The Exploratory Factor Analysis (EFA) of Modified DASS-21 Index: A Case Study of UiTM Students

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Abstract. The presence of the COVID-19 pandemic, which has infected people all over the world, has led to the implementation of movement restriction guidelines in every country, including Malaysia. Many industries have been impacted, including the educational sector, which has transitioned from a physical class to an online distance learning (ODL) environment. The aim of this study was to evaluate the construct validity of the Depression, Anxiety, and Stress scale (DASS-21) and modify the existing instrument by utilising an instrumental design and exploratory factor analysis with structural equations to assess students' psychological well-being during ODL mode using reliable mental health predictors. **The DASS-21** and a combined new subscale instrument were evaluated for validity and reliability using exploratory factor analysis (EFA) and reliability analysis. Based on ODL being a new conceptual model, 30 items from four subscales of depression, anxiety, stress, and challenges during ODL were designated for the initial instrument. A study conducted by EFA found that the instrument used to examine students' psychological well-being in ODL contained five factor-structures that explained 63 percent of the variance in the pattern of relationships between the items. The reliability of all factors was high (Cronbach's > 0.735). After removing five items that cross-loaded on multiple factors, the final questionnaire had twenty-five items (depression and stress: eight items; anxiety: eight items; challenges during ODL: six items; and environment during ODL: three items). This research has proven to work for the four-factor structure instrument, which can be used to test students' psychological well-being during ODL.

INTRODUCTION

The global outbreak of the coronavirus disease known as COVID-19 is an event that is unprecedented in the history of the modern world. It is an existential experience since it has a significant impact on a wide variety of aspects of life, both on the individual and societal levels (Blustein & Guarino, 2020). Due to the ongoing pandemic, people are being forced to spend more time alone, thus showing increased level of anxiety and stress (Brooks et al., 2020; Wang et al., 2020; Li et al., 2020; Rajkumar, 2020; Troyer et al., 2020). Some social groups are sensitive to psychological well-being issues arising from COVID-19 and the most vulnerable ones are the elderly, medical staff, and overseas migrants. Despite being the least exposed, previous research have shown that young individuals which include university students to be the most prone to psychological health problems (Manap et. al., 2019; Al-Kumaim et. al., 2021; Pappa et al., 2020). Students were found to be stressed and anxious even before the outbreak, thus it is important to keep in mind that significant levels of stress and anxiety were already present in student populations prior to the pandemic (Zeng et al., 2019; Ersan et al., 2017). Students are extremely susceptible to the adverse psychological effects of the COVID-19 pandemic, such as elevated levels of stress, because they are highly prone to the disease. Therefore, monitoring emotional levels throughout the period of distance learning during the perceived pandemic and conducting an in-depth study of students' psychological well-being throughout the pandemic are both necessary.

The key concept in discussing distance learning is "separation," which refers to the fact that the teacher and the student are studying at various times and locations. In addition, the use of technology is also used for learning and communication between teachers and students as well as between fellow students (Simonson & Berg, 2016). It is also a way of teaching that makes good use of a wide range of resources and technologies to help students learn better (Darius, 2021) and to make it easier for students and teachers to talk to each other and with each other (Simonson & Berg, 2016). One of the main essential requirements for implementing distance learning is having a stable or fast internet connection and hardware requirements, such as computers, mobile devices, and conference applications like Microsoft Team, Zoom Meeting, and others. As mentioned by Alobaid (2020), the utilisation of ICT for educational purposes ought to be interesting for students. In addition, the level of satisfaction that students obtained with ODL has a statistically significant impact on the type of online education they will choose in the future (Ploj-Virti, 2021). Due to the recent emergence of the COVID-19 pandemic, studies conducted during the pandemic must also be examined to determine the emotions of online learning students (Avsheniuk et. al., 2021). There is a paucity of research on the psychological effects that are likely to be felt by students if their schools are abruptly and permanently closed, and they are required to participate in online learning communities (Unger & Meiran, 2020).

The DASS-21 instrument published by Lovibond and Lovibond (1995) has been used by many researchers as a non-clinical preliminary screening tool in measuring an individual's levels of depression, anxiety, and stress. However, due to the new challenges that exist in the daily life of the people worldwide due to the Covid-19 pandemic, the researchers found it significant to modify the existing DASS-21, taking into considerations on the challenges faced by the respondents, to get a more accurate findings when conducting related studies. Research investigating the challenges and problems students experienced while coping with the new learning environment among others indicated that most of the students was not ready for online learning due to the limited internet access and poor internet coverage due to localities factors. Apart from the technological obstacles, medical conditions, family conflicts as well personal issues were also part of the challenges faced by them (Chung et. al., 2020; Haron et. al., 2021; Ismail et. al., 2020; Sarkar et. al., 2021; Jordan et. al., 2021). The researchers believed that these challenges are significantly important to be studied especially during the ODL sessions.

Thus, the objective of this study was to assess the construct validity of DASS-21 and to make modifications to DASS-21 through the utilisation of an instrumental design, exploratory factor analysis, and structural equation modelling. The full DASS-21 contains 21 items that addresses the three areas of subscale (Depression, Anxiety, and Stress). Hair et. al. (2006) suggested that each latent variable construct should at least contain three (3) items to be better explained. Out of 7 items, one of the items from the "Stress" subscale has been discarded due to a higher missing value of over 20% (Clark & Altman, 2003). The structure of DASS-21 has been changed, though. Ten new questions have been added to a subscale called "Challenges during Online Distance Learning (ODL)" to make it fit with the study that was done. Five Likert-type items addressed each of the 'Challenges during ODL', with each item scored on a scale of 1 = Strongly Disagree, 2 = Disagree, 3 = Uncertain, 4 = Agree, and 5 = Strongly Agree, and 4 Likert-scales (0-3) for the DASS-21 instrument already specified by Lovibond and Lovibond (1995). Figure 1 shows the items from the extra subscales (called "Challenges during ODL").

METHODOLOGY

Data collection was accomplished using online surveys administered via the Google Form platform. This platform directed participants to the online questionnaire, where they read the informed consent which explained the study's purpose, the study's voluntary nature, and that there was no right or wrong answer. The respondents for this study were UiTM students who were eligible and willing to take part. They came from different campuses and fields of study. The mean age of the exploratory factor analysis (EFA) participants was 1.84 (SD = 0.371). The first step of performing an EFA is to determine the extraction method using EFA. The aim of self-extraction of the factors is to simplify the factor structure of a group of items (Hair, 2010). There are several types of extraction methods, but the most commonly used are Principal Component Analysis (PCA) and Principal Axis Factoring (PAF). The researchers decided on the extraction method based on the data distribution or normality. Since this data analysis did not follow the normal distribution, Cudeck (2000) suggested that PAF is a better way to extract the data.

The second process is to determine the number of factors to be retained in the analysis. The Kaiser-Meyer-Olkin (KMO) test (Kaiser, 1970), and the Bartlett test of sphericity (Bartlett, 1937), are used to access the suitability of data for EFA. The KMO index ranges from 0 to 1, with a value greater than 0.5 considered suitable for factor analysis. For the Bartlett test of sphericity, the result should be significant with a p-value less than 0.05, which indicates an EFA is appropriate to be carried out. According to the rule, only factors that have eigenvalues greater than 1 are written for interpretation. The extent to which the item correlates with all other items in the analysis, or the variance contributed to the factors in the factor solution, is referred to as communalities. Higher communalities are generally preferred, with values greater than 0.8 being considered high, 0.4 to 0.7 being considered low to moderate, and less than 0.4 indicating that the item is unrelated to all other items. Therefore, the items can be removed or more items be added to explore the potential factors. The Scree test, which is also a popular method for deciding several extraction factors, involves the visual exploration of a graphical representation of eigenvalues. Identify the elbow in the data where the slope of the curve flattens. Some researchers suggested that parallel analysis should be incorporated with a scree plot (Lim & Jahng, 2019; Wood et. al., 2015). Parallel analysis uses random data simulation to determine factor numbers. The estimated eigenvalues are calculated using the Monte Carlo Simulation Technique on a random simulative (artificial) data set in addition to the actual (real) data set. Cokluk & Koçak (2016) stated that the method is significant if the number of factors where the simulated sample eigenvalue is greater than the actual data.

The third process is to choose a rotation method and describe the factors and the items loaded on each factor. Based on an article by Brown (2009), he compiled the definitions of rotations from past literature. For example, McDonald (1985) defined rotation as performing arithmetic to obtain a new set of factor loadings from a given set. In a simple case, rotation is conducted to obtain a simple structure of loadings to interpret the factors. There are two categories of rotation; orthogonal (Varimax, Quartimax, and Equamax) and oblique (Direct oblimin and Promax) rotation. In social science, it is generally expected some degree of correlation between the factors since behaviour is a complex product of many factors. Therefore, oblique rotation can be used when it is assumed that there is a link between the variables.

The next step is to examine the validity and reliability of the instrument. Every instrument has high validity, which means that the items of the instrument accurately represent the concept being studied. The discriminant validity is focused on which is the extent to which the factors are distinct and uncorrelated. A good instrument should display good discriminant validity, where the factor is able to account for more variance in the observed variables rather than other constructs within the conceptual framework. Two strategies can be used to assess discriminant validity. The first method is to examine the pattern matrix or rotated component matrix. There should be minimal cross-loading, meaning that an item desirably loads on a single factor instead of loading on several factors at the same time. The alternative is to check the factor correlation matrix. The correlation between the factors should be less than 0.07. This is the factor correlation matrix. If the correlation among the factors is high, then it will face a multicollinearity issue. To avoid this, the researchers might want to remove problematic items or improve the wording of certain items to prevent confusion. This factor correlation matrix is one of the outputs when oblique rotation is selected. It is generated automatically when using promax or direct oblique rotation.

The last analysis part for EFA is the testing of the reliability of the instrument. Reliability refers to the extent to which scores on an instrument are free from measurement errors. This analysis uses internal consistency, which is frequently represented by the Cronbach alpha coefficient. Cronbach's alpha needs to be at least 0.7 for an instrument to be considered reliable.

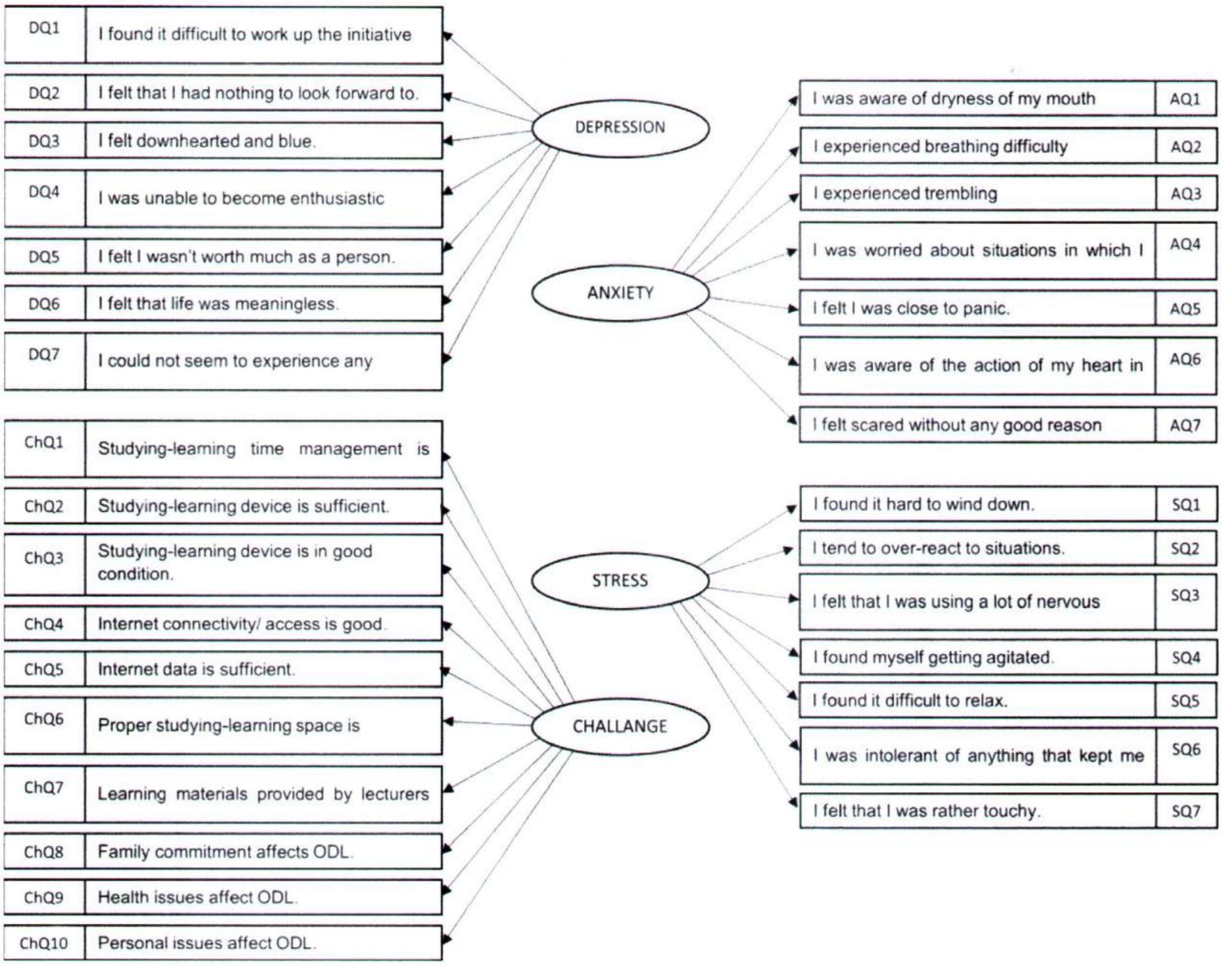

Figure 1: Theoretical framework EFA

RESULTS AND DISCUSSION

The pilot test sample was composed of 800 respondents of UiTM undergraduate and graduate students from a random selection of UiTM campuses. The theoretical framework (Figure 1) gives a clear four-factor solution (Depression, Anxiety, Stress, and Challenge during ODL). The purpose of this analysis was to determine whether the results obtained are significantly different depending on the extraction method used. The first analysis revealed a five-factor structure that explained 66 percent of the variance in the original data. The Kaiser-Meyer-Olkin (KMO) gave a value of 0.940 and Bartlett's test of sphericity indicated that the correlation matrix was not random, $\chi2(435) = 14622.891$, $p < .001$. Therefore, it was determined that the correlation matrix was appropriate for factor analysis. For all items, the commonality results were relatively stable by more than 0.40 across all extraction methods; and only one item from the 'Challenge during ODL' subscale was removed. The second exploratory factor analysis was carried out on the remaining 29 items, and the result showed a five-factor structure that explained 61 percent of the variance in the original data, KMO = 0.945, and Bartlett's test of sphericity, $\chi2(406) = 14436.965$, $p < .001$

The eigenvalues from Principal Axis Factoring (PAF) were used for the extraction method. The first two criteria, theory, and eigenvalues suggested a four and five factor solution, respectively. Eigenvalue suggested five factors that contain 3 factors from the DASS subscale (Depression, Anxiety, and Stress) and the balance of two factors were

Challenge during ODL and Environment during ODL. The result of the scree plot posed an interesting dilemma with the suggestion of either four or five factors due to the way the slope levels off twice (Figure 2).

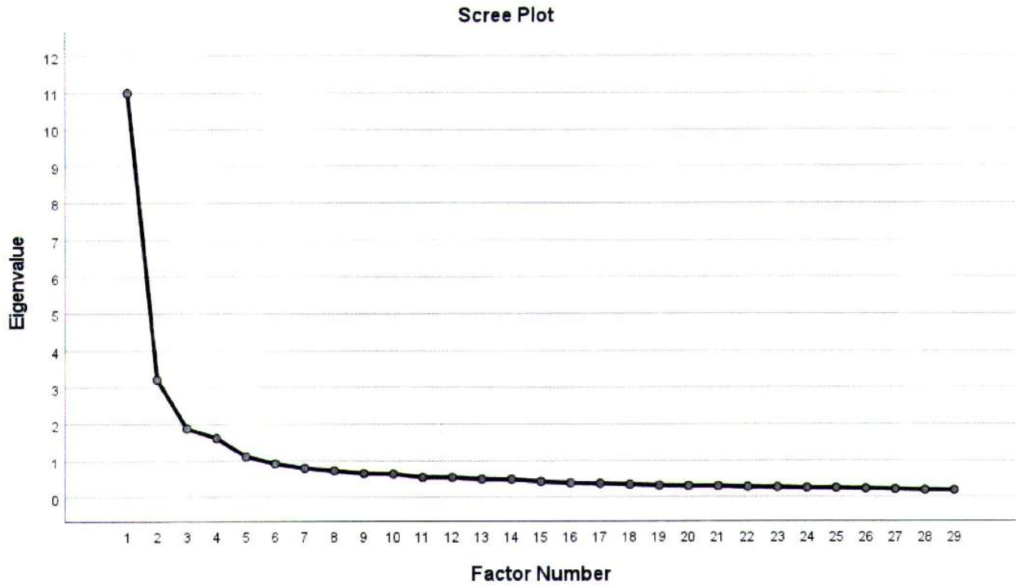

Figure 2: Scree Plot

The researchers assume that the research of this study can use the original subscale of DASS-21 without the addition of a new subscale as well as use a modified version of DASS-21. Since the concept of DASS-21 is too general, the researchers are relating the purpose of this study to a modification of DASS-21. However, the scree plots do not always have one clear elbow. The Monte Carlo software made by Watkins et al. (2005) was used to do parallel analysis.

Table 1 Results of EFA vs Parallel Analysis (PA).

No	Observed (Eigenvalue)	Expected (PA)
1	10.994	1.3698
2	3.219	1.3178
3	1.885	1.2814
4	1.624	1.2474
5	1.122	1.2178
6	0.921	1.1901
	⋮	⋮
29	0.191	0.6834

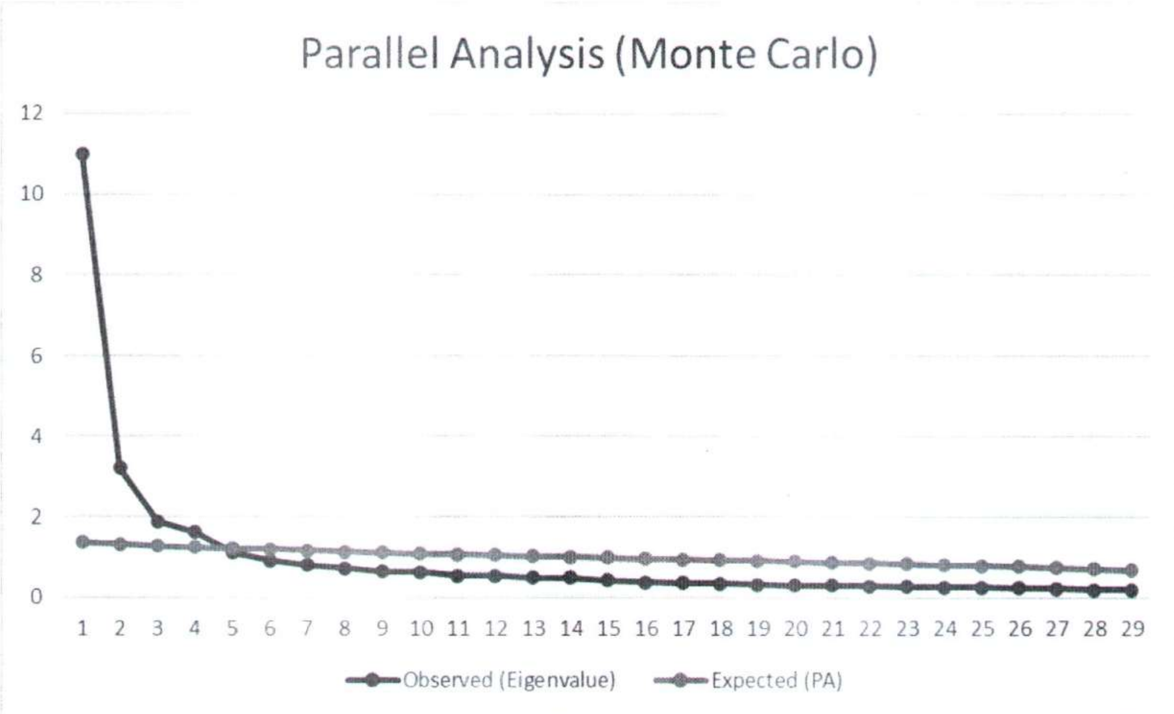

Figure 3: Results of EFA vs Parallel Analysis

From Table 1 and Figure 3, The researchers decided to retain four factors to be extracted based on a series of analyses such as kaiser criteria and scree plot. The Promax rotation will be chosen based on assumptions among the variables and on discriminant validity. The results are as shown in Table 2 of the pattern matrix, the coefficient by suppressing the small coefficient at 0.4 as a cutoff point and removing the cross loadings for items SQ1, SQ2, SQ3 and SQ5.

Depression (combined with two stress subscale items, SQ6 and SQ7) and anxiety (combined with one stress subscale item, SQ4) are the same as those proposed in the original theory. The remaining two factors are "challenge during ODL" and "environment during ODL'. From the result, there was no correlation above the value of 0.7, which means safe discriminant validity was achieved and no multi-collinearity issues was present.

The last analysis part for EFA was testing the reliability of the instrument. Reliability refers to the extent to which scores on an instrument are free from measurement errors. This analysis focused on internal consistency, which is frequently represented by Cronbach's alpha coefficient. A minimum value of 0.7 for Cronbach's alpha is considered acceptable for a reliable instrument. For all factors from EFA obtained, a value of Cronbach's alpha was 0.903, 0.918, 0.829, and 0.738, which is considered very good. All items were kept because the deletion of any item would result in a lower Cronbach's alpha.

Table 2: Pattern matrix of Promax rotation

Pattern Matrix[a]

	Factor			
	1	2	3	4
DQ1		.657		
DQ2		.859		
DQ3		.726		
DQ4		.893		
DQ5		.739		
DQ6		.788		
AQ1	.523			
AQ2	.819			
AQ3	.827			
AQ4	.713			
AQ5	.848			
AQ6	.930			
AQ7	.824			
SQ1	.487	.367		
SQ2	.399	.405		
SQ3	.568	.315		
SQ4	.618			
SQ5	.531	.305		
SQ6		.492		
SQ7		.403		
ChQ2			.739	
ChQ3			.747	
ChQ4			.695	
ChQ5			.723	
ChQ6			.651	
ChQ7			.423	
ChQ8				.569
ChQ9				.770
ChQ10				.764

Table 3: Pattern matrix after removing cross-loading

Pattern Matrix[a]

	Factor			
	1	2	3	4
DQ1		.657		
DQ2		.859		
DQ3		.726		
DQ4		.893		
DQ5		.739		
DQ6		.788		
AQ1	.523			
AQ2	.819			
AQ3	.827			
AQ4	.713			
AQ5	.848			
AQ6	.930			
AQ7	.824			
SQ4	.618			
SQ6		.492		
SQ7		.403		
ChQ2			.739	
ChQ3			.747	
ChQ4			.695	
ChQ5			.723	
ChQ6			.651	
ChQ7			.423	
ChQ8				.569
ChQ9				.770
ChQ10				.764

CONCLUSION

The COVID-19 pandemic outbreak in Malaysia and the concerning 4,683 positive Covid-19 cases as of April 12, 2020, have prompted the top management of Universiti Teknologi MARA (UiTM) to switch all its campuses nationwide to Open and Distance Learning (ODL) mode beginning on April 13, 2020. The idea of learning remotely without teachers and lecturers has caused a lot of worries and anxieties among the students nationwide due to the unfamiliarity of the new environment as well as the challenges that they must face to survive the situation. Students' psychological well-being has always been the priority of the institution, thus the negative views and worrisome comments posted by the students on social media during the early stages of ODL mode has alerted the researchers to conduct a study using DASS-21 instrument. In ensuring accurate findings to the study, consistent with the new challenges faced by the students during the ODL mode, modification has been made to the existing DASS-21 items, thus the establishment of modified DASS-21. The Exploratory Factor Analysis (EFA) and reliability analysis were used to assess the validity and reliability of the DASS-21 and a combined new subscale instrument. Thirty (30) items from four subscales, namely, depression, anxiety, stress, and problems during ODL, were chosen for the initial instrument since the ODL is a novel conceptual paradigm. According to a study done by EFA, the instrument used to assess students' psychological well-being in ODL comprised five factor-structures that accounted for 63 percent of the variance in the way the items were related to one another. All factors had strong reliability ratings.

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