Tunku Abdul Rahman University College, Jalan Genting Kelang, Setapak, 5330 Kuala Lumpur, Malaysia
*Corresponding author. Email: kwekcl@tarc.edu.my, bil-wr18@student.tarc.edu.my

ABSTRACT
Social commerce is growing and gaining popularity among Generation Y due to the advancement of technology, in which it creates a new marketplace for sellers and buyers. It allows an individual to browse, compare and purchase the products on social media sites such as Facebook, Twitter and Instagram. Therefore, online comments, bandwagon effect and perceived credibility may have potential influences on the perceived credibility of the information given through social media sites. This study was carried out among the social commerce users in Malaysia with the purpose to investigate the determinants of perceived credibility within the context of social commerce. This study concluded that both online comments and bandwagon effects have positive relationship with the perceived credibility, whereas online comments are positively related to the bandwagon effect. In addition, the findings also revealed that perceived acceptance moderates the relationship between online comments and perceived credibility, whereas bandwagon effect mediates the relationship between online comments and perceived credibility.

Keywords: Social commerce, online comments, perceived credibility, bandwagon effect, perceived acceptance.

1. INTRODUCTION

With the ease of utilizing the Internet as the tool of information searching, CyberSecurity Malaysia revealed that cases involving online fraud including online purchasing of goods, Internet banking transactions, phishing, and scams have increased to a total number of 3921 cases in the first quarter of 2017 (Bernama, 2017). The distribution of false information is a serious matter which may lead to long-term negative effects to the community and the country (Bernama, 2017). In due respect, it is important for the social commercial users to identify the determinants of the credibility of information in the social commercial platforms. With the advancement of information technology, online users share their opinions through online comments (Dijck 2013; Kaul, Yates & Gruteser 2012). However, the study from Xu (2014) primarily focused on the number of trusted members that drove bandwagon effect to perceived credibility, but there was an absence of study in regards to the effect of online comments on social media that could lead bandwagon effect to perceived credibility (Kim 2015). Hence, this research would like to investigate the impacts of online comments and bandwagon effects on the perceived credibility of the information on the social commerce, as well as the role of

perceived acceptance in moderating the relationship between online comments and the perceived credibility of information on the social commerce.

2. LITERATURE REVIEW

2.1 Heuristic-Systematic Processing Model

Chaiken's (1980) model of Heuristic-Systematic Processing (HSM) explains that there are two information processing modes, which are the heuristic and systematic modes. According to Sundar *et al.* (2008), HSM is an information processing that people are inclined to rely on the mental shortcuts such as expertise heuristic and bandwagon heuristic in judging the information that is already stored in memory. This form of interpretation may invoke bias, when they process the content of the information (Sundar *et al.* 2008).

2.2 Theory of Bandwagon Heuristic

Bandwagon heuristic is one of the many heuristics (mental shortcuts) that is proposed by Sundar *et al* (2008). The

bandwagon heuristic is triggered when a person perceives that something is popular or good, when there is a large group of people agreed on it that leads to quick evaluations of the statement without the scrutiny of the content. This heuristic has an impact on the perceived trustworthiness of the online information (Sundar *et al*. 2007).

2.3 Perceived Credibility

O'Keefe (2002) stated that credibility is a decision of a message recipient on how he/she perceives the source or the message sender. Kang, Hollerer and O'Donovan (2015) argued that perceived credibility is not necessarily inherent to an entity, but it varies on the basis of the way of the entity is represented by the online information provider and the personal characteristics of the online information receiver who makes the credibility assessment.

2.4 Online Comments and Perceived Credibility

In social media, the online comments plug-in allows users to share their opinions related to the product information and view on how other people response to it (Kim 2015). People often use others' comments as a public opinion cue in evaluating information credibility (Walther *et al*. 2010). From the social commerce perspective, if the comments are favorable to the product, consumers will perceive that the product is reliable and trustworthy (Huang & Chen 2006). Therefore, the relationship between online comments and perceived credibility has proven to be positively related (Kim 2015), and the proposed hypothesis is developed as follow:

H_1: *Online comments are positively related to perceived credibility*

2.5 Acceptance, Online Comments and Perceived Credibility

Rogers (1980) defined perceived acceptance as a relationship-specific and generally stable intellectual evaluation, that the information receivers care for and that their concern is independent upon the information providers' holding specific mentalities or acting uniquely on contrast to how they normally act (Brock *et al*. 1998). Based on Kim (2015), perceived acceptance affected by the online comments will influence a user's perceived credibility on the social media. It is found that individuals often evaluate information according to others' online comments. This is possibly due to the willingness of users to accept others' opinion as valid information and tend to believe what most other people believe (Aronson, Wilson & Akert 2005). Hence, the moderating effect of perceived acceptance in the relationship between online comments and perceived credibility is supported by Kim (2015) and the proposed hypothesis is developed as follow:

H_2: Perceived acceptance moderates the relationship between online comments and perceived credibility

2.6 Bandwagon Effect and Online Comment

According to Moe and Schweidel (2012), the tendency to adopt the opinion of the majority is said to be the bandwagon effect. If an online reviewer is endorsed by many people, the consumers would then apply the bandwagon heuristic to perceive that the reviewer is credible (Sundar *et al*. 2008). Hence, bandwagon cues will appear if the users evaluate information solely based on online comments (Sundar, Knobloch-Westerwick & Hastall 2007). Sundar *et al*. (2008) support the above argument by explaining that individuals will judge the information based on the online comments available, when they are exposed to bandwagon cues such as higher review ratings. Therefore, online comments are likely to drive bandwagon effect.

H_3: *Online comments are positively related to bandwagon effect*

2.7 Bandwagon Effect and Perceived Credibility

Li & Chen (2005) argued that the consumers tend to purchase the products with higher star rating, sales rank, and customer reviews as they have a more favorable impressions due to the effect of bandwagon heuristic (Kim, Brubaker & Seo 2015). This means that the bandwagon effect creates positive impact on the higher purchasing intention and consumer attitudes towards the products due to its influence on their message perception, evaluation, judgement and behavior of the consumers (Kim et al 2015). As a result, a strong bandwagon effect strengthens the perceptions of credibility, quality and value, as the consumers receive more positive feedbacks on the product (Sundar *et al*. 2008).

H_4: Bandwagon effect is positively related to perceived credibility

2.8 Bandwagon Effect, Online Comments and Perceived Credibility

As individuals normally believe in the correctability of others' online comments when a large group of people shares the same opinion and information through the comments, bandwagon effect is said to be triggered as the individuals tend to follow others' beliefs (Chaiken 1987; Sundar et al. 2008). As a result, these collective voices or perceived others' views from the online comments influence the information perception such as perceived credibility (Kim 2015) as the information endorsed by the majority can trigger the bandwagon heuristic. According to Kim et al (2015), the positive comments increase others' perceptions of information credibility due to the increased perceptions of

bandwagon. Therefore, the following hypothesis is suggested:

H₅: Bandwagon effect mediates the relationship between online comments and perceived credibility
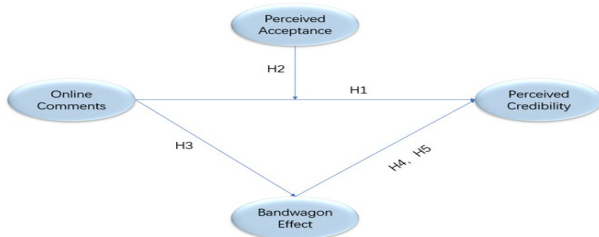

Figure 1: Conceptual Model

3. RESEARCH METHODOLOGY

Quantitative research with cross-sectional study was adopted, because it allows the researcher to analyze the research problem through justification of the relationship among the variables within a relatively short time (Creswell 2014; Kate 2006). Primary data was collected from the Generation Y who are the social media users.

Generation Y [who was born in between 1980's to the early 1990's] was chosen as the target population in this research, because Generation Y is the largest group of individuals who use social media on the daily activities (Muda *et al*. 2016). Convenience sampling was used in this research, because it is an easy and inexpensive method (Etikan, Musa & Alkassim 2016). There is a recommendation from Schwab (1980) that proposes the item-to-response ratio range of at least 1:10, which is adequate in determining the sample size. As this research contains a total of 37 measures, the sample size was targeted at 450 (more than *370 respondents*) based on the ratio suggested. This research adopted the survey through online platform (Google Forms) to allow researcher to acquire up to 450 respondents. A total of 407 samples were collected in the survey research.

Questionnaire is divided into two parts. Part A is related to the demographic aspects including gender, age range, education level, time spent on social media per day, online purchase frequency, favorite social media platform for online purchasing, product purchase the most and total spending on online purchasing. For Part B, four constructs were measured in the questionnaires. Online comments (OC) was measured by 10 items using 5 points Likert-scale ranging from "strongly disagree" (1) to "strongly agree" (5). For perceived acceptance (PA), it consisted of 6 items and was measured by 5 points Likert-scale ranging from "very unlikely" (1) to "very likely" (5). Besides, the bandwagon effect (BE) contained four items and was measured by 5 points Likert-scale ranging from "very unlikely" (1) to "very likely" (5). For perceived credibility (PC), it consisted of three items using 5 points Likert-scale ranging from "strongly disagree" (1) to "strongly agree" (5).

The statistical programs called SPSS version 25.0 and SmartPLS version 3.2.8 were applied in this study to perform the statistical analyses. Descriptive analysis,

measurement model and structural model were carried out in the data analysis.

4. DATA ANALYSIS & FINDINGS

4.1 Descriptive Analysis

Based on the statistical findings, it was observed that 36.4% of the respondents were male and 63.6% were female. Besides, majority of the respondents (65.4%) were within 21 and 23 years old. In addition, majority of the respondents (72.2%) were bachelor degree holders. The finding indicates that majority of the respondents (44.7) were spending 3-5 hours per day in social media. For the purchase frequency, 36.1% of respondents engaged in online purchasing every 2-6 months. The most preferred purchasing platform engaged by respondents was Facebook. The most popular product purchased by respondents through online commerce was clothing and accessories (46.4%). In term of spending pattern, majority of the respondents were spending below RM100 for every online shopping transaction.

4.2 PLS-SEM Assessment

There are two stages to perform SEM-PLS - a measurement model and structural model (Hair *et al*. 2017). Figure 2 presents the conceptual structural model that will be evaluated via the measurement model and structural model.
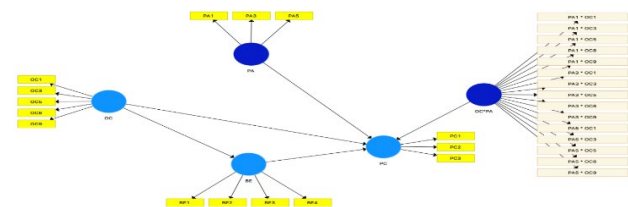

Figure 2. Conceptual Structural Model

4.3 Assessment of Measurement Model

In order to examine the reflective measurement model, factor loadings, construct reliability, convergent validity, and discriminant validity were tested by using PLS-SEM (Hair *et al*. 2017). Table 1 shows the convergent validity of constructs and Table 2 indicates the discriminant validity of constructs.

The results of all factor loadings in the measurement model, as shown in Table 1, ranging from 0.728 to 0.944, achieve above the threshold level of 0.708 (Hair *et al*. 2017). Besides, Table 1 also indicates that the inter-item consistency reliability values of Cronbach's alpha ranged from 0.809 to 0.913, which exceeded the recommend value

of 0.7 as suggested by Nunnally (1978). In addition, Dijkstra- Henseler's rho (ρA) also achieved satisfactory reliability value ranging from 0.812 to 0.919, which exceeded the recommended value of 0.7 as suggested by Dijkstra and Henseler (2015). At the same time, the Jöreskog's rho (ρc) (also known as Composite Reliability, CR) values, which refer to the degree to which the construct indicators indicates the latent construct, ranged from 0.887 to 0.945, which are all above the threshold of 0.7 (Nunnally and Bernstein, 1994). Therefore, the overall reliability has

achieved satisfactorily of high internal consistency reliability.

The values of the Average Variance Extracted (AVE) for each of the constructs ranged from 0.656 to 0.852, which are above the threshold value of 0.5 (Hair *et al*. 2017; Ringle, Sarstedt & Hair 2016). In addition, the observed t-value for each of the factors was above 1.96, which means they were all significantly (at 95% confidence-level) loaded toward their respective latent constructs. Therefore, it could be concluded that measurement model possessed adequate convergent validity.

Table 1. Convergent Validity and Reliability of Constructs

Construct	Model	Indicators	Factor Loading	T-value	Cronbach's alpha	Dijkstra- Henseler's rho (ρA)	Jöreskog's rho (ρc)	AVE
OC	Reflective	OC1	0.854	55.424	0.868	0.882	0.905	0.656
		OC3	0.870	69.865				
		OC5	0.849	35.121				
		OC8	0.739	18.966				
		OC9	0.728	23.713				
PA	Reflective	PA1	0.855	43.507	0.809	0.812	0.887	0.724
		PA3	0.871	58.566				
		PA5	0.825	36.562				
BE	Reflective	BE1	0.864	57.402	0.903	0.905	0.933	0.776
		BE2	0.908	93.079				
		BE3	0.851	47.363				
		BE4	0.899	74.881				
PC	Reflective	PC1	0.893	62.904	0.913	0.919	0.945	0.852
		PC2	0.932	121.596				
		PC3	0.944	171.335				

According to Voorhees *et al*. (2016), heterotrait–monotrait ratio of correlations (HTMT) (with a ratio cut-off less than 0.85) is the most ideal method to test the discriminant validity in comparison to both of the Fornell and Larcker's (1981) and cross-loading approaches. Based on Table 2, the result shows that the values of correlations among the latent variables were lower than 0.85, which are far below the strictest threshold of 0.85 (Kline, 2011); and the constructs in this research had significant discriminant validity, as no zero value is tracked in between the upper and lower levels of the 95% Bootstrap Confidence Interval (CI) (Preacher and Hayes, 2008). Thus, it indicated that the latent measurement constructs were clearly discriminant with each other. In overall, the measurement model appeared to have adequate reliability, convergent validity and discriminant validity. Thus, this model would be employed for further testing of the hypotheses and proving the research model in the next section.

Table 2. Discriminant Validity of Constructs

Latent Variables	BE	OC	PA	PC
BE				
OC	0.608*			
PA	0.660*	0.671*		
PC	0.655*	0.631*	0.606*	

* The value of 0 does not straddle in between the lower and upper limits in the 95% Bootstrap Confidence Interval (CI).

4.4 Assessment of Structural Model

Structural model is used to test the significances of the hypotheses in the model. Standard evaluation criteria include the collinearity (VIF), the coefficient of determination (R^2), the effect size (f^2), the validated redundancy test (Q^2) based on blindfolding, the path coefficients ' statistical significance and relevance, and

the Goodness-of-Fit (GoF). Apart from these, the model's out-of-sample predictive power would be tested by the researchers with the PLS Predict procedure (Shmueli *et al.* 2016).

Prior to the evaluation of structural model, the collinearity must be assessed to make sure it does not have the bias in the regression results; and the VIF values close to 3 and lower is the best ideal (Hair *et al.* 2017). As shown in Table 3, all the Inner VIF values for the independent variables (OC, PA, BE and PC) are less than 3, which indicates that lateral collinearity was not an issue in this research.

Table 3. Lateral Collinearity Assessment (VIF)

	BE	OC	PA	PC
BE				1.798
OC	1			1.812
PA				1.691
PC				

Notes: Dependent Variable 1: Perceived Credibility (PC); Dependent Variable 2: Bandwagon Effect (BE)

When collinearity was not a major concern, the next step was assessing R^2 value of the endogenous constructs. As indicated in Table 4, the R^2 level for PC in this research is 0.447 illustrating that 44.7% of the total variance of PC (DV1) was explained by its direct exogenous variables (H_1-OC, H_4-BE) and moderating relationship (H_2-PA). The total variation explained for BE, on the other hand, is 0.373 defining that OC could explain approximately 37.3% towards BE. Pursuant to the rules of thumb for acceptable R^2 by Cohen (1988), the R^2 levels for the respective targeted endogenous variables (PC) and (BE) in this research are 0.447 and 0.373 respectively, which are above the guideline value of 0.26, hence, they were deemed to have a substantial level of variance explained.

The assessment of f^2 level was undertaken to examine the weightings of predictor on its endogenous variables (Ramayah *et al.* 2018). As exhibited in Table 4, OC ($f^2 = 0.064$), OC*PA ($f^2 = 0.008$) and BE ($f^2 = 0.112$), has a small effect size on PC (endogenous variable). OC ($f^2 = 0.596$) has large effect size to BE by referring to Cohen (1988) threshold.

Table 4. Path Coefficients Assessment of the Structural Model

Hypotheses	Relationship	Path coefficient	S.D.	t-value	p-value	Decision	R^2	f^2	Q^2	CI LL	CI UL	Goodness of Fit
H_1	OC -> PC	0.254	0.061	4.147	0.000	Supported	0.447	0.064	0.351	0.134	0.374	SRMR=0.054 NFI=0.895 Rms_Theta=0.165
H_2	OC*PA -> PC	-0.059	0.043	1.390	0.082*	Supported#		0.008		0.092	0.195	
H_4	BE -> PC	0.333	0.062	5.409	0.000	Supported		0.112		0.221	0.458	
H_5	OC-> BE -> PC	0.204	0.041	4.922	0.000	Supported		-		0.139	0.274	
H_3	OC -> BE	0.611	0.037	16.348	0.000	Supported	0.373	0.596	0.271	0.53	0.679	

*One-tailed p-value for moderation
Based on the results of CI, R^2, f^2 and simple slope analysis

Apart from R^2 and f^2, the assessment of Stone-Geisser's Q^2 is also suggested for identifying the overall predictive relevance of each endogenous construct in the path model (Ramayah *et al.* 2018; Geisser 1974; Stone 1974). In Table 4, the Q^2 assessment shows that both PC and BE have adequate predictive relevance effects in the model, because their resulting Q^2 values (0.351 and 0.271 respectively) are above zero (Hair *et al.* 2017; Fornell & Cha 1994).

Table 5. Assessment of PLS Predict

	PLS			LM			ERROR (PLS-LM)		
	RMSE	MAE	Q^2 predict	RMSE	MAE	Q^2 predict	RMSE	MAE	Q^2 predict
BE1	0.909	0.721	0.287	0.879	0.678	0.332	0.030	0.043	-0.045
BE2	0.878	0.695	0.331	0.847	0.65	0.377	0.031	0.045	-0.046
BE3	0.949	0.766	0.243	0.917	0.719	0.294	0.032	0.047	-0.051
BE4	0.867	0.677	0.280	0.812	0.615	0.368	0.055	0.062	-0.088

PC1	0.918	0.712	0.210	0.921	0.723	0.205	-0.003	-0.011	0.005
PC2	0.900	0.721	0.303	0.881	0.694	0.332	0.019	0.027	-0.029
PC3	0.852	0.671	0.318	0.832	0.646	0.349	0.020	0.025	-0.031

In addition, PLSpredict was also being used as further studies for Q^2 in order to ensure the accuracy of predictive relevance for this study. PLSpredict generates case-level predictions on a construct to reap the benefits of predictive model assessment in PLS-SEM (Shmueli *et al.* 2016; Shmueli *et al.* 2019). Shmueli *et al.* (2016) mentioned that PLSpredict offers a mean to assess a model's out of sample predictive power. Based on Table 5, the values of $Q^2_{predict}$ for the PLS-SEM for all indicators of a measurement model is greater than zero (0). Due to the data in this research that was not normally distributed, MAE error was being used for examining the predictive relevance effect. By comparing the MAE values from the PLS-SEM analysis with the naïve LM benchmark (Table 5), the findings concluded that the PLS-SEM analysis produced lower prediction errors for minority of the indicators (1 out of 7 indicators; PLS-SEM < LM). According to Shmueli *et al.* (2019), minority of the indicators fulfill the principles [$Q^2_{predict} > 0$; MAE error-values are negative (PLS-SEM < LM)], low predictive power is existed for the PC model (Shmueli *et al.* 2019). In brief, the results based on the Q^2 from blindfolding and $Q^2_{predict}$ from PLSpredict concluded that the PC model had predictive relevance in Q^2 and low significance predictive relevance in $Q^2_{predict}$.

4.5 Direct-Effect Test

In this study, the path coefficient assessment was tested with SmartPLS 3.2.8 bootstrapping function with 5,000 bootstrap samples (Hair *et al.* 2017). There are three direct hypotheses being evaluated in this research. As in Table 4, OC ($\beta = 0.254$, t = 4.147, p < 0.05) and BE ($\beta = 0.333$, t = 5.409, p < 0.05) were found to have a significant positive direct effect on PC, indicating that H_1 and H_4 were validated and supported. Moreover, OC ($\beta = 0.611$, t = 16.348, p < 0.05) were also found to have a positive and significant direct effect on BE, thus, H_3 was supported.

4.6 Mediation-Effect Test

There was one mediation hypothesis (i.e. H_5) being formed in this research with the aim to investigate the indirect effect of BE in the relationship between OC and PC. Table 4 exhibits that the indirect effect, H_5 ($\beta = 0.204$) was significant with t-values of 4.922. The indirect effect 95% Boot CI BC of [0.139, 0.274], does not straddle a zero in between, thus it demonstrates that there is a mediation relationship (Preacher & Hayes 2004; 2008). Hence, the mediation effect was statistically significant.

4.7 Moderation-Effect Test

Although initially it was statistically proven that the relationship of moderated hypothesis (H_2) was unsupported as Moderating Effect (OC*PA) to PC with ß = -0.059, t-value = 1.390, p>0.05; however, CI value does not have zero (0) straddle in between [0.092, 0.195], as indicated in Table 4). At the same time, another test was examined between the direct relationship between OC and PC, R^2 has changed from 0.324 to 0.387, f^2 also has changed from 0.478 to 0.174 after the moderator PA was added, which means that there was a moderating effect. In order to further test whether the relationship of moderated hypothesis (H_2) was supported or not, the simple slope analysis as presented in Figure 3 was used to show the interaction effect of PA between OC and PC.
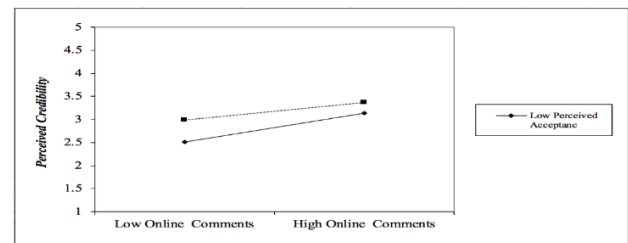

Figure 3. Linear Interaction Effect Analysis
Note: Predictor Variable (X) = Online Review ; (Y) = Group Buying; Moderating Variable (Z) = Trust
$Y = b_0 + b_1X + b_2Z - b_3XZ$

Graphical depiction for linear interaction effect is shown in Figure 3, in which there is no parallel between the two slopes. Thus, there was a moderating effect between PA and OC. By referring to Gardner *et al.* (2017), different directionality of coefficient between independent variables and moderating relationship are considered as a weakening moderating relationship. As shown in Table 4, path coefficient of OC and OC*PA are in the opposite (path coefficient of OC = 0.245; path coefficient of OC*PA = -0. 059), thus there is a weakening moderating effect between OC and OC*PA in the model.

By comparing the directionality between OC and PA, the path coefficients are considered having the same direction as both of the path coefficients are positive (0.254 and 0.180) as indicated in Figure 3. Hence, substituting the weakening moderating effect is existing in this model. When there is a high level of *perceived acceptance,* the relationship between *online comments and perceived credibility* will be weakened. In other words, buyer is less depending on the *online comments* before *perceived credibility*, if they have high level of *perceived acceptance*. In conclusion, although it was

statistically proven that the relationship of moderating hypothesis (H₂) was unsupported as Moderating Effect (OC*PA) to PC by the path coefficient based on p-value and t-value; however, CI, R^2, f^2 and simple slope analysis all could give enough evidences for a moderating effect, which means that the relationship of moderating hypothesis (H₂) was supported.

4.8 Goodness-of-Fit

The structural model complies with measures of goodness-of-fit as suggested by recent literature on technological research (Henseler *et al*. 2016). Model fitness indices enable researchers to judge how well a model structure fits the empirical data and, thus, model misspecifications could be identified (Hair *et al*. 2017). In order to identify the model misspecification, three criteria could be applied, the Standardized Root Mean Square Residual (SRMR < 0.08) (Hu & Bentler 1998), Bentler-Bonett index or normed-fit index (NFI > 0.90) (Bryrne, 2008), and root mean square error correlation (RMS_theta < 0.12) (Henseler *et al* 2016). As demonstrated in the Table 4, the SRMR values are 0.054 (less than 0.08) indicating that the model had a considerably good fit; whereas, the NFI (0.895) does not achieve the criteria (NFI > 0.90) as well as the RMS theta (0.165) does not achieve the criteria (RMS theta < 0.12), indicating a lack of model fit. However, even bootstrap-based model fit assessments on the grounds of, for example, some distance measure or the SRMR (Henseler *et al*. 2016; Henseler *et al*. 2017), which quantify the divergence between the observed and estimated covariance matrices, should be considered with extreme caution. For composite models, thresholds for the NFI are still to be determined. This is because NFI does not penalize for adding parameters, therefore it should be used with caution for model comparisons. In general, the use of the NFI is still rare (Ziggers & Henseler 2016). Scholars have questioned whether the concept of model fit, as applied in the context of CB-SEM research, is of value to PLS-SEM applications in general (Hair *et al*. 2017; Rigdon 2016; Lohmöller 1989). In conclusion, although the overall model fit is not good, the model fit in PLS SEM should be evaluated with reference to the significance of path coefficient, which are the explanation ability and prediction ability of the model. Therefore, by considering from many aspects, this model has reached the academic requirements for the overall model fitness (陳寬裕, 2018, p.433).

5. CONCLUSION

In conclusion, the study has contributed to the theoretical context by concluding that both online comments and bandwagon effect have positive relationships with the perceived credibility; whereas, online comments are positively related to the bandwagon effect. In addition, the findings also revealed that perceived acceptance moderates the relationship between online comments and perceived credibility, whereas, bandwagon effect mediates the relationship between online comments and perceived credibility. These findings also provide various insights to the practitioners on how to enhance the perceived credibility of the information in the social commerce. The credibility of the source that provides online comments and the degree of the trustworthiness to the information circulated in the web sites were not well addressed in this research. Therefore, future research may look into the impacts of source credibility and information trustworthiness on the bandwagon effect and perceived credibility of the information in social commerce.

REFERENCES

[1] Aronson, E., Wilson, T.D. and Akert, A.M., 2005. *Social psychology*, 5th edition. Pearson: United Kingdom.

[2] Bernama Malaysia, http://www.bernama.com

[3] Brock, DM., Sarason,IG., Sanghvi, H & Gurung, RA.R. 1998, 'The perceived acceptance scale: Development and validation', *Journal of Social and Personal Relationships*, vol. 15, no. 1, viewed 29 November 2017, https://www.researchgate.net/publication/233845133_The_Perceived_Acceptance_Scale_Development_and_Validation

[4] Chaiken 1980, 'The heuristic model of persuasion', *Social Influence*, vol. 5, pp. 3-39, viewed 29 November 2017, <http://onlinelibrary.wiley.com.ezproxy1.hw.ac.uk/doi/10.1111/1539-6924.00314/full>.

[5] Chaiken, S 1987, 'The heuristic model of persuasion', *Social Influence*: The Ontario symposium, vol. 5, pp. 3–39, viewed 26 November 2017, <http://psycnet.apa.org/record/1987-97608-001>.

[6]Chen 陳寬裕 (2018). *結構方程模型分析實務：SPSS 与 SmartPLS 的運用* (初版), 台北市: 五南圖書

[7] Cohen, J 1988, *Statistical power analysis for the behavioral sciences*, viewed 30 November 2017, <http://www.sciencedirect.com/science/book/9780121790608>.

[8] Creswell, J.W., 2014. *A concise introduction to mixed methods research*. SAGE publications.

[9] Dijck, J.V 2013, *The culture of connectivity: A critical history of social media*, Oxford University Press, viewed 29 November 2017, <https://books.google.com.my/books?hl=en&lr=&id=t5 RpAgAAQBAJ&oi=fnd&pg=PP1&dq=history+of+soci al+media&ots=pmZs_QytHF&sig=6SIcWZ5tyFVMeW MbWSaQDRjxYB8#v=onepage&q=history%20of%20s ocial%20media&f=false>.

[10] Dijkstra, T.K & Henseler, J 2015. 'Consistent partial least squares path modeling'*, Management Information Systems Quarterly*, vol.39, no.2, pp.297-316

 [11] Etikan, I, Musa, S.A & Alkassim R.S 2016, 'Comparison of convenience sampling and purposive sampling', *American Journal of Theoretical and Applied Statistics*, vol. 5, no. 1, pp. 1-4, viewed 29 November 2017, <https://pdfs.semanticscholar.org/79a2/c4a4111275b3ef bfa0522284ccd0fecc556a.pdf>.

[12] Fornell, C. and Larcker, D.F. (1981), 'Evaluating structural equation models with unobservable variables and measurement error', *Journal of Marketing Research*, vol. 18, no. 1, pp. 39-50.

[13] Fornell, C & Cha, J 1994, 'Partial least squares', in Bagozzi, RP (ed.), *Advanced methods of marketing research*, Blackwell Publishers, Cambridge, pp. 52-78.

[14] Gardner, R.G., Harris, T.B., Li, N., Kirkman, B.L. and Mathieu, J.E., 2017. Understanding "it depends" in organizational research: A theory-based taxonomy, review, and future research agenda concerning interactive and quadratic relationships. *Organizational Research Methods*, vol.20*, no.4, pp.610-638.

[15] Geisser, S., 1974. 'A predictive approach to the random effect model'. *Biometrika*, vol.61, no.1, pp.101-107.

[16] Hair, JF, Hult, GTM, Ringle, CM & Sarstedt, M (eds) 2017, *A primer on partial least squares structural equation modelling (PLS-SEM)*, 2nd edn, SAGE Publications, Los Angeles.

[17] Henseler, J., Hubona, G. and Ray, P.A., 2016. 'Using PLS path modeling in new technology research: updated guidelines'. *Industrial management & data systems*, vol.116, no.1, pp.2-20.

[18] Hu, Li-tze & Bentler, P.M 1998, 'Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification', *Psychological Methods*, vol.3, no.4, pp.424-453.

[19] Huang, J. H & Chen, Y. F 2006, 'Herding in online product choice', *Psychology & Marketing*, vol. 23, no. 5, pp. 413–428, viewed 27 November 2017, <http://onlinelibrary.wiley.com.ezproxy1.hw.ac.uk/doi/ 10.1002/mar.20119/full>.

[20] Kang, B, Hollerer, T & O'Donovan, J 2015, 'Believe it or not? Analyzing information credibility in microblogs', *International Conference on Advances in Social Networks Analysis and Mining*, vol. 2015, no. 2, viewed 25 November 2017, <http://penguinkang.com/research/publications/10_AS ONAM_kang.pdf>.

[21] Kate, A.L 2006, 'Study design III: Cross-sectional studies', *Evidence-Based Dentistry*, vol. 7, no. 1, pp. 24-5, viewed 29 November 2017, <https://doi:10.1038/sj.ebd.6400375>.

[22] Kaul, S., Yates, R. and Gruteser, M., 2012, March. Real-time status: How often should one update?. In *2012 Proceedings IEEE INFOCOM* (pp. 2731-2735). IEEE.

[23] Kim, H.S., Brubaker, P. and Seo, K., 2015, 'Examining psychological effects of source cues and social plugins on a product review website', *Computers in Human Behavior*, vol.49, pp.74-85.

[24] Kim, Y 2015, 'Exploring the effects of source credibility and others' comments on online news evaluation', *Electronic News*, vol. 9, no. 3, pp 160-176, viewed 27 November 2017, <http://journals.sagepub.com/doi/abs/10.1177/1931243 115593318>.

[25] Kline, R.B. (2011), *Principles and practice of structural equation modeling*, Guilford Press: New York.

[26] Lohmöller, J.B., 1989. Predictive vs. structural modeling: PLS vs. ML. In *Latent variable path modeling with partial least squares* (pp. 199-226). Physica, Heidelberg.

[27] LI, A. and CHEN, M.L., 2005, 'The influence of profitability and bandwagon pressure on new technology diffusion: A Empirical study on EC Technology', *R&D Management*, *2*.

[28] Moe, WW., & Schweidel, DA. 2012, 'Online product opinions: Incidence, evaluation, and evolution', *Marketing Science*, vol. 31, no. 3, pp. 372–386, viewed 25 November 2017, http://eds.b.ebscohost.com.libezp.utar.edu.my/eds/pdfvi

ewer/pdfviewer?vid=8&sid=daaa0603-52cb-4f35-9f07-a9e75f21309a%40pdc-v-sessmgr01>.

[29] Muda, M, Mohd, R & Hassan, S 2016, 'Online purchase behavior of Generation Y in Malaysia', *Procedia Economics and Finance*, vol.37, pp.292-298.

[30] Nunnally, J.C. 1978, *Psychometric Theory*, McGraw-Hill: New York.

[31] Nunnally, J. C., & Bernstein, I. H. 1994, *Psychometric theory*. McGraw-Hill: New York.

[32] O'Keefe, DJ 2002, *Persuasion: Theory and research*, viewed 29 November 2017, <https://www.scholars.northwestern.edu/en/publications/persuasion-theory-and-research>.

[33] Preacher, K.J, & Hayes, A.F 2004, 'SPSS and SAS procedures for estimating indirect effects in simple mediation models', *Behavior Research Methods, Instruments and Computers*, vol. 36, no. 4, pp. 717-731, viewed 1 December 2017, <https://link.springer.com/content/pdf/10.3758%2FBF03206553.pdf>.

[34] Preacher, KJ & Hayes, AF 2008, 'Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models', *Behaviour Research Methods*, vol. 40, no. 3, pp. 879-891.

[35] Ramayah, T, Cheah, J, Chuah, F, Ting, H & Memon, M.A 2018, *Partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3.0*. 2nd edn, Pearson: Malaysia.

[36] Rigdon, E.E. 2016, 'Choosing PLS path modeling as analytical method in European management research: a realist perspective', *European Management Journal*, vol. 34, no.6, pp.598-605.

[37] Rogers, C. 1980, *Client Centered Psychotherapy*, viewed 29 November 2017, http://dx.doi.org/10.4135/9781446289051>.

[38] Schwab, D. P.: 1980, 'Construct validity in organizational behavior', in B. M. Staw and L. L. Cummings (eds.), *Research in Organizational Behavior*, vol.2, pp.3–43.

[39] Shmueli, G., Ray, S., Velasquez Estrada, J.M. and Chatla, S.B. 2016, 'The elephant in the room: Evaluating the predictive performance of PLS models', *Journal of Business Research*, vol. 69, no.10, pp.4552-4564.

[40] Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.H., Ting, H., Vaithilingam, S. and Ringle, C.M., 2019.

'Predictive model assessment in PLS-SEM: guidelines for using PLSpredict'. *European Journal of Marketing*, vol.53, no.11, pp.2322-2347.

[41] Stone, M., 1974. 'Cross-validation and multinomial prediction', *Biometrika*, *61*(3), pp.509-515.

[42] Sukamolson, S 2007, 'Fundamentals of quantitative research', *Quantitative and Qualitative*, viewed 29 November 2017, <https://pdfs.semanticscholar.org/336b/6928c8ee7f3fac6bbeb1e0e1769169c447f7.pdf.>.

[43] Sundar, S.S, Oeldorf-Hirsch, A & Xu, Q 2008, 'The bandwagon effect of collaborative filtering technology', *CHI 2008*, vol. 26, pp. 3453–3458, viewed 25 November 2017, <file:///C:/Users/Surtees/Downloads/The_Bandwagon_Effect_of_Collaborative_Fi.pdf>.

[44] Sundar, S.S & Nass, C 2001, 'Conceptualizing sources in online news', *Journal of Communication*, vol. 5, no. 1, pp. 52-72, viewed 29 November 2017, <https://pdfs.semanticscholar.org/e99e/5c845d6bda14490a0dacd0d7143c20320e2b.pdf>.

[45] Sundar, S.S, Knobloch-Westerwick, S & Hastall, M.R 2007, 'News cues: Information scent and cognitive heuristics', *Journal of the American Society for Information Science and Technology*, vol. 58, no. 3, pp. 366-378, viewed 29 November 2017, <https://dl.acm.org/citation.cfm?id=1228994>.

[46] Voorhees, C.M., Brady, M.K., Calantone, R. and Ramirez, E. (2016), 'Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies', *Journal of the Academy of Marketing Science*, vol. 44, no. 1, pp.119-134.

[47] Walther, J.B, DeAndrea, D, Kim, J & Anthony, J.C 2010, 'The influence of online comments on perceptions of anti-marijuana public service announcements on YouTube', *Human Communication Research*, vol. 36, no. 4, pp. 469–492, viewed 27 November 2017, <http://onlinelibrary.wiley.com/doi/10.1111/j.1468-2958.2010.01384.x/abstract>.

[48] Xu, Q 2014, 'Should I trust him? The effects of reviewer profile characteristics on eWOM credibility', *Computers in Human Behavior*, vol. 33, pp. 136-144, viewed 29 November 2017, <https://ac-els-cdn-com.ezproxy1.hw.ac.uk/S0747563214000326/1-s2.0-S0747563214000326-main.pdf?_tid=2b306904-d4fb-11e7-b392-00000aab0f26&acdnat=1511956268_ce21750e0f7083e cad902d9b207315c8>.

[49] Ziggers, G. W., & Henseler, J. (2016), 'The reinforcing effect of a firm's customer orientation and supply-base orientation on performance', *Industrial marketing management*, vol.52, 18-26.