ICIC Express Letters
Part B: Applications
Volume **13**, Number **3**, March **2022**

ICIC International ©2022 ISSN 2185-2766
pp. 241–247

ANALYSIS OF SOCIAL INFLUENCE FACTORS ON PURCHASE INTENTION FACTORS IN ELECTRONIC COMMERCE AT THE TIME OF THE IMPLEMENTATION OF LARGE-SCALE SOCIAL RESTRICTIONS DUE TO COVID-19

Surjandy[1], Meyliana[1] and Yuli Eni[2]

[1]School of Information Systems
[2]Management Department, BINUS Business School Undergraduate Program
Bina Nusantara University
Jl. K. H. Syahdan No. 9, Kemanggisan, Palmerah, Jakarta 11480, Indonesia
surjandy@binus.ac.id; { meyliana; yeni }@binus.edu

Received May 2021; accepted August 2021

Abstract. *COVID-19 occurs all over the world and affects all aspects, including social aspects where regulations on social limitations are applied. On the other hand, the influence of social factors is one factor that significantly influences the purchase intention factor. Therefore, this study attempts to analyze how social factors influence purchase intention during the COVID-19 pandemic, which is still happening at the time of data collection. As a sample in the study, there were 471 respondents from one of the largest electronic commerce companies in Indonesia. The data analysis process uses structural equation modeling and partial least square (SEM-PLS) using the Warp PLS application. Apart from that, this study also looks at how gender, age, and longtime use application factors affect social influence and purchase intention factors. The results of this study found that during the COVID-19 pandemic, social factors influenced the purchase intention of customers. Likewise, gender, age, and length of time using the application significantly affect social and purchase intention factors. The results of this study are beneficial for the customer service development of electronic commerce in the future.*
Keywords: COVID-19, Social influence, Purchase intention, Warp PLS, Electronic commerce

1. **Introduction.** The COVID-19 pandemic that is occurring around the world is currently changing the lifestyle of all people, including in Indonesia. In conditions of epidemic still occurring, this research was conducted. There is an Indonesian government regulation known as PSBB (large scale social restriction) and PPKM (public activity restrictions) limiting the space for people to move in social activities for school, work, or shopping [1,2]. On the other hand, the social influence factor is an essential factor and a factor that can influence a person's purchase intention [3-5]. Previous research reports that there is a shift in the way people shop in Indonesia from face-to-face to technology-based [6,7] and shopping using electronic commerce during the COVID-19 pandemic [8,9]. This study aims to see the social influence on shopping interest in one of Indonesia's most considerable electronic commerce during the pandemic with the PSBB (large scale social restriction) and PPKM (public activity restrictions) regulations. Previous research on purchase intention states that fear during a pandemic affects buying interest [10]. In other research on purchasing via electronic commerce during a pandemic [11-13], and during the lockdown situation, people show interest in buying for certain brands [14]. This study aims to see the influence of social influence at the time of the pandemic. PSBB (large scale social restriction) and PPKM (public activity restriction) are imposed by the COVID-19 pandemic on purchase intention factors, especially for one of the largest e-commerce in Indonesia customers. The

DOI: 10.24507/icicelb.13.03.241

471 electronic commerce customers became respondents of this study. This research was conducted using quantitative methods with SEM-PLS techniques and using Warp PLS 3.0 for data processing. The results of the calculations show that during the COVID-19 pandemic, there were limitations to socializing physically. However, the social influence factor still strongly influenced the purchase intention with a value of 65.3%. Writing this paper begins with a background that explains the situation and problems that exist as well as research questions, methods used to conduct research, research results, discussion and the last is the conclusion.

2. **Methodology, Research Model Development, and Data Source.** This research uses quantitative methods, using semantic equation modeling and partial least square (SEM-PLS) techniques. This technique uses to see the impact or influence of social factors on buying electronic commerce customers and the data analysis process facilitated by Warp PLS 3.0 [15,16]. Exhibiting in Figure 1 is the research model.

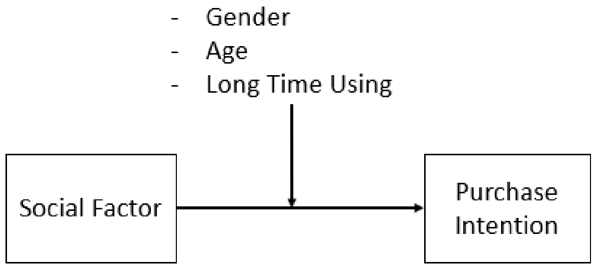

FIGURE 1. Research model

2.1. **Research model development.** Humans are social creatures; in the day, they will continue to socialize. At present, there are many ways to carry out socialization in today's era, not only face-to-face but can also be done online through social media (Line, WhatsApp, Facebook chat, etc.) or even on chat pages in e-commerce applications [17]. Social factors are very influential for a person because these factors can impact decision-making, such as the example to purchase products [18,19]. Interestingly, this data research collection was carried out during the COVID-19 pandemic, when the Indonesian government enforced the PSBB (large scale social restriction) regulation, including in Jakarta. With this enforcement, all face-to-face social activities are minimal, including in offices, because there are limited employees present so that all residents feel the limitations of social activities. On the other hand, there are restrictions on social activities or activities in shopping places. Based on the report from the research results, there has been a change in how to shop in the community using online purchases [20]. It can also be seen from the reports on the number of accesses (clicks) to electronic commerce in Indonesia [6] (Shopee 93.44 million clicks, Tokopedia 86.1 million clicks). Therefore, this study tries to see how the influence of social factors on purchase intention factors that occur in electronic commerce when the COVID-19 pandemic occurs. The hypothesis in this study is whether social relationships influence purchase intentions during COVID-19 in terms of gender, age, and longtime use (LTU) in electronic commerce.

2.2. **Data source.** The survey was conducted from October 2020 to January 2021. At the time, the PSBB was still in effect or regulations that limited physical meetings, so it is not possible to collect data directly from electronic commerce customers, and data collection is carried out by using a google form and distributing the google form link on WhatsApp both to groups and individuals. The data used in this study were 471 respondents, and data collection used the snowball sampling technique which is sometimes

Table 1. Respondent

Gender		Age/years old (YO)		Longtime use (LTU)	
Male	213 (45.2%)	17-24 YO	237 (50.3%)	< 6 months	25 (5.3%)
Female	258 (54.8%)	25-34 YO	76 (16.1%)	6-12 months	83 (17.6%)
Total	471 (100%)	35-44 YO	114 (24.2%)	1-3 years	235 (49.9%)
		> 44 YO	44 (9.4%)	> 3 years	128 (27.2%)

called chain referral or respondent-driven sampling. This method is often used for research related to people or organizations [21]. Table 1 shows the data respondent statistics.

2.3. **Social factor.** Social factor is a factor for describing social interaction. Social interaction reflects the intrinsic demand of human life and the motivation of behavior. It was found that, the sellers who benefited the most in a social trading environment were sellers who have more access to users [22]. This is due to the effect of grouping the characteristics and behavior of community users. Their buying behavior tends to be influenced by their friends around them [23] and the retail systems [24]. Social influence based on the subjective norm describes the influence of people who are essential to the subject making decisions, even if these other views go against the buyer's views in terms of the purchase [25]. Therefore, this concept has been linked directly with online buying, adding social factors to it [26].

3. **Results.** The results of data processing calculations using Warp PLS can be seen in Figure 2.

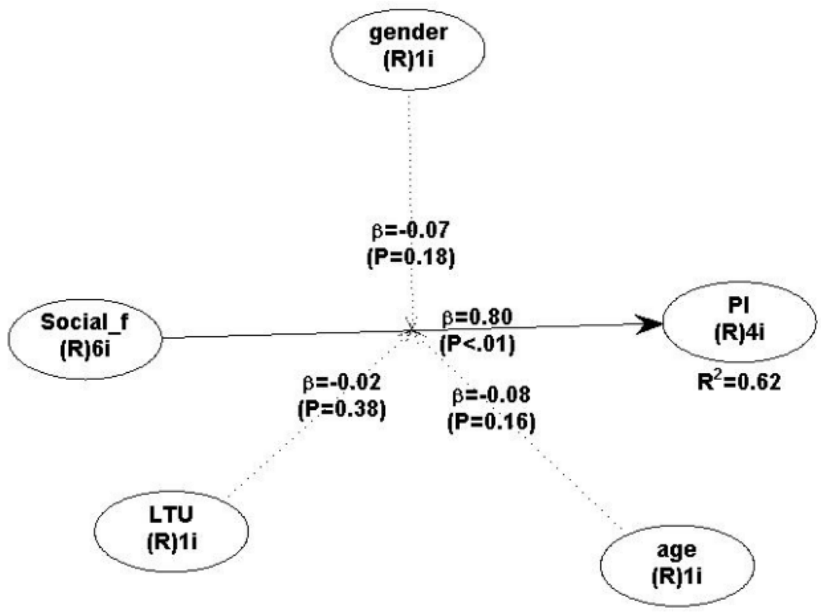

Figure 2. Research calculation result

The resulting test of this structural model looks at the R-squared value (the goodness of the model). The results show that the R-squared value on the purchase intention (PI) variable influenced by a social factor (SF) is 0.62. It means the exogenous latent variable in this study SF, can influence the PI by 62% or in other words, this research model. Classified as strong, this is assessed from the coefficient of determination R-squared 0.75, 0.50, and 0.25 for each endogenous latent variable in the structural model, which means substantial, moderate, and strong.

3.1. **Fit model.** The fit model in the PLS Warp program can be seen from the value based on the fit index model and p-value, namely, 1) the average path coefficient (APC) has a p-value < 0.05, 2) average R-squared (ARS) has p-value < 0.05 and 3) the average block variance inflation factor (AVIF) has a score of 4.092 (< 5), and the ideal score is 3.3. The validity and reliability test results are exhibited in Table 2.

Table 2. Validity and reliability result

Factor	SF	PI	Gender	Age	LTU	Gender*SF	Age*SF	LTU*SF	p-value
SF1	0.737								< 0.001
SF2	0.754								< 0.001
SF3	0.856								< 0.001
SF4	0.839								< 0.001
SF5	0.848								< 0.001
SF6	0.807								< 0.001
PI1		0.828							< 0.001
PI2		0.864							< 0.001
PI3		0.881							< 0.001
PI4		0.843							< 0.001
Gender			1.000						< 0.001
Age				1.000					< 0.001
LTU					1.000				< 0.001
Gender*SF1						0.738			< 0.001
Gender*SF2						0.750			< 0.001
Gender*SF3						0.816			< 0.001
Gender*SF4						0.813			< 0.001
Gender*SF5						0.812			< 0.001
Gender*SF6						0.762			< 0.001
Age*SF1							0.729		< 0.001
Age*SF2							0.726		< 0.001
Age*SF3							0.816		< 0.001
Age*SF4							0.813		< 0.001
Age*SF5							0.812		< 0.001
Age*SF6							0.762		< 0.001
LTU*SF1								0.710	< 0.001
LTU*SF2								0.713	< 0.001
LTU*SF3								0.857	< 0.001
LTU*SF4								0.804	< 0.001
LTU*SF5								0.848	< 0.001
LTU*SF6								0.745	< 0.001

Table 2 shows that all the values are above 0.5 and the p-value is < 0.05, which means all factors are declared valid, and the indicators are declared fit.

From Table 3, the fit indices and p-values model section display the results of three fit indicators, namely the average path coefficient (APC), average R-squared (ARS), and average block variance inflation factor (AVIF). The p-value given for the APC and ARS indicators must be less than 0.05 or be significant. In addition, AVIF as an indicator of multicollinearity must be less than 5. The criteria for the goodness of fit model have been met, namely with an APC value of 0.241 and ARS 0.617 and significant. The AVIF value of 4.092 (< 5) has also met the criteria. Composite reliability and Cronbach's alpha > 0.7 which means that all factors are reliable. Apart from that, the AVE value is 0.653 (> 0.5), which means that the factors in the model influence 65.3%, and 34.7% are other factors. Apart from that the average block variance inflation factor (AVIF) value is 4.092

Table 3. R^2, composite reliability, Cronbach's alpha, and AVE

Factor	SF	PI	Gender	Age	LTU	Gender*SF	Age*SF	LTU*SF
R-squared		0.617						
Composite reliability	0.918	0.915	1.000	1.000	1.000	0.918	0.901	0.904
Cronbach's alpha	0.893	0.876	1.000	1.000	1.000	0.892	0.868	0.871
Avg. var. extract (AVE)	0.653	0.730	1.000	1.000	1.000	0.651	0.604	0.611
Full collin VIF	3.231	2.888	1.042	1.250	1.030	1.021	1.460	1.034
Q-squared		0.619						

(< 5), while the APC value is 0.241 with a p-value < 0.001 and an ARS value $= 0.617$ with a p-value < 0.001. The implication obtained from the results is that social factors influence 91.8% of purchase intention. This social factor uses as a variable that has an important role, with the moderation of gender, age, and longtime use. For example, during a pandemic, many e-commerce sites are targeted by people to buy a product. Social factors here have a role in purchase intention. It shows in the R^2 (R-squared) value. The value of composite reliability indicates the value of reliability. The social factor is reliable on purchase intention, meaning that the social factor has a consistent effect when reviewed for questionnaires distributed on purchase intention. Besides that, the AVE value describes the amount of variance or variety of manifest variables that latent constructs can have. Thus, the greater the variance or variety of manifest variables that can be contained by latent constructs, the greater the manifest variable representation of the latent constructs. In this study, the AVE value was below 10, which means that all variables in this study were valid. A minimum AVE value of 0.5 indicates a good measure of convergent validity. That is, latent variables can explain an average of more than half the variance of the indicators. AVE value is obtained from the sum of the loading factor squares divided by the error. AVE is used to measure the reliability of the latent variable component score, and the results are more conservative than composite reliability (CR).

3.2. **Direct influence.** The results of calculations use the Warp PLS application. Warp PLS is a software application developed by Ned Kock using the Matlab compiler and Java. This software can analyze variant-based SEM models or better known as partial least square. The SEM analysis model with Warp PLS can identify and estimate the relationship between latent variables, whether the relationship is linear or non-linear. The research result shows a direct influence on gender, age, and duration of use, which is shown in Figure 2 of explanation of the social influence (SF) on purchase intention (PI). Means, influenced by age, has the greatest value of 0.08 (8%) followed by gender with a value of 0.07 (7%), and the last is the longtime use (LTU) of 0.02 (2%).

3.3. **Indirect influence.** Testing of this structural model is carried out by looking at the R-squared, which is the goodness fit model test. The results show that the R-squared value of the PI variable influence SF is 0.62. It means that the exogenous latent variable in this study influences the PI by 62%. In other words, this research model is classified as strong, based on the coefficient determination of R-squared 0.75, 0.50, and 0.25 for each endogenous latent variable in the structural model that can be interpreted as substantial, moderate, and strong. In Figure 2, it shows the estimated direct effect by looking at the value of $\beta = 0.80$ and p-value ($p < 0.05$ means significant). The coefficient of determination (determinant)/KD can be obtained with the formula $\mathrm{KD} = \mathrm{R}^2 \times 100\%$ where $\mathrm{R} = 0.80$, and then it can be obtained $\mathrm{KD} = (0.80)^2 \times 100\% = 0.64 \times 100\% = 64\%$, showing that the SF variance of 64% can be explained by the PI. The indirect effect can be seen in Table 3, by looking at the magnitude of the Cronbach's alpha value where the largest value is age with a value of 0.868 (86.8%) followed by a longtime use with a value of

0.871 (87.1%) and finally gender with a value of 0.892 (89.2%). It can be interpreted that indirect influence has a bigger role in buying decisions.

4. **Discussion.** This section describes the findings obtained from the SEM-PLS technique using the Warp PLS 3.0. This research found that during the COVID-19 pandemic, with the enforcement of PSBB (large scale social restriction), no direct or face-to-face social activities, social influence was an important thing that influenced customers' purchase intention using electronic commerce (online). It happens because social behavior (physically or online) effectively performs online [17,19], which means during the COVID-19 pandemic situation, there has been a change in social activities for customer electronic commerce, which is carried out online or behavioral changes [27].

Apart from that, it was also found that electronic commerce customer age is a factor that can influence both, directly and indirectly, the decision to buy during the COVID-19 pandemic. Another thing supporting this study's findings is that Internet usage in Indonesia has increased [28], which means social activities performed using social media efficiently.

5. **Conclusion.** The conclusion obtained from this study is that the social factor (SF) has an essential role in purchase intention (PI). Although there is a PSBB where people are socially limited to meeting face-to-face with technology, social activities can happen online. It is concluded that online social behavior has an influence on purchase intention during the COVID-19 pandemic. The age factor is a factor that can control the social influence on purchase intention, either directly or indirectly.

This study still has an unknown influence factor of 34.8%, so it is possible to conduct further research to discover other factors. Besides that, the online shopping habits of Indonesians during the COVID-19 pandemic, which used impression data from Google Analytics, contained several interesting highlights about the increased interest in products, namely health products, homework, food, and beverages. This is the primary need of people in Indonesia and of course, related to social factors.

REFERENCES

[1] D. Pangestika, What you need to know about Indonesia's newest COVID-19 restrictions – National, *The Jakarta Post*, https://www.thejakartapost.com/news/2021/01/14/what-you-need-to-know-about-indonesias-newest-covid-19-restrictions.html, Accessed on Feb. 14, 2021.

[2] Y. Omae, Y. Kakimoto, J. Toyotani, K. Hara, Y. Gon and H. Takahashi, Impact of removal strategies of stay-at-home orders on the number of COVID-19 infectors and people leaving their homes, *International Journal of Innovative Computing, Information and Control*, vol.17, no.3, pp.1055-1065, 2021.

[3] X. Qi, H. Yu and A. Ploeger, Exploring influential factors including COVID-19 on green food purchase intentions and the intention-behaviour gap: A qualitative study among consumers in a Chinese context, *Int. J. Environ. Res. Public Health*, vol.17, no.19, pp.1-22, DOI: 10.3390/ijerph17197106, 2020.

[4] B. Tungen et al., Social influence matters: We follow pandemic guidelines most when our close circle does, *Br. J. Psychol.*, pp.1-18, DOI: 10.1111/bjop.12491, 2021.

[5] E. S.-T. Wang and N. P.-Y. Chou, Consumer characteristics, social influence, and system factors on online group-buying repurchasing intention, *J. Electron. Commer. Res.*, vol.15, no.2, pp.119-132, 2014.

[6] Statista.com, *Indonesia: Top 10 E-Commerce Sites 2020*, https://www.statista.com/statistics/869700/indonesia-top-10-e-commerce-sites/, Accessed on Feb. 14, 2021.

[7] A. Sitorus, M. Gultom and V. Andini, E-commerce boosts the logistics sector in Indonesia, *The Jakarta Post*, https://www.thejakartapost.com/academia/2021/01/03/e-commerce-boosts-the-logistics-sector-in-indonesia.html, Accessed on Feb. 14, 2021.

[8] J. Koch, B. Frommeyer and G. Schewe, Online shopping motives during the COVID-19 pandemic – Lessons from the crisis, *Sustain.*, vol.12, no.24, pp.1-20, DOI: 10.3390/su122410247, 2020.

[9] S. Laato, A. K. M. N. Islam, A. Farooq and A. Dhir, Unusual purchasing behavior during the early stages of the COVID-19 pandemic: The stimulus-organism-response approach, *J. Retail. Consum. Serv.*, vol.57, no.3, DOI: 10.1016/j.jretconser.2020.102224, 2020.

[10] N. Shah, M. S. Kalwar and B. A. Soomro, Early COVID-19 outbreak, individuals' mask attitudes and purchase intentions: A cohesive care, *J. Sci. Technol. Policy Manag.*, vol.2019, DOI: 10.1108/JSTPM-05-2020-0082, 2020.

[11] P. Kalia, R. Arora and S. Kumalo, E-service quality, consumer satisfaction and future purchase intentions in e-retail, *e-Service J.*, vol.10, no.1, p.24, DOI: 10.2979/eservicej.10.1.02, 2016.

[12] H. H. Chang and C. D. Meyerhoefer, COVID-19 and the demand for online food shopping services: Empirical evidence from Taiwan, *Am. J. Agric. Econ.*, vol.103, no.2, pp.448-465, DOI: 10.1111/ajae.12170, 2021.

[13] X. Gao, X. Shi, H. Guo and Y. Liu, To buy or not buy food online: The impact of the COVID-19 epidemic on the adoption of e-commerce in China, *PLoS One*, vol.15, no.8, pp.1-14, DOI: 10.1371/journal.pone.0237900, 2020.

[14] L. Alexa, A. Apetrei and J. Sapena, The COVID-19 lockdown effect on the intention to purchase sustainable brands, *Sustain.*, vol.13, no.6, pp.1-16, DOI: 10.3390/su13063241, 2021.

[15] N. Kock, PLS-based SEM algorithms: The good neighbor assumption, collinearity, and nonlinearity, *Inf. Manag. Bus. Rev.*, vol.7, no.2, pp.113-130, DOI: 10.22610/imbr.v7i2.1146, 2015.

[16] N. Kock, A note on how to conduct a factor-based PLS-SEM analysis, *Int. J. e-Collaboration*, vol.11, no.3, pp.1-9, DOI: 10.4018/ijec.2015070101, 2015.

[17] A. Usman and S. Okafor, *Exploring the Relationship between Social Media and Social Influence*, no.1, 2019.

[18] E. Akar, H. F. Yüksel and Z. A. Bulut, The impact of social influence on the decision-making process of sports consumers on facebook, *J. Internet Appl. Manag.*, vol.6, no.2, pp.5-27, DOI: 10.5505/iuyd.2015.40412, 2015.

[19] X. Wang, C. Yu and Y. Wei, Social media peer communication and impacts on purchase intentions: A consumer socialization framework, *J. Interact. Mark.*, vol.26, no.4, pp.198-208, DOI: 10.1016/j.intmar.2011.11.004, 2012.

[20] *Fahri, Tren Ecommerce di 2021, Ada Apa Saja (Ecommerce Trends in 2021, What's there)*, https://powercommerce.asia/tren-ecommerce-di-2021/, Accessed on Feb. 14, 2021.

[21] W. L. Neuman, *Social Research Methods: Pearson New International Edition: Qualitative and Quantitative Approaches*, Pearson, 2014.

[22] X. Yin, H. Wang, Q. Xia and Q. Gu, How social interaction affects purchase intention in social commerce: A cultural perspective, *Sustain.*, vol.11, no.8, DOI: 10.3390/su11082423, 2019.

[23] K. Z. K. Zhang and M. Benyoucef, Consumer behavior in social commerce: A literature review, *Decis. Support Syst.*, vol.86, pp.95-108, DOI: 10.1016/j.dss.2016.04.001, 2016.

[24] A. Goldfarb, R. C. McDevitt, S. Samila and B. S. Silverman, The effect of social interaction on economic transactions: Evidence from changes in two retail formats, *Manage. Sci.*, vol.61, no.12, pp.2963-2981, DOI: 10.1287/mnsc.2014.2030, 2015.

[25] A. T. Stephen and O. Toubia, Deriving value from social commerce networks, *J. Mark. Res.*, vol.47, no.4, pp.215-228, 2010.

[26] A. G. Parsons, Non-functional motives for online shoppers: Why we click, *J. Consum. Mark.*, vol.19, no.5, pp.380-392, DOI: 10.1108/07363760210437614, 2002.

[27] A. Butu et al., The impact of COVID-19 crisis upon the consumer buying behavior of fresh vegetables directly from local producers. Case study: The quarantined area of Suceava County, Romania, *Int. J. Environ. Res. Public Health*, vol.17, no.15, pp.1-25, DOI: 10.3390/ijerph17155485, 2020.

[28] H. Nurhayati-Wolff, *Indonesia: Internet Penetration Rate 2023 | Statista*, https://www.statista.com/statistics/254460/internet-penetration-rate-in-indonesia/, Accessed on Mar. 06, 2021.