Smart Technologies, Artificial Intelligence, Robotics, and Algorithms (STARA) Competencies During COVID-19: A Confirmatory Factor Analysis using SEM Approach

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Abstract. Public sector organisations have changed to be online offices and services while the COVID-19 outbreak attacked. The transformations also shift not only the paradigm but also the working methods of public sectors into an online system requiring a capacity to use smart technologies, artificial intelligence, robotics, and algorithms (STARA). Nevertheless, the research on the issue is still rare. This paper bridging the gap by analysing a confirmatory factor of STARA competencies of public employees during COVID-19 pandemic in Indonesia. We tested twelve items that relied on STARA competencies. The research used a survey method on 305 public servants in the Province of Special Region of Jakarta. A structural equation modelling (SEM) was utilised to assess the data. An SEM analysis suggests that the twelve indicators are valid and reliable in predicting STARA competencies' constructs. Our findings may be used by the subsequent researchers in examining STARA competencies.

1. Introduction
In late 2019, the world faces a severe pandemic in human chronicle, SARS-Coronavirus-2 (COVID-19). Started in Wuhan, China, the virus rapidly spreads around the globe. Indonesia was officially infected by the COVID-19 in March 2020. The COVID-19 outbreak induces numerous victims both to die and be infected. Moreover, after appearing the new variants of the COVID-19, the sufferer sharply enhances. Following the Indonesian COVID-19 task force data, there are 3,033,339 individuals positively infected by the COVID-19, 2,392,923 person recovery, and 79,032 persons died (07/22/2021) [1]. The COVID-19 affects not only human health but also human life, such as economic and social dimensions. In the financial aspect, many people lose their job and income because of COVID-19 [2]. In social life, many individuals are challenging to contact each other because of various physical and social distancing during the COVID-19 crisis.

The government in many countries introduces a variety of policies to prevent the spreading of the virus. One of the policies is to work and study from home during COVID-19 disease [3]. Indonesia has implemented work from home policy for central and local government public employees after several months of the COVID-19 attacked. To work from home effectively and productively, the
public employee needs to use information and technology devices to deliver public services. One of the capabilities required by a public employee is smart technologies, artificial intelligence, robotics, and algorithm, recognised as STARA competencies [4]. Smart technologies are related to the use of intelligent tools for monitoring, analysing, and reporting utilities. Artificial intelligence is the use of various features of artificial intelligence, such as machine learning, deep learning, big data, and data mining, to help the duty. Robotics refers to the ability of the employee to apply mechanical devices in finishing their job. The algorithm is defined as the skill in designing and implementing the algorithm in a daily appointment.

The concept of STARA competencies is currently evolved in the academic literature. Brougham & Harr are the two scholars who initially acknowledged the idea of STARA competencies in the literature of human resources management (HRM) [5]. They obtained warm regard from several researchers after they published their seminal work in 2018. In fact, several studies have analysed STARA competencies at the workplace. Ogbeibu et al. sought the effect leader STARA competence and environmental dynamism on green creativity skill among the manufacturing leaders in Nigeria. They found that leader STARA competence significantly impacts leader green creativity skills than environmental dynamism [4]. Ogbeibu et al. tested the influence of leader STARA competence on employee turnover intention. In addition, they also investigated the moderating role of the leader STARA competence in the relationship between green talent management and turnover intention. They reached three-manifold findings. First, they noted that the negative impact of leader STARA competence on subordinate turnover intention. Second, the positive impact of green hard talent management on turnover intention was reduced by leader STARA competence. Lastly, the negative effect of green soft talent management on turnover intention was invigorated by leader STARA competence [6].

Even though several prior works have investigated STARA competencies, it still has several empty spaces to be filled. The first one is that we still lack information about the validity of the STARA constructs. Although numerous studies have examined the effect of STARA competencies on several HRM dimensions, we still lack knowledge about the variables or dimensions constructing STARA competencies and how precise are they. The second one is that much of the research shed light on the STARA competencies among private sectors employee. There is rarely a study investigating STARA competencies in the context of public sector organisations. The third one is that previous studies merely focused on the leader's STARA competencies and overlooks STARA competencies from the perspective of the employee. The last one is that the study on the STARA competencies is conducted in normal circumstances. We have no sufficient knowledge about employee STARA competencies during the crisis. Therefore, a confirmatory factor analysis (CFA) is required to identify what factors and indicators predicted STARA competencies among public employees in time of COVID-19 and how well its validity and reliability.

Based on the research gaps identified above, the current study has three novel investigations, respectively. First, this is the first study analysing STARA competencies in the context of the employee. Because several investigations highlight leader STARA competencies, we choose to focus on the STARA competencies of the workers. Second, we assess the employee's STARA competencies in the time of the COVID-19 pandemic. The COVID-19 has transformed the culture of government workers into online service [7]. Thus, it is critical to analyse how the transformation influences the STARA competencies of public servants. Lastly, the present study examines STARA competencies in the setting of Indonesian public sector organisation.

CFA is a method of determining how well a smaller number of constructs are represented by measurable variables [8]. Unlike few studies utilising exploratory factor analysis (EFA), the CFA technique needs scholars to specify each indicator in its latent form before computing, whereas EFA does not. More crucially, CFA may help with the interconnections between the STARA competency aspects, referring to latent variables. By combining component analysis, this latent variable modelling expands and deepens CFA. Furthermore, we enable to measure the degree of independency across variables using CFA, which is exceptionally relevant in STARA competencies studies.
The central aim of this study is to assess the constructs of public employee's STARA competencies during the COVID-19 crisis. This study focused on analysing the validity and reliability of four subscales of STARA competencies, including smart technologies, artificial intelligence, robotics, and algorithm established from several indicators (Table 1 and Figure 1).

2. Methods
This study applied a cross-sectional survey approach in the Provincial Government of the Special Region of Jakarta (DKI Jakarta). DKI Jakarta was chosen as a study site because it was one of the provincial governments with the most extensive employee and most innovative local government in Indonesia. The questionnaire was transformed into an online form using google docs before distributing it to the respondents. It was conducted because of the COVID-19 pandemic situation, followed by lock-down and work from home policy in the DKI Jakarta. The research was approved by the head of departments in DKI Jakarta earlier. To help distribute the online questionnaire, we coordinated with the HRM manager in each department. The questionnaires were distributed through the WhatsApp Group (WAG) of the departments and the institutional email of the employees. To attract much more participation, we provided several balances, such as Shopee, Gojek, and Ovo, for few chosen respondents.

The STARA questionnaire was performed in the current research. It was adopted and developed by Ogbeibu et al. [4], [6]. It included four latent variables and twelve items, as summarised in Table 1. These latent variables included smart technologies (ST), artificial intelligence (AI), Robotics (RO), and algorithm (AL). The items were coded with the number respectively regarding the variable. The questions or statements were adapted in the context of Indonesian public sector organisations. To anticipate a misunderstanding on each item, we shortly explained the meaning of the construct and items in the questionnaires background. All items were measured using a five-point Likert's scale, 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree).

The data were collected from all departments in DKI Jakarta. A total of 305 public employees responded to this survey. The participants in this study consisted of various backgrounds. More than half of the respondents were male (61.97%). Much of the respondents were young, 20-30 years old (26.89%), and 31-40 years old (32.79). The three tops of working experience of the respondent were less than 5 years (28.20%), 5-10 years (26.89%), and 11-15 years (21.97%). Most of the respondents was a permanent employee (68.85) coming from undergraduates (61.97%).

The data were run employing covariance-based structural equation modelling (SEM) using analysis of moment structure (AMOS) 24.0 [9]. An SEM approach was utilised to assess whether the data were characterised by the models defined. Statistical analyses conducted included confirmatory factor analyses and reliability analyses to determine the internal consistency of the inventory and its four STARA competencies variables, incorporating smart technologies, artificial intelligence, robotics, and algorithm (Table 1). In this study, a Maximum Likelihood parameter was employed to enforce the confirmatory factor analyses. Although it still lacks consensus about the fit indices of the model, we measured goodness of fit indices through a series of parameters, including absolute fit measures and incremental fit measures. It involved the assessment of adjusted goodness of fit index (AGFI), root means square error of approximation (RMSEA), the goodness of fit index (GFI), Tucker-Lewis index (TLI), normed fit index (NFI), incremental fit index (IFI), and comparative fit index (CFI) (Table 3). If the initial model did not pass the goodness of fit evaluation, we converted the model based on the suggestions of the AMOS programme.

To present the results of this study, we used Schreiber et al. guidance in this paper [10]. Firstly, we offered the assessment of data distribution to measure whether the data were standard or not. The normality evaluation was applied by calculating the critical ratio (CR) of multivariate using AMOS. If the data were not normal and conceived many outliers, we changed the analytical procedure to a bootstrapping method with 5,000 resamples [11]. Then, we assessed the model fit using several parameters of the goodness of fit recommended by SEM, followed by measuring mean, standard deviation (SD), internal reliability, and intercorrelations among the variables. In the final step, we
measured the validity and reliability of the constructs. The validity was assessed using convergent and discriminant validity [12], [13].

Table 1. Items in the Questionnaire

| Construct          | Item | Statement                                                                 |
|--------------------|------|---------------------------------------------------------------------------|
| Smart Technologies | ST1  | I understand how to use smart technologies in my duty                     |
|                    | ST2  | I can apply smart technologies vehicles in my duty                         |
|                    | ST3  | I know how to fix the problem of smart technologies I use                 |
|                    | ST4  | I can finish my job quickly using smart technologies                      |
| Artificial Intelligence | AI1 | I understand how to use artificial intelligence in my job                 |
|                    | AI2  | I can apply artificial intelligence in my job                             |
|                    | AI3  | I know how to fix the problems of artificial intelligence in my job       |
|                    | AI4  | I can finish my job quickly using artificial intelligence                  |
| Robotics           | RO1  | I understand how to use robots or mechanical devices in my duty            |
|                    | RO2  | I can apply robotics or mechanical devices to make my job easier           |
|                    | RO3  | I can finish my job quickly using mechanical devices                      |
|                    | RO4  | I know how to fix the problems of mechanical devices I used               |
| Algorithm          | AL1  | I understand how to use an algorithm in my job                            |
|                    | AL2  | I can apply an algorithm to help my job                                   |
|                    | AL3  | I know how to fix the problems of an algorithm in my job                  |
|                    | AL4  | I can finish my job quickly using an algorithm                            |

3. Results and discussion

3.1. Evaluation of Normality and Outliers

Table 2 indicates the skewness and kurtosis of the twelve parameters of STARA competencies. It shows a non-normal distribution of the data in order not to fill the normality assumption because the critical ratio (CR) of the multivariate statistics is 5.22. The data are expected if the CR is less than 3 [8]. Therefore, there are two solutions to address the issue, explicitly deleting the outliers or transforming the estimation method to be a bootstrap approach. After analysing the data, we have to delete more than 100 outlier's Data if we choose the first option. Thus, we decided to change the estimation method using bootstrap to maximize the data exhausting collected.

Table 2. Assessment of Normal Distribution

| Variable | Min | Max | Skew | C.R. | Kurtosis | C.R.  |
|----------|-----|-----|------|------|----------|-------|
| ST1      | 1   | 5   | -1.125 | -8.019 | 0.850   | 3.030 |
| ST2      | 1   | 5   | -0.897 | -6.393 | 0.377   | 1.342 |
| ST3      | 2   | 5   | -0.749 | -5.338 | 0.038   | 0.135 |
| ST4      | 1   | 5   | -1.063 | -7.579 | 1.403   | 5.002 |
| AI1      | 2   | 5   | -0.937 | -6.682 | 0.306   | 1.090 |
| AI2      | 1   | 5   | -1.249 | -8.906 | 1.783   | 6.357 |
| AI3      | 1   | 5   | -0.96  | -6.844 | 0.631   | 2.249 |
| AI4      | 1   | 5   | -0.809 | -5.767 | 0.012   | 0.041 |
| RO1      | 1   | 5   | -1.073 | -7.649 | 1.000   | 3.565 |
| RO2      | 1   | 5   | -0.723 | -5.156 | -0.249  | -0.888 |
| RO3      | 1   | 5   | -0.795 | -5.671 | 0.229   | 0.816 |
| RO4      | 1   | 5   | -0.846 | -6.035 | 0.605   | 2.157 |
| AL1      | 1   | 5   | -0.414 | -2.955 | -0.474  | -1.689 |
| AL2      | 1   | 5   | -0.655 | -4.669 | -0.089  | -0.316 |
| AL3      | 1   | 5   | -0.527 | -3.756 | -0.337  | -1.201 |
| AL4      | 1   | 5   | -0.515 | -3.675 | -0.194  | -0.690 |

Note: C.R., critical ratio

Multivariate 14.436 5.220
3.2. Evaluation of Model Fit

A goodness of fit indices criteria was applied to measure the model of fit [14]. Two series of the measurement model of fit were performed in this study to evaluate the model's goodness, namely absolute fit and incremental fit calculation. Absolute fit measures were conducted by analysing GFI (goodness of fit index), AGFI (adjusted goodness of fit index), and RMSEA (root means square error of approximation). In contrast, incremental fit calculations were measured by evaluating the value of NFI (normed fit index), IFI (incremental fit index), TLI (Tucker-Lewis index), and CFI (comparative fit index). Furthermore, we also measured Chi-square ($\chi^2$), degree of freedom (df), and Chi-square/degree of freedom ($\chi^2$/df). Similar to the coefficient of determination ($R^2$) in multiple linear regression, most validity measures required that the value be as high as possible. According to the rule of thumb, $\chi^2$ should has $p$-value more than 0.05 ($p > 0.05$) and $\chi^2$/df was < 3 [15]. In terms of absolute fit indices, there were several cuts of value entailed for each measure, such as GFI (0.90), AGFI (0.90), and RMSEA (0.07) [8]. For incremental fit indices, the measures should be greater than 0.90 for NFI and higher than 0.95 for CFI, TLI, and IFI [16]. Table 3 showed that initial model successively; $\chi^2$ ($p < 0.05$), $\chi^2$/df (3.88), GFI (0.85), AGFI (0.79), RMSEA (0.10), NFI (0.87), CFI (0.90), TLI (0.88), and IFI (0.90). It implied that the initial model had not filled the measurement of goodness of fit. To address the problem, we modified the model by adding few correlations among the items as recommended by AMOS. A total of five correlations was executed, specifically e6 to e7, e5 to e16, e10 to e11, e8 to e9, and e12 to e13 (Figure 1). After modifying the model, it was more fit and better while it yielded the value of measures as follow, $\chi^2$ ($p > 0.05$), $\chi^2$/df (2.26), GFI (0.92), AGFI (0.89), RMSEA (0.06), NFI (0.93), CFI (0.96), TLI (0.95), and IFI (0.96).

| Measures   | Cut of Value | Before Modified | After Modified |
|------------|--------------|-----------------|----------------|
| $\chi^2$  | $p > 0.05$   | 380.31          | 210.10         |
| df        | -            | 98              | 93             |
| $\chi^2$/df | < 3.0          | 3.88          | 2.26          |
| **Absolute Fit Indices** | | | |
| GFI       | > 0.90       | 0.85            | 0.92           |
| AGFI      | > 0.90       | 0.79            | 0.89           |
| RMSEA     | < 0.07       | 0.10            | 0.06           |
| **Incremental Fit Indices** | | | |
| NFI       | > 0.90       | 0.87            | 0.93           |
| CFI       | > 0.95       | 0.90            | 0.96           |
| TLI       | > 0.95       | 0.88            | 0.95           |
| IFI       | > 0.95       | 0.90            | 0.96           |

*Note:* $\chi^2 =$ Chi-square; df, degree of freedom; NFI, normed fit index; CFI, comparison fit index; Tucker-Lewis index; RMSEA, root mean square error of approximation

We also display mean, standard deviation (SD), reliability, and intercorrelation among studied variables. As shown in Table 4, smart technologies (ST) have a greater mean than other variables. Otherwise, the algorithm (AL) has a lower mean compared to other variables. The mean of all variables ranges from three to four, indicating public employee STARA competencies during COVID-19 are high. The data are more diffuse because the standard deviation of the variables is above 0.8, which is high. The Cronbach's alpha ($\alpha$) of the variables is greater than 0.6, exhibiting the variables were reliable [17]. Table 4 also presents coefficient correlations among the variables. Smart technologies tremendously correlate with artificial intelligence ($r = 0.952$, $p < 0.001$), robotics ($r = 0.857$, $p < 0.001$), and algorithm ($r = 0.596$, $p < 0.001$). Artificial intelligence strongly correlates with robotics ($r = 1.104$, $p < 0.001$) and algorithm ($r = 0.792$, $p < 0.001$). Eventually, robotics positively and immensely correlate with algorithm ($r = 0.924$, $p < 0.001$).
Table 4. Descriptive Statistics, Internal Reliability, and Correlation among the Constructs

| Construct | Mean | SD  | α   | Correlations |
|-----------|------|-----|-----|--------------|
| (1) ST    | 4.216| 0.838| 0.837| 0.952***     |
| (2) AI    | 4.205| 0.862| 0.830| 0.857***     |
| (3) RO    | 4.089| 0.899| 0.819| 1.104***     |
| (4) AL    | 3.930| 0.915| 0.857| 0.596***     |

Note: ST, smart technologies; AI, artificial intelligence; RO, robotics; AL, algorithm; SD, standard deviation; α, Cronbach's alpha; *** p < 0.001

3.3. Validity and Reliability

Table 5 and Figure 1 summarize the validity and reliability of the construct. The convergent validity was measured by concerning the factor loadings of the item [18]. All items were valid because the factor loadings exceed 0.5 as recommended by Hair et al. [8]. The discriminant validity was evaluated by concerning average variance extracted (AVE). The AVE values above 0.5 indicated that the data filled discriminant validity. Regarding our results, only smart technologies and algorithms were valid, while artificial intelligence and robotics were conversely valid. Even though the discriminant validity has a problem, the data were convergently accurate. The data were also reliable because Cronbach's alpha was greater than 0.7 and composite reliability was higher than 0.7 [19].

Table 5. Validity and Reliability

| Variable/Item | Factor Loading | CR    | AVE |
|---------------|----------------|-------|-----|
| Smart Technologies |                |       |     |
| ST1: I understand how to use smart technologies in my duty | 0.829 | 0.837 | 0.565 |
| ST2: I can apply smart technologies vehicles in my duty | 0.807 |       |     |
| ST3: I know how to fix the problems of smart technologies | 0.654 |       |     |
| ST4: I can finish my job quickly using smart technologies | 0.702 |       |     |
| Artificial Intelligence |                |       |     |
| AI1: I understand how to use artificial intelligence in my job | 0.647 | 0.788 | 0.482 |
| AI2: I can apply artificial intelligence in my job | 0.702 |       |     |
| AI3: I know how to fix the problems of artificial intelligence | 0.707 |       |     |
| AI4: I can finish my job quickly using artificial intelligence | 0.720 |       |     |
| Robotics |                |       |     |
| RO1: I understand how to use robots or mechanical devices | 0.752 | 0.732 | 0.469 |
| RO2: I can apply robotics or mechanical devices | 0.650 |       |     |
| RO3: I can finish my job quickly using mechanical devices | 0.683 |       |     |
| RO4: I know how to fix the problems of mechanical devices | 0.648 |       |     |
| Algorithm |                |       |     |
| AL1: I understand how to use an algorithm in my job | 0.820 | 0.752 | 0.577 |
| AL2: I can apply an algorithm to help my job | 0.770 |       |     |
| AL3: I know how to fix the problems of algorithm | 0.729 |       |     |
| AL4: I can finish my job quickly using an algorithm | 0.714 |       |     |

Note: CR, composite reliability; AVE, average variance extracted; All items have t-value above critical t table (3.322) for p < 0.001

3.4. Discussion

STARA competencies are crucial abilities that should be able to perform by the government employee during the COVID-19. This study analyses STARA competencies of public employees during the COVID-19 pandemic using confirmatory factor analysis. The results reveal four validated subscales
and twelve items of STARA competencies. We note that smart technologies 1 (ST1), "I understand how to use smart technologies in my duty," is the item with the highest factor loadings. Meanwhile, the item of artificial intelligence 1 (AI1) has the lowest factor loadings. It indicates that all statements or items in this study can represent and measure public employee STARA competencies. The findings of this study are not similar to Ogbeibu et al.’s research examining STARA competencies in the private sector [6]. The factor loadings of STARA competencies subscales found by the current study are quietly lower than previous research. However, Ogbeibu et al. [6] solely consisted of one item for each STARA competencies variable, while our research has four items. The difference among the studies is clearly shown in Table 6.

Table 6. The Difference of Validity Results between Prior and Current Studies

| Measures          | Prior Study | Our Study |
|-------------------|-------------|-----------|
| Smart Technologies| 0.841       | 0.748     |
| Artificial Intelligence| 0.709     | 0.694     |
| Robotics          | 0.754       | 0.683     |
| Algorithm         | 0.857       | 0.758     |

*Note: Factor loadings of our study are extracted from the average of each dimension.*

Figure 1. Bootstrap Standardized Coefficient for Final Model of the STARA Competencies

The work presented here makes several main research contributions, not only to the body of literature but also to the practice. In theoretical terms, our study enriches the literature of STARA competencies by offering validated constructs of STARA competencies. In addition, this study contributes to the body of knowledge because it highlights the items, variables of public servant's STARA competencies at the time of the COVID-19 outbreak. Thus, the constructs and items validated in this research can be further used and tested by scholars. The findings of our study also have several implications for the practice of HRM in the public sector. First, the government should offer continuous training to improve the knowledge of public employees in applying smart technologies, artificial intelligence, robotics, and algorithm. Second, the government should provide sufficient technologies and facilities, including hardware and software supporting public service delivery and
work outcome [20]. Finally, the manager in the public sector should qualify for the use of smart technologies, artificial intelligence, robotics, and algorithm at the same time. These competencies are crucial to the managers because they will lead the subordinates with sufficient capability in the skills.

Despite the contribution of this study, several limitations are necessary to be revealed. First, the sample in this study is limited to the government worker in DKI Jakarta. Consequently, the construct extracted in this paper is also limited to DKI Jakarta. In the future, we need an extensive sample crossing few regional governments to obtain more robust indicators and variables. The researchers use a single method in collecting the data, a self-administration questionnaire on public employees in DKI Jakarta. Future research can mix the method between qualitative and quantitative to obtain much more items [21], [22]. Third, the current investigation only identifies several items constructed STARA competencies. The scholars can expand this research by attaching diverse variables and examine the effect of STARA competencies on various HRM factors, such as individual performance, motivation, and organisational culture. Finally, our study is merely a confirmatory factor analysis on the construct of STARA competencies [23]. The subsequent research can examine the influence of STARA competencies on HRM dimensions with another statistical analysis, such as regression and correlation.

4. Conclusion
In this study, we provide empirical evidence on the factors affecting STARA competencies by exploring the case of public sector employees during the COVID-19 crisis. Using the SEM approach, we validate twelve items establishing STARA constructs, specifically smart technologies, artificial intelligence, robotics, and algorithm. The results of this study reveal that twelve items were valid and reliable in estimating these constructs. Our investigation contributes to the current theory of STARA competencies by offering good and reliable latent variables and indicators of STARA competencies in the context of the public sector utilised by other researchers. This study also has practical and managerial implications for developing STARA competencies at the multilevel governance in the public sector. At the policy level, the government should establish a policy encouraging employees to maximize and grow their STARA competencies. At the level of organisation, a variety of training and education enhancing employee's STARA competencies are required.

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