

# The Perceived Privacy Risk in the Modern Society (Case in Customer E-Commerce)

Sambudi Hamali<sup>1\*</sup>, Vincent Polim<sup>2</sup>, Yohanes<sup>3</sup>

<sup>1-3</sup>Management Department, BINUS Business School Undergraduate Program,  
Bina Nusantara University,  
Jakarta 11480, Indonesia  
sambudi\_hamali@binus.ac.id; vincent.polim@binus.ac.id;  
yohanes011@binus.ac.id

\*Correspondence: sambudi\_hamali@binus.ac.id

## ABSTRACT

*One of the main characteristics of modern society is technological progress in everyday life, but on the other hand, challenges in modern society include the spread of fake news, disinformation, and leaks of personal data. The study's goal is to investigate the influence of social commerce information sharing (SCIS) on consumer trust and the risk of privacy perceived by consumers, as well as the effect of consumer trust on the risk of privacy perceived by Tokopedia users, as mediated through trust. A questionnaire was issued to 100 Tokopedia customers to collect data. SEM-PLS (Structural Model) with WarpPLS software version 8.0 is used for data analysis. SCIS has an effect on trust and consumer-perceived privacy risk, while trust has no effect on consumer-perceived privacy risk, according to the findings. SCIS has a higher impact on consumer trust than on their perceived privacy risks. This demonstrates the need for Tokopedia to build consumer trust.*

**Keywords:** *Perceived Privacy Risk; Social Commerce Information Sharing; Trust; E-Commerce; Modern Society*

## INTRODUCTION

Modern society is the present era, marked by the widespread use of technology, a focus on individualism and human rights, and growing interconnectivity (Forgeard, 2023). Challenges in modern society include the spread of fake news, disinformation, and personal data leaks. Digital businesses also feel this technological progress. Based on the 2022 Indonesian economic report issued by Bank Indonesia, the value of digital banking transactions in 2022 will increase by 28.72% (yoy) to IDR 52,545.8 trillion. It will grow 22.13% to reach IDR 64,175.1 trillion in 2023. The acceleration of digitalization of payment systems has encouraged e-commerce transactions to grow rapidly, growing 18.7% to IDR 476 trillion in 2022 and then increasing 11.8% to IDR 533 trillion in 2023. E-commerce transactions are growing rapidly, with a Compound Annual Growth Rate (CAGR) in 2018-2022 of 35.1% (Bank Indonesia, 2023).

In addition to e-commerce, there is also a social commerce trend that is very popular and is being implemented by companies. One is Tokopedia, which implements Tokopedia Play with the concept of implementing video streaming that brings sellers and buyers together through shows, two attractive offers, and the Tokopedia Affiliate Program. This differs slightly from the concept that Tokopedia offers reviewers by providing additional coins. In Indonesia, there is an excellent opportunity to implement successful social media trading because many social media users are very active (Meilatinova, 2021).

This research was carried out on e-commerce users. Problems often encountered and doubted by e-commerce application users are data-related problems, namely data leaks. One example on a global scale that can be seen and has just happened in recent years is the data breach of Facebook users, where billions of data Facebook users are auctioned off on the Hacker Forum, which is a hacker forum commonly used for data trading (Morgan, 2021). In addition, Tokopedia experienced a leak of 91 million user data in May 2020; as many as 91 million Tokopedia users were leaked on hacker forums and could be downloaded for free in May 2020 (Burhan, 2021). Due to negligence in maintaining customer privacy, disappointment can also be seen in tweets given by users on the Twitter application (Rahmania, Pradekso & Ayun, 2021). There are shortcomings in using applications in e-commerce, such as perceived privacy risks, consumer trust in e-commerce platforms, and social commerce information sharing. These three problems, if good measures are not taken by companies carrying out E-commerce, can reduce consumer activity in online purchases and the risk of user privacy being leaked.

Based on research by Bugshan & Attar (2020), it shows that “Social Commerce Information sharing increases trust in trading platforms and reduces perceived privacy risks, which can significantly improve the decision-making process and intention to purchase.”

Trust has a positive effect on perceived privacy risk (Bugshan & Attar, 2020). Furthermore, research by Alraja, Farooque & Khashab (2019) shows that the level of security, privacy, and familiarity influence trust in IoT. Trust in IoT influences user’s risk perception. However, research by Xu, et al., (2005), Zhou (2015), and Wang & Lin (2017) show that trust has a negative effect on perceived privacy risk. The statement suggests that the topic of the relationship between trust and perceived risk is worth exploring further because there are inconsistent results on this topic.

Based on the description above, the author formulates the problem as follows: Does social commerce information sharing have a significant influence on consumer trust? Does social commerce information sharing have a significant influence on the privacy risk perceived by consumers? Does customer trust have a significant influence on the privacy risk perceived by consumers? Does social commerce information sharing have a significant influence on the privacy risk perceived by consumers by being mediated by customer trust?.

## METHODS

This study uses quantitative methodologies and is a Causal Study, which aims to determine whether one variable causes another variable to change or not (Saunders, Lewis & Thornhill, 2019). The person, or Tokopedia Jakarta Consumers, is the unit of analysis in this research. The data collection method is a questionnaire distributed via Google Forms. Respondents in this study are Tokopedia consumers who live in the Jakarta region. The sample size for this study uses the Cochran formula (Sugiyono, 2017) as follows:  $n = (z^2 \cdot p \cdot q) / e^2$ , where: n = number of samples, z = value in the normal curve for an alpha value of 5% = 1.96, p = 50% chance of being correct, q = 50% chance of being wrong, e = margin of error = 10%. With this formula, the minimum sample size is n=96.04, which is then rounded up to 97 respondents. To avoid a non-responsive sample, the researchers collected 204 respondents. The data was collected from October 2022 to January 2023.

This research uses a non-probability sampling technique, which is purposive sampling. The data obtained from the questionnaire was analyzed using Structural Equation Modeling-Partial Least Square (SEM-PLS) with the WarpPLS version 8.0 application. This concept was measured indirectly with several indicators (Hair, et al., 2022). The measurement of trust indicators refers to Chang, et al., (2018), an example of the questionnaire is, “I believe that Tokopedia has a privacy policy to protect consumers’ personal information.” The measurement of social commerce information-sharing indicators refers to Tajvidi, et al., (2020), an example of the questionnaire is, “Consumer reviews on Tokopedia can be used as a recommendation to buy.” and the measurement of perceived privacy risk indicators refers to Chang, et al., (2018), an example of the questionnaire is, “There is a risk that personal information provided to Tokopedia could be sold to third parties.”

## Research Model and Hypotheses

The researchers formulated a research model with four hypotheses (see Figure 1).

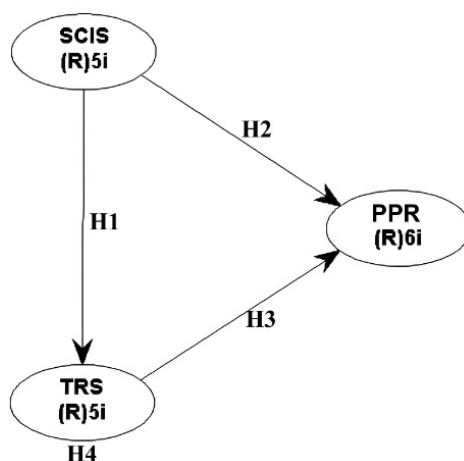


Figure 1. Research Model

### Social Commerce Information Sharing (SCSI)

Social Commerce Information Sharing can be defined as exchanging information through social media sites, which builds consumer social support (Weining, et al., (2021). Meanwhile, according to Tajvidi, et al., (2020), Social Commerce Information Sharing is an individual interested in sharing and requesting information related to trade in online forums or communities, ratings, reviews, and recommendations. According to Bugshan & Attar (2020), Social Commerce information sharing influences trust and perceived privacy risks.

Therefore,

**H<sub>1</sub>:** There is an influence between social commerce information sharing and consumer trust.

**H<sub>2</sub>:** There is an influence between social commerce information sharing and the privacy risk perceived by consumers.

### Trust (TRS)

According to Chanthasaksathian & Nuangjamnong (2021), Trust is a situation when someone takes the risk to buy some product or service or carry out some activity with a certain third party, which later experience becomes trust that will be felt by the related party. Trust allows users to believe that service providers will handle their privacy information properly, which can help reduce their concern about information privacy (Zhou, 2015). In other words, the more trust a consumer has in a provider's information practices, the less likely she is to anticipate the privacy risk associated with revealing personal information to the service provider. Trust has a negative effect on perceived privacy risk (Xu, et al., 2005; Zhou, 2015; and Wang & Lin, 2017).

Therefore,

**H<sub>3</sub>:** There is an influence between customer trust and the privacy risk perceived by consumers.

### Perceived Privacy Risks (PPR)

“Perceived privacy risk refers to users’ uncertainty in using chatbot services due to the potential negative outcomes associated with disclosing customers’ personal information (Wang & Lin, 2017).” Bugshan & Attar (2020) research shows that “social commerce information sharing influences both perceived privacy risk and trust. Trust also has a strong effect on perceived privacy risk.” Thus, this research proposes the following hypothesis:

**H<sub>4</sub>:** There is an influence between social commerce information sharing and the privacy risk perceived by consumers through customer trust as mediating.

## RESULTS AND DISCUSSION

“A PLS path model consists of two elements. First, the structural model (the deep model in the PLS-SEM context) represents the construct. Structural models also display relationships (paths) between constructs. Second, the construct measurement model (the outer model in PLS-SEM) displays the relationship between the construct and indicator variables (Hair, et al., 2022).”

“The rules of thumb for validity are that the loading of each indicator on contrast must be above 0.7, the p-value must be significant at <0.05, The average variance extracted values (AVEs) are often recommended as 0.5, and the root mean square of the AVEs is higher than the coefficient value of the correlation with latent variables. Any latent variable is reliable if the composite reliability (CR) or Cronbach’s alpha coefficient (CA) must be at least 0.7. Another version sets a limit of 0.6 (Kock, 2022).”

### Measurement Model

Results of Loading Factor, AVE, Sq. AVE, CR, and CA are presented as follows.

Table 1. Measurement Model

| <i>Variable</i> | <i>Items</i> | <i>Loading factor</i> | <i>p-value</i> | <i>AVEs</i> | <i>sq. rts. of AVEs</i> | <i>CR</i> | <i>CA</i> |
|-----------------|--------------|-----------------------|----------------|-------------|-------------------------|-----------|-----------|
|                 | 1            | 0.564                 | <.001          |             |                         |           |           |
|                 | 2            | 0.760                 | <.001          |             |                         |           |           |
| SCSI            | 3            | 0.602                 | <.001          | 0.414       | 0.643                   | 0.776     | 0.693     |
|                 | 4            | 0.707                 | <.001          |             |                         |           |           |
|                 | 5            | 0.557                 | <.001          |             |                         |           |           |
|                 | 1            | 0.790                 | <.001          |             |                         |           |           |
|                 | 2            | 0.825                 | <.001          |             |                         |           |           |
| TRS             | 3            | 0.742                 | <.001          | 0.613       | 0.783                   | 0.888     | 0.842     |
|                 | 4            | 0.763                 | <.001          |             |                         |           |           |
|                 | 5            | 0.793                 | <.001          |             |                         |           |           |
|                 | 1            | 0.784                 | <.001          |             |                         |           |           |
|                 | 2            | 0.833                 | <.001          |             |                         |           |           |
| PPR             | 3            | 0.835                 | <.001          | 0.64        | 0.8                     | 0.914     | 0.886     |
|                 | 4            | 0.846                 | <.001          |             |                         |           |           |
|                 | 5            | 0.791                 | <.001          |             |                         |           |           |
|                 | 6            | 0.701                 | <.001          |             |                         |           |           |

From Table 1, all items are valid and reliable.

### Structural Model Analysis

“The model’s ability to predict and the correlation between variables is evaluated in this stage. The key factors in this stage are the significance of the path coefficient, the R<sup>2</sup> value, and the effect size (f<sup>2</sup>) (Kock, 2022).”

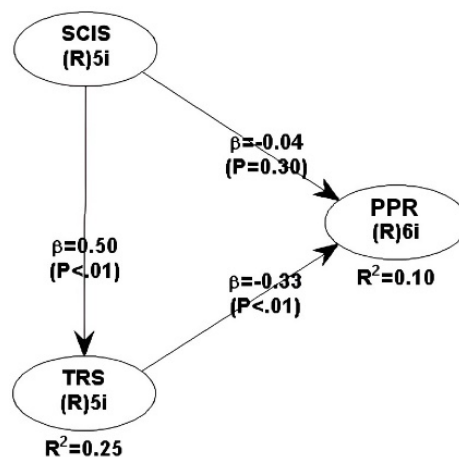


Figure 2. Output of Research Model

Table 2. Structural Model Result

| Hypothesis | Path             | Coefficient | p-value | f <sup>2</sup><br>Effect Size | Result      |
|------------|------------------|-------------|---------|-------------------------------|-------------|
| H-1        | SCSI → TRS       | 0.499       | <0.001  | 0.249                         | Ho Rejected |
| H-2        | SCSI → PPR       | -0.037      | 0.295   | 0.002                         | Ho Accepted |
| H-3        | TRS → PPR        | -0.326      | <0.001  | 0.103                         | Ho Rejected |
| H-4        | SCSI → TRS → PPR | -0.163      | <0.001  | 0.010                         | Ho Rejected |

The hypothesis testing in this research uses a significance level of 5% (0.05). The null hypothesis is accepted if the p-value is more significant than the significance level. Table 2 shows the results of the hypothesis test for this research.

Hypothesis one (H1) SCIS affects TRS, where the p-value <0.05, then the Ho is rejected for H1, meaning that the clearer and more complete the SCIS, the more consumers trust Tokopedia. Therefore, Tokopedia must pay attention to SCIS. Companies can manage SCIS by ensuring that opinions expressed by consumers will reach Tokopedia, and consumers can search for information related to Tokopedia easily. These results are in line with research by Bugshan & Attar (2020), which explains that there is a significant relationship between SCIS and trust. The magnitude of the SCIS effect on JS is 0.249, which demonstrates that the effect is classified as moderate.

Hypothesis two (H2) SCIS does not affect PPR, where the p-value is > 0.05, then the Ho is accepted for H2. The results of this research are not in line with a study conducted by Bugshan & Attar (2020), which shows that social commerce information sharing has a positive effect on perceived privacy risks.

The results related to H3 show that TRS has a significant negative influence on PPR (p-value below 0.05) and supports H3, meaning that the higher the satisfaction of consumer trust in Tokopedia, the lower the privacy risk perceived by consumers and vice versa. The results of this research are in line with research (Xu, Teo, & Tan, 2005; Zhou, 2015; Wang & Lin, 2017), which states that trust has a negative and significant effect on perceived privacy risk. Furthermore, the effect size of TRS on PPR has an influence of 0.103, which means it is a medium influence.

Findings related to H4 show that TRS mediates the effect of SCIS on PPR (p-value smaller than 5%) and rejects Ho. Because SCIS does not affect PPR, TRS becomes a full mediating variable in the relationship between SCIS and PPR. Total effect of SCIS on PPR through TRS is 0.013, which means that it is included in the small influence.

As shown in Figure 2, the R<sup>2</sup> TRS and PPR values are 0.25 and 0.10 respectively. This figure shows that the dependent variable TRS can be explained by the independent variable SCIS by 25% and the variable PPR can be explained by the independent variables SCIS and TRS by 10%, the rest is explained by other variables not included in the model.

The practical implication of this research is to increase Tokopedia consumer confidence. From the results of the questionnaire distributed, researchers learned that consumer reviews on Tokopedia could be used as recommendations to buy, reaching 92% user approval. Therefore, Tokopedia must build a better company image and spread positive consumer reviews through social media such as Instagram, Facebook and YouTube, and be responsible for not misusing consumer data.

## CONCLUSION

This study provides a response to the hypothesis proposed in the Tokopedia consumer experience case study. The results showed that SCIS influences trust and consumer perceived privacy risk, and trust has no influence on consumer perceived privacy risk. SCIS has a greater influence on trust than on consumers' perceived privacy risks. This research has limitations, including the fact that the research object is only one e-commerce platform, namely Tokopedia, in the city of Jakarta. For future research, the research object should be expanded to several e-commerce platforms and several cities in Indonesia. Additionally, future research could explore what factors can increase awareness and knowledge about various aspects of social commerce.



## REFERENCES

- Alraja, M. N., Farooque, M. M. J., & Khashab, B. (2019). The effect of security, privacy, familiarity, and trust on users' attitudes toward the use of the IoT-based healthcare: the mediation role of risk perception. *IEEE Access*, 7, 111341-111354.
- Bank Indonesia. (January 2023). *Laporan Perekonomian Indonesia (LPI) 2022: Sinergi dan Inovasi Memperkuat Ketahanan dan Kebangkitan Menuju Indonesia Maju*. Retrieved 20/02/2023 from [https://www.bi.go.id/id/publikasi/laporan/Pages/LPI\\_2022.aspx](https://www.bi.go.id/id/publikasi/laporan/Pages/LPI_2022.aspx).
- Bugshan, H., & Attar, R. W. (2020). Social commerce information sharing and their impact on consumers. *Technological forecasting and social change*, 153, 119875.
- Burhan, F. A. (2021). *Tokopedia Ungkap Cara Atasi Kasus Kebocoran Data Pribadi*. Retrieved 25/10/2022 from <https://www.cshub.com/attacks/articles/iotw-facebook-data-leak-impacts-533-million-users>
- Chang, Y., Wong, S. F., Libaque-Saenz, C. F., & Lee, H. (2018). The role of privacy policy on consumers' perceived privacy. *Government Information Quarterly*, 35(3), 445-459.
- Chanthasaksathian, S., & Nuangjamnong, C. (2021). Factors influencing repurchase intention on e-Commerce platforms: a case of GET application. *International Research E-Journal on Business and Economics*, 6(1), 28-45.
- Forgeard, V. (April, 2023). *What Is Modern Society and How Has it Evolved Over Time?*. Retrieved 20/09/2023 from <https://brilliantio.com/what-is-modern-society/#:~:text=Modern%20society%20refers%20to%20the%20contemporary%20period%20in%20which%20we,human%20rights%2C%20and%20increasing%20interconnectedness>
- Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)*. (3<sup>rd</sup> ed.). Los Angeles : SAGE
- Kock, N. (2022). *WarpLPS 7.0 User Manual: Vesion 8.0*. Texas: ScriptWarp SystemTM.
- Meilatinova, N. (2021). Social commerce: Factors affecting customer repurchase and word-of-mouth intentions. *International Journal of Information Management*, 57, 102300.
- Morgan, L. (2021). *IOTW: Facebook Data Leak Impacts 533 Million Users*. Retrieved 25/10/2022 from <https://www.cshub.com/attacks/articles/iotw-facebook-data-leak-impacts-533-million-users>.
- Rahmania, T., Pradekso, T., & Ayun, P. Q. (2021). Pengaruh Terpaan Berita Tentang Kebocoran Data Pengguna Tokopedia dan Aktivitas Word of Mouth Terhadap Tingkat Kepercayaan Dalam Menggunakan Tokopedia. *Interaksi Online*, 9(2), 161-169.
- Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students*. Eight Edition. London: Pearson Education Limited.
- Tajvidi, M., Richard, M. O., Wang, Y., & Hajli, N. (2020). Brand co-creation through social commerce information sharing: The role of social media. *Journal of Business Research*, 121, 476-486.
- Wang, E. S. T., & Lin, R. L. (2017). Perceived quality factors of location-based apps on trust, perceived privacy risk, and continuous usage intention. *Behaviour & Information Technology*, 36(1), 2-10.
- Weining, Z., Yunpeng, C., Xingyi, W., Huawei, L., & Ying, Z. (2021). Antecedents and Outcomes of Social Commerce Information Sharing in China: From Multi-medium Marketing to Consumer Behaviour. *Higher Education and Oriental Studies*, 1(2).
- Xu, H., Teo, H. H., & Tan, B. (2005). Predicting the adoption of location-based services: the role of trust and perceived privacy risk. *International Conference on Information Systems (ICIS) 2005 Proceedings, Paper 71*, 897-910
- Zhou, T. (2015). Understanding user adoption of location-based services from a dual perspective of enablers and inhibitors. *Information Systems Frontiers*, 17, 413-422.