Factors affecting teachers’ social media use during covid-19

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Abstract: This study aims to provide an empirical report to understand the key predictors of Teachers’ Social Media Use during Coronavirus Disease 2019 (TSMU Covid-19). A survey instrument adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) was established and validated. The instrument consisted of two sections. Section one collected demographic data, and section two gained data regarding performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and TSMU Covid-19. The main data were collected from 1249 teachers from 3 Indonesian provinces. The data were computed through measurement and structural model supported by Multi-Group Analysis (MGA) in PLS-SEM. The findings informed that facilitating condition emerges as the strongest predictor of teachers’ behavioral intention to use social media during Covid-19 distance education. TSMU Covid-19 was significantly predicted by behavioral intention. The findings also revealed that demographic information significantly moderates the hypothesized paths.

Subjects: Information & Communication Technology; ICT; Communication Technology; Internet & Multimedia; Teaching & Learning - Education

Keywords: Social media; covid-19; K-12 teachers; UTAUT

1. Introduction
The Covid-19 pandemic has spread to almost all countries of the world. Social distancing policies and quarantine, such as lockdowns of educational institutions, business centers, religious places, and entertainment spaces, have been implemented to decrease the virus spread rate (Jinia et al., 2020). To date, current rapid technological advancement and innovation are fundamental to increasing the ways people deal with pandemics that change the history of pandemic quarantine. In education, schools and universities were also closed, affecting millions of teachers’ and billions of students’ activities, tasks, and responsibilities. For example, the school closure in Indonesia, initiated in March 2020, involved more than 600 thousand schools at all levels (Azhari & Faji, 2021). The school closure, aiming to reduce the spread of Covid-19, has accelerated the implementation of technology-based instructional activities through distance education.

Among the technology implemented during distance education are social media, such as Facebook, WhatsApp, Twitter, YouTube, and Instagram. Social media use in education has been informed to benefit teachers and students to communicate, interact, and build networking (Estapa et al., 2017; Khoo, 2019). Studies on factors affecting social media use in education are important to understand the phenomenon and offer policies on social media technology adoption (Chen Hsieh et al., 2017; Estapa et al., 2017). Limited studies were conducted in analyzing social media use in developing countries and during Covid-19; current research by Sobalh et al. (2020) reported
that proper use of social media encourages a new era of social learning and presence as well as becomes alternative platforms, improving distance learning through online tools. Therefore, this study was done to meet two objectives:

1. To inform the key factors affecting social media use in teaching during the Covid-19.
2. To estimate predicting effects between involved variables based on the moderating role of gender and teaching experience.

Practically, the findings of this research would be a great practical contribution for teachers and students in using social media for teaching and learning activities and for policymakers in preparing policies supporting technology integration during distance learning, especially social media use. Besides, this work could help establish helpful benchmarks and preliminary references for technology integration during future school closures due to pandemics.

2. Literature review

2.1. Education and technology integration during Covid-19 in Indonesia

Covid-19 has caused much devastation to many aspects of lives where policymakers or governments worldwide require their people to extend lockdown times to press the spread of the virus, including school closures as a preventive measure in educational sectors (Daniel, 2020). Regarding the situation, the integration of technology-enabled instructional activities are done mostly within the approach of distance education (Liguori & Winkler, 2020; Mulenga & Marbán, 2020; Verawardina, 2020); online technology are focused on improving new normal instruction, a new normal under the pretext of the Covid-19 or other future pandemics (Gurukkal, 2020). For example, Mulenga and Marbán (2020) reported that social media as one of the digital technologies could be a positive response to distance education during the Covid-19 school closure. As a result, terms such as “WhatsApp,” “Facebook group,” “Zoom,” and “Teams” have been mentioned in students’ and teachers’ everyday lexicon as platforms for teaching and learning activities.

On 3 July 2021, Indonesia officially entered the enforcement period of emergency community activity restrictions or lockdown in the red zone area since it was recorded as a new daily case record. This policy was taken as the government’s response to the increase in infection cases occurring in the community. Consequently, many activities were limited, such as non-essential office activities, places of worship, shopping center operations, and especially teaching and learning activities. Based on the joint decree of the Indonesian Minister of Education and Culture (MoE), Minister of Religion, Minister of Health, and Minister of Home Affairs regarding the guidelines for the implementation of learning the Covid-19 Pandemic (MoE, 2020). The decree has allowed face-to-face learning activities at schools in green zone areas in July 2021. Areas with yellow, orange, and red zones were still prohibited from conducting face-to-face learning activities.

2.2. Social media use in education

The use of social media in education facilitates teachers and students to obtain useful information linked with group learning and other benefits and makes teaching more convenient (Mukminin et al., 2022). They can provide educational stakeholders and institutions with many opportunities to improve learning methods (Carpenter et al., 2019). Through the systems, teachers and students can incorporate plugins enabling communication, sharing, and interaction. Teachers and students can get many advantages from online tutorials and resources (Estapa et al., 2017). A fundamental knowledge could be gained from social media use, namely analytics and insights on topics or issues of research purposes. Social media can help students and teachers develop helpful links for their tasks (Sobaih et al., 2016). They were reported to be crucial to helping create a better learning environment, especially during Covid-19 distance education (Mulenga & Marbán, 2020; Sobaih et al., 2020). Previous studies have focused on social media integration for teaching (Chen Hsieh et al., 2017; Escobar-Rodríguez et al., 2014; Manca & Ranieri, 2016; Tess, 2013).
2.3. Framework and hypotheses
UTAUT was developed to examine the factors affecting employees’ technology use and acceptance (Venkatesh et al., 2003). UTAUT has also been implemented to report key factors affecting various technologies in education, such as animation (Suki & Suki, 2017), interactive whiteboard (Sumak & Šorgo, 2016), electronic document management system (Ayaz & Yanartaş, 2020), Enterprise Resource Planning software (Chauhan & Jaiswal, 2016), and social media (Escobar-Rodríguez et al., 2014; Shokery et al., 2016). UTAUT identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as direct determinants of behavioral intention and use behavior (Venkatesh et al., 2003). Figure 1 informs the proposed model of this, where eight hypotheses guide the presentation of the findings.

2.4. Performance expectancy
In this study, performance expectancy (Venkatesh et al., 2003) is defined as the degree to which teachers believe that using social media will help them attain gains in teaching during school closures due to Covid-19. Earlier research has indicated that performance expectancy has positive effects on behavioral intention to use technology (Ayaz & Yanartaş, 2020; Escobar-Rodríguez et al., 2014; Khecine et al., 2020; Suki & Suki, 2017). For example, students' behavioral intention to use animation for higher education students was influenced by performance expectancy, the highest correlation (Suki & Suki, 2017). Performance expectancy was also reported to significantly predict the intention to use electronic document management systems among staff in a Turkey university (Ayaz & Yanartaş, 2020). Consistent with the previous studies, the current study proposed one hypothesis:

H1. Performance expectancy significantly influences teachers’ behavioral intention to use social media during distance education due to Covid-19.

2.5. Effort expectancy
Effort expectancy in this study is described as the degree of ease associated with system use (Venkatesh et al., 2003). It is described as the degree of comfort associated with the use of social media for Indonesian teachers during distance education. Prior studies disclosed the significant relationship between effort expectancy and behavioral intention (Ayaz & Yanartaş, 2020; Hamid; Shokery et al., 2016; Escobar-Rodriguez et al., 2014; Khecine et al., 2020; Suki & Suki, 2017). One hypothesis was proposed:

Figure 1. Proposed model.

![Figure 1. Proposed model.](image-url)
H2. Effort expectancy has a positive effect on teachers’ behavioral intention to use social media during Covid-19.

2.6. Social influence
Social influence is the extent to which others (family, friends, and peers) beliefs (good or bad) influence someone’s decision to utilize a new system; the process through which someone’s attitudes, beliefs, or behavior are influenced by the presence or behavior of others (Venkatesh et al., 2003). The current study considers social influence as support from peers and school principals to encourage the use of social media during distance education in Covid-19 time among Indonesian teachers. Previous studies informed that peers’ social influence significantly affects users’ intentions and actual use of technologies, like Google Applications, iPads, and media systems, to support collaboration in instruction (Cheung & Vogel, 2013; Falloon & Khoo, 2014; Khechine et al., 2020). On the other hand, contradictory findings were also reported (Chauhan & Jaiswal, 2016; Suki & Suki, 2017), informing the insignificant relationships between social influence and intention to use technology. One hypothesis was included:

H3. Social influence has a positive effect on teachers’ behavioral intention to use social media during Covid-19.

2.7. Facilitating condition
Facilitating conditions term in this study is defined as the accessibility of an appropriate learning environment and infrastructure that can foster the use of social media technologies in teaching during Covid-19. Previously, the correlations between facilitating conditions and behavioral intention and actual use of technology integration during instructional processes were reported to be statistically significant (Chauhan & Jaiswal, 2016; Habibi et al., 2020; Suki & Suki, 2017). Two hypotheses are formulated regarding facilitating conditions:

H4. Facilitating conditions have a positive effect on teachers’ behavioral intention to use social media during Covid-19.

H5. Facilitating conditions have a positive effect on TSMU Covid-19.

2.8. Behavioral intention
The original definition of behavioral intention is “the person’s subjective probability that he or she will perform the behavior in question” (Venkatesh et al., 2003). This study describes behavioral intention as teachers’ subjective probability that they will perform social media integration in teaching during Covid-19. Many studies have explored the critical role of behavioral intention in predicting technology in particular teaching and learning environments (Khechine et al., 2020; Lakhal & Khechine, 2017; Suki & Suki, 2017). One hypothesis is presented concerning behavioral intention:

H6. Social influence positively affects teachers’ behavioral intention to use social media during Covid-19.

2.9. The moderation of gender and teaching experience
In addition to the structural model, gender and teaching experience were applied as the moderating variables for the UTAUT framework (Baptista & Oliveira, 2015; Suki & Suki, 2017). Two hypotheses are proposed:
H7. Teachers’ gender moderates the relationships of Hypotheses 1, 2, 3, and 4.

H8. Teachers’ experience moderates the relationships of Hypotheses 1, 2, 3, and 4.

3. Method

3.1. Instrumentation
The questionnaire includes closed questions with two sections: section 1 asks for socio-demographic information, and section 2 provides measurement indicators to assess the factors predicting TSMU Covid-19. The indicators were adapted from previous studies (Suki & Suki, 2017; Šumak & Šorgo, 2016; Venkatesh et al., 2003) with a thorough examination of the literature review. We discussed the indicators with five teachers and five educational experts. Some indicators’ wordings were revised based on the discussions (Authors 2020; Halek et al., 2017). Using a five-point Likert Scale ranging from 1 (strongly disagree) to 5 (strongly agree), 19 UTAUT indicators were used that consist of performance expectancy (4 indicators), effort expectancy (4 indicators), social influence (4 indicators), facilitating conditions (4 indicators), and behavioral intention (3 indicators). The construct of TSMU Covid-19 encompasses one indicator of “How many times do you use social media for distance education during Covid-19?” with a scale from 1 (never) to 5 (always). PLS-SEM facilitates a single item to include in a construct (Sarstedt et al., 2022). Similar studies in educational technology also used a single-item measure (Hoi, 2020; Suki & Suki, 2017; Yueh et al., 2015).

3.2. Data collection
The current study employs a quantitative research design where online questionnaires were distributed from August to October 2021 with informed consent during Indonesian school closures. This online distribution method was opted because physical access was limited for printed material questionnaire distribution. The sampling was applied based on G* power with nine path lines proposed in the study; the samples should be ≥ 250 responses. G*Power was a statistical examination tool that provided established effect size calculators; it provides distribution and design-based input types, including sampling size. However, we managed to collect 1249 measurable responses; 405 respondents are females, and 844 respondents are females. Table 1 informs detailed information about the respondents.

3.3. Analysis
For the Partial Least Square Structural Equation Modeling (PLS-SEM) evaluation, the current study involved three main procedures. Procedure 1 examines the measurement models where in this study, the model includes a reflective approach. Procedure 2 consists of the evaluation of the structural model (Hair et al., 2019; Sohail et al., 2020). In procedure 3, Multi-Group Analysis (MGA) in the PLS-SEM was addressed to report the role of gender and teaching experience in moderating the relationships among four proposed paths (Alt, 2018). Like other statistical analysis methods, PLS-SEM depends on thresholds for the model estimation evaluation, and this study applied reflective measures (Habibi et al., 2020).

4. Findings

4.1. Reflective measurement model
In these reflectively measured constructs, we began the first procedure by evaluating the indicator loadings. Indicators’ loading higher than .700 should be implemented (Hair et al., 2014; Parker et al., 2012). Table 2 shows that all loading values are above .700, ranging from .7600 to .9233 for a non-single item variable; FC4 from facilitating conditions obtains the lowest loading, and the highest loading is achieved by BI2. The next part of the assessment includes the constructs’ reliability, Cronbach’s alpha, and Composite Reliability (CR). The Cronbach’s alpha values should
be above .700 (Hair et al., 2019). Meanwhile, CR is typically examined using the measurement of Jöreskog’s (1971); the value should range from .708 to .923 (Hair et al., 2019). Table 2 shows the details of both values that meet the thresholds. All values of CR (.8980 to .9241) and Cronbach’s alpha (.8292 to .8652) meet the threshold values.

### Table 1. Respondents (n.1249)

| Information                  | Frequency | Percentage |
|------------------------------|-----------|------------|
| Gender                       |           |            |
| Male                         | 405       | 32.4%      |
| Female                       | 844       | 67.6%      |
| Teaching experience          |           |            |
| ≤ 5 years                    | 228       | 18.3%      |
| > 5 years                    | 1021      | 81.7%      |
| School location              |           |            |
| Urban                        | 659       | 52.8%      |
| Rural                        | 590       | 47.2%      |
| School-level                 |           |            |
| Primary                      | 143       | 11.4%      |
| Secondary                    | 1106      | 88.6%      |

### Table 2. Loading, α, CR, AVE

| Construct                     | Item | Load   | α       | CR  | AVE  |
|-------------------------------|------|--------|---------|-----|------|
| Behavioral intention         | BI1  | .8955  | .8766   | .9241 | 0,8025 |
|                              | BI2  | .9233  |         |      |      |
|                              | BI3  | .8678  |         |      |      |
| Effort expectancy            | EE1  | .7912  | .8652   | .9084 | .7129 |
|                              | EE2  | .8438  |         |      |      |
|                              | EE3  | .8743  |         |      |      |
|                              | EE4  | .8655  |         |      |      |
| Facilitating conditions      | FC1  | .8610  | .8498   | .8992 | .6910 |
|                              | FC2  | .8477  |         |      |      |
|                              | FC3  | .8523  |         |      |      |
|                              | FC4  | .7600  |         |      |      |
| Performance expectancy       | PE1  | .8232  | .8292   | .8980 | .7461 |
|                              | PE2  | .8862  |         |      |      |
|                              | PE3  | .8805  |         |      |      |
| Social influence             | SI1  | .8650  | .8622   | .9061 | .7072 |
|                              | SI2  | .8687  |         |      |      |
|                              | SI3  | .8226  |         |      |      |
|                              | SI4  | .8058  |         |      |      |
| TSMU Covid-19                | TU   | 1.0000 | 1.0000  | 1.0000 | 1.0000 |
Table 3. Fornell-Larcker

|                           | Behavioral intention | Effort expectancy | Facilitating conditions | Performance expectancy | Social influence | TSMU Covid-19 |
|---------------------------|----------------------|-------------------|-------------------------|------------------------|-----------------|--------------|
| Behavioral intention     | .894                 |                   |                         |                        |                 |              |
| Effort expectancy         | .665                 | .834              |                         |                        |                 |              |
| Facilitating conditions  | .693                 | .758              | .824                    |                        |                 |              |
| Performance expectancy   | .663                 | .717              | .659                    | .878                   |                 |              |
| Social influence         | .659                 | .664              | .697                    | .682                   | .843            |              |
| TSMU Covid-19            | .180                 | .094              | .160                    | .181                   | .231            | 1.000        |

We assessed the convergent validity of the constructs. Convergent validity is a way to measure the extent to which a construct converges in its indicators by explaining the Average Variance Extraction (AVE). The AVE is counted as the mean of the squared loadings for all indicators linked with a construct (Hair et al., 2019). A satisfactory AVE is .500 (from .6910 to .8025) or above indicates a good convergent validity. From the results of the computation, the construct explains over 50% of the indicators’ variance (Table 2). TSMU Covid-19 has a single indicator indicating 1.000 as its loading, Cronbach alpha, CR, and AVE.

Once the reliability and convergent validity are successfully assessed and developed, a further step is to conduct the discriminant validity examination. Discriminant validity assesses the extent to which a construct is different from other constructs. It depends on how much it relates to other constructs or how distinctly the indicators represent a single construct (Hair et al., 2019). The most traditional statistical process suggested to assess discriminant validity is the Fornell-Larcker criterion (Fornell & Larcker, 1981). The recommended guideline is that a construct should not exhibit shared variance with any other construct greater than its AVE value. From the data analysis results in SmartPLS 3.2 (Table 3), each construct’s AVE scores are less than its shared variance.

Another robust strategy to assess discriminant validity is to evaluate the cross-loadings. An indicator variable should exceed a more significant loading within its variable construct than any other variable in the structural model (Hair et al., 2019). Table 4 exhibits that all indicators’ loadings (italic) of every variable are higher than all its cross-loadings on the other variables. Discriminant validity issues can also emerge if the scores of HTMT are above .900 (Hair et al., 2019). The variable is considered similar if its HTMT shows a score of > .900 and lacks discriminant validity. All HTMT scores are less than .900 (Table 5). Thus, the results show that the scores of HTMT significantly differed from 1. Based on the three assessments, the discriminant validity of the study is validated and established.

4.2. Structural model
The assessment process was initiated with collinearity computation for Variance Inflation Factor (VIF). The collinearity emerges if the VIF scores are higher than 3.000 (Hair et al., 2019). All VIF values are below 3.000, indicating that no collinearity issues emerged from the data (Table 6). The structural model, the second procedure stage in the PLS-SEM after the measurement model, was assessed by computerizing the path coefficient (β), t-value, and p-value (Table 6). H1 determines whether performance expectancy has a significant role in influencing teachers’ behavioral intention to use social media during Covid-19. The results disclose that performance expectancy significantly predicts students’ behavioral intention (β = .2022, t-value = 5.8440, p < .001), therefore supporting H1.
**Table 4. Cross-loading**

| BI   | EE   | FC   | PE   | SI   | TU   |
|------|------|------|------|------|------|
| .8955 | .5307 | .5521 | .6011 | .5802 | .5720 |
| .9233 | .5521 | .6520 | .8678 | .6011 | .6720 |
| .8678 | .6011 | .6438 | .8743 | .8655 | .6111 |
| .5307 | .5521 | .6520 | .8678 | .6011 | .6720 |
| .6011 | .6720 | .6894 | .6211 | .6686 | .6091 |
| .5802 | .6720 | .8678 | .5583 | .5716 | .5720 |
| .9233 | .5521 | .6520 | .8678 | .6011 | .6720 |
| .8678 | .6011 | .6438 | .8743 | .8655 | .6111 |
| .5307 | .5521 | .6520 | .8678 | .6011 | .6720 |
| .6011 | .6720 | .6894 | .6211 | .6686 | .6091 |
| .5802 | .6720 | .8678 | .5583 | .5716 | .5720 |

**Table 5. HTMT**

| Effort expectancy | Facilitating conditions | Performance expectancy | Social influence |
|-------------------|-------------------------|------------------------|------------------|
| .7705             |                         |                        |                  |
| .8059             | .7629                   | .7775                  |                  |
| .8706             | .8369                   | .8097                  | .7794            |
|                   |                         |                        |                  |
|                   |                         |                        |                  |

**Table 6. Structural model**

| H                  | Path                                      | VIF | β   | M   | SD  | t-value | p value |
|--------------------|-------------------------------------------|-----|-----|-----|-----|---------|---------|
| H1                 | Performance expectancy → Behavioral intention | 2.3251 | .2022 | .2019 | .0346 | 5.8440 | p < .001 |
| H2                 | Effort expectancy → Behavioral intention   | 2.9662 | .1488 | .1480 | .0449 | 3.3115 | p < .001 |
| H3                 | Social influence → Behavioral intention    | 2.3512 | .205  | .206  | .0480 | 4.276  | p < .001 |
| H4                 | Facilitating conditions → Behavioral intention | 2.7032 | .2860 | .2860 | .0373 | 7.6677 | p < .001 |
| H5                 | Facilitating conditions → TSMU Covid-19    | 1.9388 | .1253 | .1259 | .0431 | 2.9077 | p < .05  |
| H6                 | Behavioral intention → TSMU Covid-19       | 1.9388 | .0969 | .0967 | .0431 | 2.2468 | p < .05  |
Hypothesis 2 assesses whether effort expectancy significantly predicts teachers’ behavioral intention. The results show that effort expectancy significantly affects students’ behavioral intention ($\beta = .1488$, t-value = 3.3115, p < .05); H2 is endorsed. H3 hypothesized that social influence has a significant effect on teachers’ behavioral intention to use social media during school closure due to Covid-19. The PLS-SEM findings divulge that social influence had a significant predicting power on teachers’ behavioral intention ($\beta = .205$, t = 4.276 p < .001) that advocates H3. H4 focuses on whether facilitating conditions have a significant relationship with behavioral intentions; the results confirm the hypothesis ($\beta = .286$, t-value = 7.6677, p < .001). However, insignificant results emerge for H5, in which facilitating conditions are hypothesized to significantly predict TSMU Covid-19. The results do not support H5 ($\beta = .1253$, t-value = 2.9077, p = .278). The last structural hypothesis, H6, tests the relationship between behavioral intention and TSMU Covid-19. The bond between the two factors is significant, informing the t-value of 2.2468 ($\beta = .0969$, p < .05). Hence, H6 is supported.

### 4.3. Coefficient of determination, effect size, and predictive relevance

The coefficient of determination ($R^2$) is the regression analysis output scores clarified as the variance proportion of dependent variables that can be affected by the independent variables. The $R^2$ assesses the predictive accuracy of a proposed model. We applied recommended $R^2$ of .75 (substantial), .50 (moderate), and .25 (weak; Hair et al., 2019). The result of $R^2$ shows that the endogenous latent variable in this study has the coefficient of determination (Table 7), behavioral intention (.5991, moderate), and TSMU Covid-19 (.0420, weak).

Besides the size of $R^2$, $Q^2$ can also be effective as a criterion for predictive relevance (Stone, 1976). The $Q^2$ value of .02 reports a small predictive relevance, the value of .15 reveals a medium relevance, and .35 indicates a large predictive relevance. We used the blindfolding technique to report the $Q^2$. It is a sample re-use technique, allowing the calculation of Stone-Geisser’s $Q^2$. It indicated an assessment criterion for cross-validated predictive relevance. The blindfolding data (Table 7) informs that behavioral intention has the most robust predictive relevance ($Q^2 = .4760$, large), TSMU Covid-19 obtains small predictive relevance ($Q^2 = .0373$).

Effect size is a statistical concept to assess the relationship strength between two variables. The statistic in the effect size computation helps determine if the difference is real or due to a factor change. We used Cohen’s $f^2$ method to measure the effect size in this study. The $f^2$ value of .02 is defined as a small effect, the value of .15 obtains a medium effect, and the value of .35 has a large effect (Benitez et al., 2020). Through PLS-SEM computation, the $f^2$ values ranged from .0051 to .0755. The detailed information about the $f^2$ value and the effect size is shown in Table 8.

### Table 7. $R^2$ & $Q^2$

|                        | $R^2$ | $Q^2$ |
|------------------------|-------|-------|
| Behavioral intention   | .5991 | .4760 |
| TSMU Covid-19          | .0420 | .0373 |

### Table 8. Effect size

|                        | Behavioral intention | TSMU Covid-19 |
|------------------------|----------------------|--------------|
| Behavioral intention   |                      | .0051        |
| Effort expectancy      | .0186                |              |
| Facilitating conditions| .0755                | .0085        |
| Performance expectancy | .0439                |              |
| Social influence       | .0654                |              |
4.4. MGA results
Regarding the moderating roles of gender and teaching experience, the PLS-SEM findings informed that gender is significant in moderating the relationship between performance expectancy and teachers’ intention to use social media during Covid-19 with β -diff (female—> male) of .0926, H7a is accepted. Similarly, H7b, H7c, and H7d are also supported since all β differences between females and males are computed. Females are more enunciated on two aspects, performance expectancy -> behavioral intention and facilitating conditions -> behavioral intention. Meanwhile, males are more enunciated on the other two path coefficients: effort expectancy -> behavioral intention and social influence -> behavioral intention (Table 9). All relationships are also significantly moderated by teaching experience. For example, the relationship between Social influence and Behavioral intention to use social media during Covid-19 is significantly moderated by teaching experience (Δβ = .0658); teachers with ≤5 years (β = .463, p < .001) have more significant relationship than the less experienced group (β = .267, p < .001). Table 10 informs detailed information about the moderating effect of teaching experience.

5. Discussion
We developed an instrument to meet the objectives of the study. Through the face, content validity, and measurement model assessment, the scale adapted from UTAUT (Suki & Suki, 2017; Šumak & Šorgo, 2016; Venkatesh et al., 2003) was valid and reliable for social media use for teaching during Covid-19 in the Indonesian context. The measurement model in PLS-SEM is the main step to assess the reliability and validity of the data. Previous studies also used a similar approach to establish the scales of their studies (Connell et al., 2018; Deng et al., 2020; López-Bonilla & López-Bonilla, 2017).

Empirically, the results of the current study inform that the relationship between performance expectancy and teachers’ behavioral intention to use social media use during distance education is significant. This discovery corroborates previous studies’ results (Ayaz & Yanartaş, 2020; Escobar-Rodríguez et al., 2014; Khechine et al., 2020; Suki & Suki, 2017). This significant relationship improves Indonesian teachers’ productivity and provides opportunities to improve teaching their students during school closures due to pandemics like Covid-19.

Effort expectancy significantly influences teachers’ behavioral intention to social media use during covid-19. In normal conditions when Covid-19 has not yet existed, this variable was also reported to predict behavioral intention in UTAUT-based studies (Ayaz & Yanartaş, 2020; Khechine et al., 2020; Shokery et al., 2016; Suki & Suki, 2017). Teachers could enjoy the interaction by using social media for teaching during pandemics. Social media that have been part of teachers’ daily tools might be perceived as user-friendly and fun. Therefore, their intention to use social media as a teaching tool during school closures is improved by the effort expectancy.

The study findings, supporting H3, demonstrate that the teachers emphasize the significant role of social influence on teachers’ behavioral intention in using social media during Covid-19 education. Indonesian people are considered friendly and have a culture of respecting other people and their opinions. It might be the reason why the relationship is significantly correlated. Some prior research also reported similar reports on the critical role of social influence in the use of technology in education (Cheung & Vogel, 2013; Falloon & Khoo, 2014; Khechine et al., 2020). However, some studies opposed this finding, revealing an insignificant relationship between the two (Chouhan & Jaiswal, 2016; Suki & Suki, 2017). Based on the current study findings, helpful peers and principals could promote teachers’ intention to use social media during Covid-19.

Facilitating conditions are also reported to positively affect teachers’ behavioral intention to use social media; thus, H4 is upheld. However, it is not significantly related to TSMU Covid-19. Previous studies also disclosed the significant effect of facilitating conditions and behavioral intention to use technology in instruction (Chauhan & Jaiswal, 2016; Muaimin et al., 2019; Suki & Suki, 2017). Teachers expressed their opinion that the accessibility of infrastructure and learning environment
Table 9. Moderating effect of gender

| H  | Relationship                         | Female | Male      | Results                                           | MGA |
|----|--------------------------------------|--------|-----------|--------------------------------------------------|-----|
|    |                                      | β      | t value   | p value                                          | β  |
| H7a| Performance expectancy -> Behavioral  | .2353  | 6.499     | p < .001                                        | .1427 |
|    | intention                             |        |           |                                                 | 21.666 | p < .05 |
|    |                                      |        |           | Female, supported | Male, supported | .0926 |
| H7b| Effort expectancy -> Behavioral       | .0976  | 18.214    | .0686                                           | .2364 |
|    | intention                             |        |           |                                                 | 31.934 | p < .05 |
|    |                                      |        |           | Female, unsupported | Male, supported | -.1388 |
| H7c| Social influence -> Behavioral        | .2089  | 46.560    | p < .001                                        | .3224 |
|    | intention                             |        |           |                                                 | 53.846 | p < .001 |
|    |                                      |        |           | Female, supported | Male, supported | -.1135 |
| H7d| Facilitating conditions -> Behavioral | .3222  | 37.566    | p < .001                                        | .2185 |
|    | intention                             |        |           |                                                 | 37.566 | p < .05 |
|    |                                      |        |           | Female, supported | Male, supported | .1937 |
| H   | Relationship                      | ≤5 years | > 5 years | Results | MGA  
|-----|-----------------------------------|----------|-----------|---------|------|
|     | Model: | β       | t value  | p value | β   | t value  | p value | β -diff (≤5 years—> 5 years) |
| H8a | Performance expectancy -> Behavioral intention | .0990 | 1.343 | .3010 | .2224 | 63.756 | p < .001 | ≤5 years, unsupported | > 5 years, supported |
| H8b | Effort expectancy -> Behavioral intention | .2155 | 16.985 | .0895 | .1361 | 29.257 | p < .05 | ≤5 years, unsupported | > 5 years, supported |
| H8c | Social influence -> Behavioral intention | .3039 | 38.083 | p < .001 | .2381 | 58.708 | p < .001 | ≤5 years, supported | > 5 years, supported |
| H8d | Facilitating conditions -> Behavioral intention | .2927 | 26.426 | p < .05 | .2830 | 72.274 | p < .001 | ≤5 years, supported | > 5 years, supported |

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in their location can affect behavioral intention to use social media during distance education. In short, the better ground and facilities that the teachers have, the more likely they intend to use technology. Toward the insignificant correlation between facilitating conditions and the actual use, TSMU Covid-19, a more in-depth study should be carried out to reconfirm whether the availability of supporting infrastructure and environment could predict the actual use of technology, especially during school closures or distance education.

Finally, teacher social media use during Covid-19 (TSMU Covid-19) is significantly predicted by behavioral intention. Similar research findings also revealed the significant role of behavioral intention in predicting technology in teaching (Khechine et al., 2020; Lakhal & Khechine, 2017; Suki & Suki, 2017). This significant influence on teachers’ subjective probability of using social media use during distance learning can be a maximum result. Therefore, policymakers should consider improving teachers’ and students’ intention to use technology during pandemics like Covid-19. The situations are unprecedented and cause disruption, especially in education.

Besides the structural model, we also included moderating variables: gender and teaching experience. Through MGA computation in SmartPLS 3.2, the results inform that age and teaching experience significantly moderate the path between the exogenous variables (performance expectancy, effort expectancy, social influence, facilitating conditions) and teachers’ behavioral intention as the endogenous construct. The results support the finding of previous research, where Suki and Suki (2017) revealed that the survey’s work supported gender and level of experience. Social media has played a significant role in shaping how people live their lives. Nowadays, almost all activities are done through social media, namely, communication, information search, entertainment, and learning media. The significant differences in the MGA should be more discussed. The first-time experience with distance learning can also be why the differences have resulted from the computation.

6. Conclusion, implications, and limitations of the study
Social media with many platforms are helpful in seeking and sharing information. Students regularly use social media to keep updated, which helps them become aware. Teachers should adapt to this situation and make social media available for instructional activities during distance learning caused by pandemics like Covid-19 education. The current study’s findings inform that the facilitating condition is the most significant predictor affecting teachers’ behavioral intention to use social media during Covid-19 distance education. It is followed by the role of performance expectancy, social influence, and effort expectancy.

Some practical implications are recommended based on the findings of this study. Significant issues resulting from the findings of the study like funding, infrastructure, teachers’ training, curriculum, and social support should be the focus of online learning, especially during pandemics like Covid-19. Incentives should be provided for teachers and students who cannot afford for internet packages and online learning tools. Parents who cannot facilitate their children with the tools and internet access should also be provided with incentive. Providing proper resources for social media use would provide teachers and students with a sense of self-control, easiness, and enjoyment. If the infrastructure is unprepared accordingly, distance learning could be frustrating for both teachers and students.

Online training regarding the utilization of digital resources for pedagogical practices should also be sustainable to improve teachers’ performance. The inclusion of social media in teachers’ lesson plans and curriculums can also lead to a better instruction environment during future pandemics. Teachers should actively promote the use of technology to students’ parents. When schools close, parents must assist their children in studying at home, which can be challenging for those with little knowledge and financial means, and teachers can play significant roles for those with difficulties. Teachers also need to help each other use technology during the school closure. Students should be active in the instructional process; the efforts can be made by following
every procedure required by their teachers, namely, to always respond to social media posts or turn on the camera if they have online learning sessions.

Even though demographic information is mostly insignificant in moderating the hypothesized paths, the findings could theoretically guide future studies regarding social media use to enlighten the roles of these moderating factors in other contexts and settings. The research is beneficial to address a significant contribution to literature, especially regarding the use of social media during distance learning. Finally, the valid and reliable scale from the statistical processes within this study can be adopted and adapted for technology integration during school closure in developing countries.

However, some limitations emerge, and additional work is recommended. The sample is suggested to be expanded for a wider geographical area beyond the Indonesian context to recognize various values that may influence technology integration. Researchers with similar interests would require more sophisticated research methodologies for more valid and generalizable findings (Fetters & Molina-Azorin, 2020). Besides, other moderating variables, such as school location, educational background, and age, can be included to expand the explanatory information regarding social media use in education.

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