

The Impact of the Number of Trusted Members on the Perceived Credibility of the Information on Social Commerce: The Mediating Roles of Cognitive Trust and Affective Trust

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ABSTRACT

With the advancement of internet technology, the transaction conducted via social commerce has become a trend. However, the credibility of social commerce is in doubt due to many fraudulent cases and scams being discovered frequently. Therefore, this study would like to evaluate the impacts of the number of trusted members, cognitive trust and affective trust on the perceived credibility on the information given on social media sites among the social commerce users in Malaysia. A total of 405 actual samples were collected and analyzed in this study. This research has contributed to the theoretical context by concluding that the number of trusted members, cognitive trust and affective trust have direct, positive, and significant effects on the perceived credibility; while the number of trusted members has direct, positive, and significant effect on both the cognitive trust and affective trust. Besides, the study also concluded two mediating hypotheses in which the cognitive trust mediates the relationship between the number of trusted members and perceived credibility as well as the affective trust mediates the relationship between the number of trusted members and perceived credibility.

Keywords: *Social commerce, number of trusted members, cognitive trust, affective trust, perceived credibility*

1. INTRODUCTION

The use of social media as a business platform has encouraged individuals to share their knowledge, experiences, and information about products more freely, and thus social word of mouth (sWOM) is developed to allow users to access detailing evaluation by consumers about a product through social media (Hajli 2016). As affected by sWOM, social commercial users are concerned about the credibility of information in these platforms, because it can shape individuals' decision-making (Hajli 2016). Xu (2014) has advocated that the number of trusted members influences the bandwagon effect on perceived credibility. However, the degree of trust among the social commerce users towards the information provided by various number of trusted members that sharing across the social commerce platform, is not covered in the study of Xu (2014). Therefore, this study would like to evaluate the impacts of the number of trusted members, cognitive trust, and affective trust on the perceived credibility on the information given on social media sites among the social commerce users in Malaysia.

2. LITERATURE REVIEW

2.1 Perceived Credibility

Kang, Hollerer, and O'Donovan (2015) claimed that credibility is about how a message recipient judges a message sender's believability. Rieh and Hilligoss (2008) argued that personal characteristics such as personal experiences and similar social connections do influence the credibility judgement of online or offline information. Therefore, Kang et al (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 via the number of trusted members and their personal characteristics who make the credibility assessment.

2.2 The Number of Trusted Members and Perceived Credibility

Xu (2014) referred the number of trusted members as a group of people who endorse an online information provider (reviewer) by giving favorable ratings and opinions. Their aggregated opinions and ratings then act as the collective endorsement, which can be functioned as recommendation and influence on other consumer decision making (Cantalops & Salvi 2014). Therefore, users would believe and have confidence in the information, if there are certain amounts of trusted members who appear to provide positive feedbacks on the information (Xu 2014). Therefore, the relationship between the number of trusted members and perceived credibility is hypothesized as follow:

H_1 : Large number of trusted members is positively related to more perceived credibility than that of smaller number of trusted members

2.3 The Number of Trusted Members and Trust

Giffin (1967) described trust as a mystical and intangible factor that affects the degree of confidence in the trusted person or his/her communication. Pornpitakpan (2006) argued that there is an association between trust and credibility. Cognitive and affective are the two fundamental dimensions of trust (Johnson & Grayson 2005) in which they are inter-correlated (McAllister 1995). Cognitive trust is primarily based on the individual's (trustor's) evaluation of other people's (trustee's) ability, predictability, reliability (Mayer, Davis & Schoorman 1995), integrity and dependability (Schaubroeck, Lam & Peng 2011). When a trustor has high cognitive trust, he or she will be willing to rely on the trustee as the trustee has the ability and character to represent their interests due to their beliefs on the trustee's ability and integrity (Dunn, Ruedy & Schweitzer 2012). Xu (2014) argued that the number of trusted members depends on the collective endorsement by the opinions and ratings given to an online reviewer, which is seen as his or her reputation. Subsequently, other online consumers or users will evaluate and appraise the reviewer's reliability and dependability based on the endorsement. If the opinions and ratings given by the trusted members are favorable to the reviewer, it will be regarded that the reviewer is capable and reputable, which leads other online consumers to establish cognitive trust towards the reviewer (McKnight, Cummings & Chervany 1998). Therefore, the larger the number of trusted members that an online reviewer has, the tendency of other online users to trust the reviewer is higher as well, because the reputation appraisal is likely to result in cognitive trust, which is driven by the knowledge of endorsement from the number of trusted members (Xu 2014). The following hypothesis was developed and would be tested as follow:

H_2 : Large number of trusted members is positively related to more cognitive trust than that of smaller number of trusted members

Affective trust is derived from the trustor's (information receiver's) emotional ties or connection to the trustee (information provider) (Johnson-George & Swap 1982 ; McAllister 1995 ; Miao, Newman & Huang 2014). Dunn, Ruedy and Schweitzer (2012) claimed that when trustors have high affective trust, they are willing to be emotionally vulnerable to the trustees by depending on the trustees' information due to the fundamental emotional bond established between them as the trustors hold the beliefs about the trustees' benevolence (Mayer, Davis & Schoorman, 1995), and they always expect the trustees to act supportively and considerately. The reputation of an online reviewer is directly affected by the collective endorsement (Doney & Cannon 1997). Johnson and Grayson (2005) suggested that the reputation of a reviewer is considered as a symbol of value reciprocation and also an expression of empathy for the online consumers, and thus the reputable reviewer would be perceived as responsible and keeping their interests in mind. As a result, it can strengthen the emotional response of the consumers towards the reviewers to be trusted and considerably influence their affective trust due to the positive perception that establishes the emotional bond between the consumers and reviewers (Xu, 2014). Therefore, the following hypothesis was developed and would be tested as follow:

H_3 : Large number of trusted members is positively related to more affective trust than that of smaller number of trusted members

2.4 Trust and Perceived Credibility

In the social media, cognitive trust is formed through the direct online interactions with the information provider and also through reputation of the information provider (McKnight, Cummings & Chervany 1998). Users with high cognitive trust tend to rely on the information provider and perceive that the information provided is credible, because they believe that the information provider has the ability and professionalism in providing the right and credible information (Jennifer, Nicole & Maurice 2012). Thus, the following hypothesis was developed and would be tested as follow:

H_4 : Cognitive trust is positively related to perceived credibility

Affective trust is based on a user's beliefs regarding the information provider's goodwill and social conscience (Mayer et al. 1995), as well as an affective attachment between the users and information provider (Williams 2007). Lewis and Wiegert (1985) argued that when there is an existence of emotional ties between the individuals, they are likely to rely and depend on each other as well as the information given. Therefore, users with affective trust will perceive credibility of the provider and his or her information, as they believe in the provider due to the bonds established (Jennifer, Nicole & Maurice 2012). Thus, the

following hypothesis was developed and would be tested as follow:

H₅: Affective trust is positively related to perceived credibility

2.5 Number of Trusted Member, Trust and Perceived Credibility

According to Xu (2014), the larger the number of trusted members that an online reviewer has, the tendency of having cognitive trust among other online users to trust the reviewer is higher, because the cognitive trust is driven by the knowledge of endorsement from the number of trusted members (Xu 2014). McKnight, Cummings & Chervany (1998) argued that users with high cognitive trust tend to rely on the information provider and perceive that the information provided is credible. In due respect, there may have an indirect relationship in which cognitive trust mediates the relationship between the number of trusted member and perceived credibility. The following hypothesis was developed and would be tested as follow:

H₆: Cognitive trust mediates the relationship between the number of trusted members and perceived credibility

Johnson and Grayson (2005) argued that an online reviewer who is endorsed by a lot of individuals would be perceived as responsible and keeping other online consumers' interests in mind. As a result, it can strengthen the emotional response of the consumers toward the reviewers to be trusted and considerably influence their affective trust due to the positive perceptions that establishes the emotional bond between the consumers and reviewers (Xu 2014). Jennifer, Nicole and Maurice (2012) further argued that users with affective trust will perceive credibility of the provider and his or her information, as they believe in the provider due to the bonds established. In due respect, there may have an indirect relationship in which affective trust mediates the relationship between the number of trusted members and perceived credibility. Thus, the following hypothesis was developed and would be tested as follow:

H₇: Affective trust mediates the relationship between the number of trusted members and perceived credibility

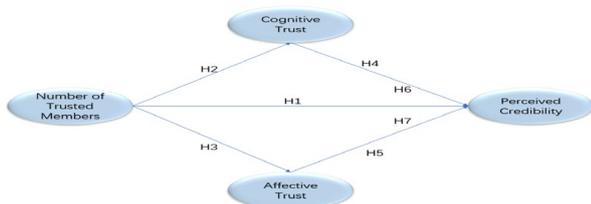


Figure 1: Conceptual Model

3. RESEARCH METHODOLOGY

Quantitative research with cross-sectional study was adopted, because it enables researchers to conduct numerical tests based on the descriptive, measurable, and

testable for a large number of respondents with the standardized, structured and formalized questioning practices in order to discover behavioral regularities (Hair, Bush & Ortinau 2009; Woodwell 2014). Primary data was collected to fit the research problem based on the first-hand information source (Woodwell 2014).

Generation Y was targeted as respondents, because this generation is knowledgeable in technological aspects of using social media in their daily activities (Muda *et al.* 2016). Convenience sampling was adopted since the representativeness of the sample group cannot accurately be measured due to the incalculable sampling errors (Rowley, 2014). Nonetheless, a large number of participants were collected to compensate the weakness of convenience sampling method. A sample size of 450 respondents was collected as this is in line with the studies of Hair, Bush and Ortinau (2009), which stated that 200 or more respondents are considered as a large sample number. In conclusion, online survey via Google Forms was utilized to access to a large number of respondents, which was 450 respondents. A total of 405 actual samples were collected in the research. There are two parts in the questionnaires. 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 are measured in the questionnaires. There were five items being used to measure the number of trusted members (NTM) by using 5 points Likert-scale ranging from "strongly disagree" (1) to "strongly agree" (5). There were three items under the construct of cognitive trust (CT) whereas 5 points Likert-scale was applied to measure the cognitive trust, the scale ranges from "strongly disagree" (1) to "strongly agree" (5). As for the affective trust (AT), there were five items covered, which were measured by 5 points Likert-scale ranging from "strongly disagree" (1) to "strongly agree" (5). For the perceived credibility (PC), it consisted of three items being measured by 5 points Likert-scale ranging from "strongly disagree" (1) to "strongly agree" (5).

The statistical programs of SPSS version 25.0 and SmartPLS version 3.2.8 were used to perform the statistical analyses. Descriptive analysis, measurement model, and structural model were carried out in the data analysis.

4. DATA ANALYSIS AND FINDINGS

4.1 Descriptive Analysis

According to the statistical findings, it is observed that 36.5% of the respondents were male and 63.5% were female. For the age category, majority of the respondents (64.2%) were within 21 and 23 years old. For the education level, majority of respondents (74.1%) were bachelor degree holders. In addition, majority of the respondents (45.4) were spending 3-5 hours per day in the social media. For the

purchase frequency, 34.8% of respondents were engaging in online purchasing for every 2-6 months. The most preferred purchase platform used by respondents was Facebook. The most popular product purchased by respondents through the online commerce was clothing and accessories (44.4%). In term of the spending pattern, majority of respondents were spending below RM100 for every online shopping transaction.

4.2 PLS-SEM Assessment

PLS-SEM is a statistical tool which is being used when ordinary assumptions such as multivariate normality is not met in the research (Graber, Czellar & Denis, 2002). There are two stages in performing SEM-PLS, which are the measurement model and the structural model (Hair *et al.* 2017). Figure 2 presents the conceptual structural model that will be evaluated via measurement model and structural model in this study.

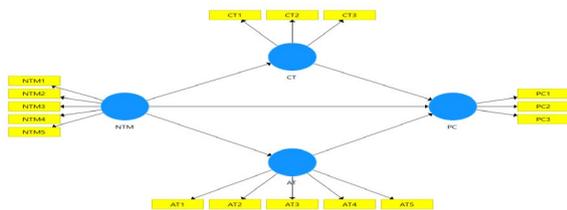


Figure 2. Conceptual Structural Model

4.3 Assessment of Measurement Model

The relationship between latent variables and observed variables is represented by the measurement model. By referring to Figure 2, reflective direct relationships were applied in the model. For examining the reflective measurement model, four tests will be conducted by using PLS-SEM: factor loadings, construct reliability, convergent validity, and discriminant validity (Mohd Suki *et al.*, 2011). The degree to which theoretically similar constructs are highly correlated with each other is indicated through

convergent validity; the degree to which a given construct is different from other constructs is indicated by discriminant validity. These two types of validity assessments could be used to ensure the reliability and validity measures of the constructs, before assessing the relationships between those constructs (Ramayah *et al.*, 2018). Table 1 presents the convergent validity of various constructs; Table 2 indicates the discriminant validity of different constructs.

In Table 1, factor loadings in the reflective measurement model were ranging from 0.824 to 0.924, in which all the factor loadings were achieved above the threshold level of 0.708 (Hair *et al.* 2017). This indicates that a latent variable explains at least 50% of indicator's variance (Hair *et al.* 2017). For reliability of the measure, three different kinds of reliability measures were used, which were Cronbach's alpha, Dijkstra-Henseler's rho (ρ_A) and Jöreskog's rho (ρ_c). According to Table 1, the inter-item consistency reliability values of Cronbach's alpha ranged from 0.862 to 0.919, which exceeds the recommend value of 0.7 as suggested by Nunnally (1978). In addition, Dijkstra-Henseler's rho (ρ_A), the most consistent reliability measuring the PLS construct scores, also achieved the satisfactory reliability value that ranged from 0.871 to 0.921 (Dijkstra and Henseler, 2015). At the same time, the Jöreskog's rho (ρ_c) (also known as Composite Reliability, CR) values, which refers to the degree to which the construct indicators indicate the latent construct, ranged from 0.915 to 0.939, 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 figure of the Average Variance Extracted (AVE) value as indicated in Table 1 for each of the constructs ranged from 0.726 to 0.821, which are above the threshold value of 0.5 (Hair *et al.* 2017; Hair, Ringle & Sarstedt 2013), and it provides the evidence that at least 72.6% of variance was explained by the factors to their respective constructs. Also, the observed t-value for each of the factors is above 1.96, which means that they were all significantly (at 95% confidence-level) loaded toward their respective latent constructs. Therefore, it could be concluded that this measurement model possessed adequate convergent validity.

Table 1. Convergent Validity and Reliability of constructs

Construct	Model	Indicators	Factor Loading	T-value	CR	AVE	Cronbach's alpha	Rho_A
AT	Reflective	AT1	0.859	54.65	0.939	0.756	0.919	0.921
		AT2	0.888	84.551				
		AT3	0.869	66.291				
		AT4	0.868	60.876				
		AT5	0.862	50.135				
CT	Reflective	CT1	0.866	49.313	0.915	0.783	0.862	0.871
		CT2	0.912	108.513				
		CT3	0.876	64.79				
NTM	Reflective	NTM1	0.865	56.034	0.93	0.726	0.906	0.909
		NTM2	0.873	60.425				
		NTM3	0.867	65.096				

		NTM4	0.830	33.372				
		NTM5	0.824	41.72				
PC	Reflective	PC1	0.891	69.952	0.932	0.821	0.891	0.897
		PC2	0.903	75.533				
		PC3	0.924	116.408				

According to Voorhees *et al.* (2016), compared to Fornell and Larcker’s (1981) and cross-loading approaches, HTMT (with a ratio of cut-off less than 0.85) is the most ideal method to test the discriminant validity. Thus, heterotrait–monotrait ratio of correlations (HTMT) is utilized in order to test if the construct is truly distinct from other constructs. Preacher and Hayes (2008) stated that zero-value which does not straddle in between lower and upper-limits in the 95% Bootstrap Confidence Interval (CI), are considered as significant discriminant validity between the constructs. Based on Table 2, the result shows that the values of correlation among the latent variables ranged from 0.587 to 0.632, which are far below the strictest threshold of 0.85 (Kline, 2011); and this research also had significant discriminant validity between the constructs as no zero-value was tracked in between the upper and lower-levels of confidence-interval. Thus, the results indicate that the latent measurement constructs were clearly discriminant with each other. In conclusion, the measurement model appeared to have adequate reliability, convergent validity, and discriminant validity. Consequently, this model would be employed for further testing the hypotheses via structural model in the next section.

Table 2. Discriminant Validity of Constructs

Latent Variables	AT	CT	NTM	PC
AT				
CT	0.587*			
NTM	0.621*	0.592*		
PC	0.618*	0.632*	0.610*	

Note:

* 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

The assessment of structural model was adopted to evaluate the significance of the hypotheses in the model. The standard criteria of evaluation comprise the collinearity (VIF), the coefficient of determination (R^2), the level of effect size (f^2), the predictive relevance (Q^2) which is based on blindfolding, the path coefficients’ statistical significance and relevance, and Goodness of Fit. Moreover, Shmueli *et al.* (2016) also suggested that researchers should examine the out-of-sample predictive power of the model with the PLS Predict procedure.

The assessment of structural model begins with the Collinearity test to identify the availability of the regression results bias in the research. The VIF value of 5 or above means that there is a potential presence of collinearity

problem among the predictor constructs; even the VIF value is between 3 and 5, the collinearity problems can also occur (Mason and Perreault, 1991; Becker *et al.* 2015). As shown on Table 3, all the Inner VIF values for the independent variables (AT, CT & NTM) were less than 3, which indicates that lateral collinearity was not an issue in this research.

Table 3. Lateral Collinearity Assessment (VIF)

Construct	AT	CT	NTM	PC
AT				1.653
CT				1.550
NTM	1	1		1.655
PC				

Notes: *Dependent Variable 1: Perceived Credibility (PC); Dependent Variable 2: Cognitive Trust (CT); Dependent Variable 3: Affective Trust (AT)*

When collinearity was not a concerned issue in this research, the next step was to evaluate R^2 value of the endogenous constructs. Hair *et al.* (2017) mentioned that the assessment of R^2 level is important as it measures the variance, which demonstrates the amount of variance in the exogenous constructs on endogenous constructs in the model. The R^2 value ranges from 0 to 1, in which higher value indicates a greater explanatory power.

As indicated in Table 4, the R^2 level of PC in this research was 0.448 illustrating that 44.8% of the total variance of PC (DV1) was explained by its direct effects from the exogenous variables (H_1 -NTM, H_4 -CT & H_5 -AT) and indirect effects from two mediating relationships (H_6 & H_7). The total variations explained for CT & AT were 0.279 and 0.324 respectively, defining that NTM could explain 27.9% and 32.4% towards CT & AT respectively. According to the rules of thumb for acceptable R^2 by Cohen (1988), the R^2 levels for the respective targeted endogenous variables in this research (PC- R^2 : 0.448; CT- R^2 : 0.279; AT- R^2 : 0.324) were above 0.26, hence, they were deemed to have substantial level of variance explained.

The assessment of f^2 level is undertaken to examine the weightings of predictor on its endogenous variables (Ramayah *et al.* 2018). According to Cohen (1988)’s guideline, the value of 0.02, 0.15 and 0.35 represent small, medium, and large-effect size to the endogenous variable. As exhibited in Table 4, NTM ($f^2 = 0.064$), AT ($f^2 = 0.082$) and CT ($f^2 = 0.097$), had slightly weak-effect size on PC (endogenous variable). Meanwhile, NTM had large-effect size to AT ($f^2 = 0.478$) and large-effect size to CT ($f^2 = 0.387$) by referring to the Cohen (1988) threshold.

Table 4. Path Coefficients Assessment of the Structural Model

Relationship	Path Coefficient	Standard Deviation (STDEV)	t-value	p-value	Decision	R ²	f ²	Q ²	95% CI LL	95% CI UL	Goodness of Fit
NTM → AT	0.569	0.053	10.717	0	supported	0.324	0.478	0.228	0.454	0.663	SRMR = 0.079
NTM → CT	0.528	0.039	13.469	0	supported	0.279	0.387	0.205	0.447	0.598	NFI = 0.869
NTM → PC	0.243	0.054	4.496	0	supported	0.448	-	0.343	0.138	0.35	RMS Theta = 0.184
CT → PC	0.152	0.024	6.35	0	supported	-	-	0.205	0.106	0.201	
NTM → At → PC	0.155	0.031	5.073	0	supported	0.448	-	0.343	0.1	0.222	
AT → PC	0.273	0.049	5.537	0	supported	-	0.082	0.343	0.173	0.369	
CT → PC	0.288	0.044	6.525	0	supported	-	0.097	0.343	0.196	0.371	

Apart from R² and f², the assessment of Stone-Geisser’s Q² is also suggested for identifying the overall predictive relevance of each endogenous construct in the path model; Q² is applied to the endogenous constructs that have a reflective measurement model specification (Ramayah *et al.*

2018; Geisser 1974; Stone 1974). In Table 4, the Q² assessment shows that all AT, CT and PC had an adequate predictive relevance effect in the model, because their resulting Q² values (0.228, 0.205 and 0.343 respectively) are above zero (Hair *et al.* 2017; Fornell & Cha 1994).

Table 5. Assessment of PLSpredict

	PLS			LM			ERROR (PLS-LM)		
	RMSE	MAE	Q ² predict	RMSE	MAE	Q ² predict	RMSE	MAE	Q ² predict
AT2	0.868	0.681	0.263	0.875	0.684	0.252	-0.007	-0.003	0.011
AT1	0.833	0.66	0.235	0.836	0.667	0.23	-0.003	-0.007	0.005
AT3	0.902	0.697	0.216	0.905	0.703	0.209	-0.003	-0.006	0.007
AT5	0.887	0.7	0.219	0.888	0.702	0.217	-0.001	-0.002	0.002
AT4	0.85	0.635	0.25	0.851	0.642	0.248	-0.001	-0.007	0.002
CT1	0.984	0.83	0.184	0.979	0.812	0.192	0.005	0.018	-0.008
CT2	1.005	0.817	0.261	1	0.805	0.268	0.005	0.012	-0.007
CT3	1.028	0.837	0.194	1.031	0.84	0.19	-0.003	-0.003	0.004
PC3	0.898	0.736	0.263	0.899	0.737	0.261	-0.001	-0.001	0.002
PC2	0.894	0.751	0.241	0.904	0.758	0.224	-0.01	-0.007	0.017
PC1	0.907	0.756	0.226	0.909	0.754	0.224	-0.002	0.002	0.002

Besides, PLSpredict was also used as the advanced studies for Q² in order to ensure the accuracy of predictive relevance in the research. 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 Q² predict for the PLS-SEM for all indicators of a measurement model were 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 conclude that the PLS-SEM analysis produced lower

prediction errors for majority of the indicators (8 out of 11 indicators; PLS-SEM < LM). According to Shmueli *et al.* (2019), if majority of the indicators fulfill the principles [Q² predict > 0; MAE error values are negative (PLS-SEM < LM)], the medium predictive power existed for the PC model (Shmueli *et al.* 2019). In brief, the results based on the Q² from blindfolding and Q² predict from PLSpredict conclude that the PC model had predictive relevance in Q² and medium significance predictive relevance in Q² predict.

In conclusion, the results from the R², f² and Q² have empirically corroborated that the assessment of the structural model in this research was fully satisfied, since the assessments of R², f² and Q² of the path model have met the thresholds of the analysis.

4.5 Direct-Effect Test

In this research, researchers assessed the path coefficient by using the SmartPLS 3.2.8's bootstrapping function with 5,000 bootstrap resamples (Hair *et al.* 2017). There were five direct hypotheses being evaluated in this research. As in Table 4, NTM ($\beta = 0.243$, $t = 4.496$, $p < 0.05$), AT ($\beta = 0.243$, $t = 4.496$, $p < 0.05$), and CT ($\beta = 0.288$, $t = 6.525$, $p < 0.05$) had direct, positive and significant effect on PC indicating that H₁, H₄, and H₅ were validated and supported. Moreover, NTM had direct, positive and significant effect on CT and AT with different indices ($\beta = 0.569$, $t = 10.717$, $p < 0.05$) & ($\beta = 0.528$, $t = 13.469$, $p < 0.05$) respectively. Therefore, H₂ and H₃ were validated and supported.

4.6 Mediation-Effect Test

There were two mediating hypotheses (H₆ & H₇) being formed in this research with the objective to investigate the indirect effects of CT & AT on the relationships between NTM and PC. Table 4 shows that the indirect effects, H₆ ($\beta = 0.152$) and H₇ ($\beta = 0.155$) were significant with t-values of 6.35 and 5.073 respectively. For H₆ and H₇, the results of confidence-interval indicate that a zero value does not straddle in between the lower and upper limits of the 95% Boot CI BC. Thus, the mediation relationships were validated and supported (Preacher & Hayes 2004; 2008).

4.7 Goodness of Fit

Henseler *et al.* (2016) suggested to assess the goodness of fit of a structural model. Hair *et al.* (2017) argued that the model fitness indices enable researchers to judge how well a model structure fits the empirical data; thus, model misspecifications could be identified. Hu & Bentler (1998) suggested to apply the three criteria to identify the model's goodness of fit: the Standardized Root Mean Square Residual (SRMR < 0.08) (Hu & Bentler 1998), Bentler-Bonett index or Normed-Fit-Index (NFI > 0.90) (Bentler & Bonett, 1980), and Root Mean Square Error Correlation (RMS_theta < 0.12) (Henseler *et al.* 2016). As demonstrated in the Table 4, the SRMR value was 0.079, (less than 0.08), which has already met the requirement of Goodness of Fit. The value of NFI (0.869) is less than 0.9, but close to the guideline. However, the value of RMS_theta (0.184) does not meet the criteria (< 0.12). 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). 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, the explanation ability and prediction ability of the model. By considering from these aspects, this model has reached the academic requirements for the overall model fitness.

5. CONCLUSION

In conclusion, this study has contributed to the theoretical context by concluding that the number of trusted members, cognitive trust, and affective trust have direct, positive, and significant effects on the perceived credibility. The number of trusted members has direct, positive, and significant effect on both the cognitive trust and the affective trust. Besides, this study also concludes two mediating hypotheses, in which cognitive trust mediates the relationship between the number of trusted members and perceived credibility as well as the affective trust mediates the relationship between the number of trusted members and perceived credibility. These findings provide significant information for practitioners to craft the strategies on how to enhance the perceived credibility of the information in social commerce. The level of competence, integrity, and benevolence of trust between the users and information providers were not well addressed in this research. Therefore, future research may investigate the impacts of competence, integrity, and benevolence of trust between the users and information providers on the number of trusted members and perceived credibility of the information in social commerce.

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