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STATISTICAL LITERACY OF EDUCATION POLICY MAKERS: A PLS SEM APPROACH

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ABSTRACT

In this new era drenched with data, statistical literacy becomes more essential for individuals to be able to read, communicate, and make informed decisions. Moreover, statistical literacy is highly essential for education policy makers who are highly accountable for all policy outcomes including school improvement, resource allocation, curriculum planning and intervention. Hence, there is a need to understand their perceptions and beliefs. The aim of this study is to explore whether attitude towards statistics and statistical anxiety are related to the education policy makers' statistical literacy. Considering that statistics coursework is the basis and major contributor to a statistically literate society, real problems with statistics are likely due to non-cognitive factors, which include attitudes or beliefs towards statistics. There is a global increase in literature exploring beliefs and attitudes of teachers towards statistics, indicating that studies on attitudes towards statistics do not stop at the students' level but should also be extended to education personnel who uses statistics in their workplace. While pre-service teachers in college claimed that statistics anxiety is the main obstacle to get their teaching degree. This is alarming as they are the future teachers and education policy makers with anxiety may develop avoidance to read educational diagnoses containing statistical information. Participants self-reported their statistical literacy with 20 multiple choice items tailor made to the work of education policy makers. Data were drawn from a survey elicited using a cross-sectional method on 328 education personnel working at different levels in Ministry of Education. The findings show that attitude towards statistics is not significantly related to statistical literacy while statistics anxiety has a significant negative relationship with statistical literacy. Statistical anxiety also has a negative significant relationship with attitudes towards statistics. These findings help strengthen Model of Statistical Literacy, where dispositional element including beliefs and attitude was addressed while confirming Anxiety Expectation Model. Future studies to explore other potential predictors of statistical literacy and suggested to investigate possible difference in attitude towards statistics between adult workers and students.

Keywords: *Education Policy Makers, Statistical Literacy, Attitudes Towards Statistics, Statistics Anxiety*

INTRODUCTION

The emphasize on statistical literacy has elevated in the past few decades, as statistical literacy construct and definitions evolves in line with the heightened needs in the current pandemic situation (Budgett & Rose, 2017; Watson & Callingham, 2020). Statistical literacy is essential for individuals regardless of their socioeconomic classes, to be able to read, understand, and communicate with statistical statement in media reports to make informed decisions in their life (Gal & Ograjensek, 2017; Reeves & Chiang, 2018; Sharma, 2017). Gal (2002) initially described statistical literacy as the heart of participation in society and then further explained that statistical literacy is the ability to interpret, critically evaluate and when appropriate, express opinions about statistical information, data-related arguments or any daily issues and phenomena. In education workplace, as in other workplace settings, accountability, quality control, and forward planning could be enlightened by exploration of statistical data (Chick & Pierce, 2012).

The education policy makers are held accountable for all policy decisions made regarding school improvement, resource allocation, curriculum planning and also intervention programs (Pierce et al., 2014; Reeves & Chiang, 2018; Sharma, 2017; United Nations Economic Commission for Europe, 2012). Thus, they are expected to better understand statistics published in their workplace such as statements, media reports, research and statistical reports including national and international assessments. Evidence-based decision-making has become increasingly paramount as the government is publicly held accountable for policy outcomes, increasing the need for the ability to interpret statistical information in order to make strategic decisions in ensuring optimal return in investments in education and also the direction of future growth (United Nations Economic Commission for Europe, 2012). In the Malaysia Education Blueprint 2013-2025, it is mentioned that there is a limited use of data for informed decision-making. Although for more than a decade, one of the most capital-intensive investments by the ministry is the data collection and management systems, data-driven decision making is still not as widespread or effective as desired (Ministry of Education, 2013).

In summation, this study attempts to investigate the relationship of attitude towards statistics and statistics anxiety with statistical literacy in Putrajaya, Kuala Lumpur and Selangor using the newly developed instrument, SL-EdP. This paper aims to investigate these relationships using advanced statistical analysis approaches. The remainder of this paper is organized as follows: reviews of the existing literature on statistical literacy, attitude towards statistics and statistics anxiety. Following the literature review, the research methodology was outlined followed by subsequent methods of analysis and next, the findings and results are elaborated, followed by the undertaken discussion of findings. This paper concludes with the study's implications and offer suggestions for future research.

LITERATURE REVIEW

The model of statistical literacy was proposed by Gal (2002) where a statistically literate person should possess two components namely the knowledge and dispositional element as the other facilitating process for he/she to understand, critically evaluate, interpret, and communicate with statistical statements that she/he come across every day in the media and reading contexts. The knowledge elements consist of literacy skills, mathematical knowledge, statistical knowledge, context knowledge and critical questions. Meanwhile, the dispositional elements consist of beliefs and attitude, and critical stance.

The Anxiety-Expectation Mediation (AEM) Model which was initially employed in foreign language learning and then widely used in research was theorized and tested by Onwuegbuzie et al. (2002). Path analysis techniques were used to develop this model. In this model, a cognitive variable such as achievement and an affective variable such as anxiety are reciprocally correlated to each other. They further explained that to maintain the equilibrium, any changes occurring to either anxiety or achievement would culminate changes in the other variable making them reciprocally related. For example, anxiety has a direct negative effect to achievement, and a similar direct negative effect from achievement to anxiety.

Attitudes towards statistics was generally defined as a multidimensional concept representing a person's tendency to respond positively or negatively to statistics and their perception of its relevance, value and difficulty (Schau et al., 2012). It involves traits concerning beliefs, emotions, motivation, and behaviour in statistics learning process. Four dimensions of attitudes towards statistics were identified by (1) effect of positive and negative feelings towards statistics; (2) cognitive competence which involves attitudes about their cognitive knowledge and skills when using statistics; (3) value which involves attitudes pertaining to worth of statistics, its usefulness, and relevance; (4) difficulty which involves attitudes on difficulty in regards to statistics (Schau et al., 1995). According to Nielsen and Kreiner (2018), attitudes towards statistics are emphasized as the primary psychological barriers that affect statistics teaching and learning environment as well as performance in statistics. In addition, Emmioğlu and Capa-Aydin (2012) ascertained that it is vital for an individual to acquire positive attitudes towards statistics in various ways in believing that his/her ability in comprehending and utilizing statistics; perceive that statistics is interesting, useful, and ready to devote additional efforts in learning statistics; as well as believe that statistics is not that difficult to understand (Gopal et al., 2018).

There is a general fear of statistics, widespread among students worldwide which is known as statistics anxiety. Statistics anxiety was found to weaken statistical performance (Cui et al., 2019; Macher et al., 2013; Paechter et al., 2017). Statistics anxiety is defined as the fear that a person's experiences in a learning situation, in contexts related to statistics, or while engaging on statistical tasks or a state-anxiety reaction to any situation in which a person is confronted with statistics in any form and at any time (Onwuegbuzie et al.,1997; Cui et al., 2019).

Attitudes Towards Statistics and Statistical Literacy

According to Gal's Model of Statistical Literacy (2002), beliefs and attitudes are the essential parts for occurrence and sustainability of statistical literacy. Almost all empirical studies examined showed that attitudes towards statistics is related to statistics performance (Mira Khalisa & Siti Mistima, 2017; Sesé et al., 2015), achievement (Nguyen et al., 2016; Ratanaolarn, 2016) or engagement (Gopal et al., 2018). As statistics achievement meant measuring a person's statistical and mathematical knowledge and skills, which is included in the knowledge component in statistical literacy, hence, statistics achievement or performance could be described as the approximates of statistical literacy. Based on the findings of empirical studies, four out of five studies found that the weight of the influence of attitude towards statistics on statistics achievement is in the range of β from 0.36 to 0.54 while a study showed a positive significant relationship of $r=0.366$, $p<0.01$. This goes to show that all the studies investigated showed consistent findings of the contribution of statistics towards attitude to statistics achievement. However, a study in Romania attempted to examine the relationship of attitude towards statistics with statistical literacy in a statistics course for students enrolled in an Applied Modern Language course found that there is no significant correlation between attitudes, beliefs, and statistical literacy (Cimpoeru & Roman, 2018).

Although many studies have been conducted on the association of attitude towards statistics to statistics performance and have thus far pointed out the important contributions, until recently, there has been no reliable evidence that it could also predict the level of statistical literacy. This study however will examine the significance of attitude towards statistics in the rise of statistical literacy among education policy makers. This study therefore hypothesized that:

Hypothesis 1: Attitudes towards statistics has a significant positive relationship with statistical literacy of education policy makers.

Statistics Anxiety and Statistical Literacy

Onwuegbuzie et al. (2022) proposed in their AEM model that a cognitive variable such as achievement and an affective variable such as anxiety is related reciprocally, which meant that there is a direct negative path from anxiety to achievement with a similar direct negative path from achievement to anxiety. Additionally, Onwuegbuzie (2003) showed that the AEM model was also applicable in statistics learning, where there was a direct negative relationship between statistics anxiety and statistics achievement. Many empirical studies were conducted which showed the negative relationship of statistics anxiety with statistics achievement. Two out of the five studies examined found that statistics anxiety had a direct negative relationship with statistics achievement with regression weight (β) ranging from -0.1 to -0.57 (Paechter et al., 2017; Ratanaolarn, 2016) while two other studies found that statistics anxiety has only indirect negative relationship with statistics achievement through attitude and state anxiety (β=-0.15 to -0.26) (Macher et al., 2015; Sesé et al., 2015). However, a study on psychology students in Malaysia found that statistics anxiety is not related to statistics achievement (Abdul Hamid & Sulaiman, 2015). However, two recent studies, showed support that mathematics anxiety was a strong predictor of mathematics literacy (Gabriel et al., 2020; Hiller et al., 2021). As statistics is almost always related to mathematics, we would further examine these studies to examine the connections. These mixed findings invite further investigations on statistics anxiety as a predictor of statistical literacy in this study.

Hypothesis 2: Statistics anxiety has a negative significant relationship with statistical literacy of education policy makers.

Statistics Anxiety and Attitudes Towards Statistics

The AEM model also suggested that two affective construct such as anxiety and attitudes is reciprocally related. In line with the AEM model, evidence from several empirical studies also showed negative contributions of statistics anxiety on attitudes towards statistics. Both studies by Ratanaolarn (2016) and Sesé et al. (2015) showed a good range of regression weight (β) from -0.40 to -0.49 while a quasi-experimental study by Ciftci et al. (2014) showed that statistics anxiety decreases when positive attitudes increase. However, the study by Adegboye and Jawid (2016) showed contradictory results where between genders, male has higher statistics anxiety with higher positive attitudes. These findings showed the need for further investigations on the negative contributions of statistics anxiety on attitudes.

Hypothesis 3: Statistics anxiety has a negative significant relationship with attitude towards statistics among education policy makers.

METHODOLOGY

Research Design

This study is a quantitative study employed via a cross-sectional survey study using a questionnaire. It is also a correlational study research design to explore causal relationships between statistical literacy, attitude towards statistics and statistics anxiety. The data were collected around September 2020 using self-administrated surveys.

Participants

The questionnaire was administered among education policy makers working in Putrajaya, Kuala Lumpur and Selangor in Malaysia where many of the policy making took place. The population of the education policy makers totalled 3826, using random proportionate cluster sampling, leading to the distribution of 390 questionnaires. Of these, 341 questionnaires (87.44%) were returned. From these responses, 13 were outliers and excluded from the analysis. Thus, only 328 responses were analysed.

Instrumentation

A questionnaire which was self-developed to measure education policy makers' statistical literacy (20 items), attitude towards statistics (28 items) (Schau et al., 1995) and statistics anxiety (38 items) by Cruise et al. (1985) which was adapted from previous studies. For statistical literacy, items were custom made with issues and statistics related to education with 20 multiple choice items with three response options. Each item in Attitude towards Statistics items were scaled on a 7-point Likert scale and responses to each item are on the scale of strongly disagree, disagree, somewhat disagree, neither disagree or agree, somewhat agree, agree and strongly agree. Respondents were also assessed on Statistics Anxiety where each item was ranked on a 5-point Likert scale. In the first part, given situation was to be responded on a scale with no anxiety, not much anxiety, undecided, somewhat anxiety to strong anxiety. In the second part, items were ranked in a 5-point Likert scale with degree of agreement where all items were scored with strongly disagree, disagree, somewhat disagree, neither disagree or agree, somewhat agree, agree and strongly agree.

Data Analysis

In this study, the path analysis to test the predictors of statistical literacy was done using the PLS SEM software, SmartPLS 3 (Ringle et al., 2015). PLS-SEM was selected as a method of analysis as it is a causal modelling approach to SEM, intended on maximizing the explained variance of the dependent latent constructs in this study which are the attitude toward statistic and statistics anxiety.

FINDINGS

Demographics

The education policy makers in this study consisted of 37.2% male and 62.8% female. As for the highest academic qualifications of the policy makers', almost half are PhD holders, 40.5% were Masters' degree holders, and only 12.8 % were bachelor's degree holders. In terms of work experience, only 3.7% of the respondents have experience of less than 10 years, most of them (46%) had tenure in service for 10-19 years, 38.7% of them have been working between 20 to 29 years, while another 11.6 % were already in service for 30 to 39 years. The education policy makers surveyed in this study involved mostly of officers, 190 (57.9%) in the federal level of the ministry followed by 15.2% in the state level and 26.8% from the district level.

Measurement Model Analysis

Convergent Validity

Convergent validity suggested that indicators of a construct shared a high proportion of variance (Hair et al., 2006). Generally, the measurement of the constructs' convergent validity of the scale is ascertained by using three criteria. Firstly, as proposed by Hair et al. (2017), the factor loadings should be larger than 0.40. Secondly, each construct should have composite reliability of greater than 0.70, and finally, the average variance extracted (AVE) for each variable should be more than 0.50 (Fornell & Larcker, 1981). AVE is the total of the squared loadings divided by the number of items. Next step is to assess internal consistency reliability, which prioritized in PLS SEM to use Jöreskog (1970) composite reliability (CR). Higher values of internal consistency reliability indicated higher levels of reliability.

From the findings as tabulated in Table 1, almost all factor loadings showed support for convergent validity for all three variables. Many indicator loadings were higher than 0.708, with most of the loadings larger than 0.50 with values ranging from 0.323 to 0.920. The high factor loadings could conclude that the variable established convergent validity. As mentioned previously, indicator loadings between 0.30 and 0.70 should be examined (Hair et al., 2011; Henseler et al., 2009). Indicators with loadings higher than 0.6 were kept. From the findings, we found three indicator loadings that seemed problematic which are Statistical Literacy (Level 4) 0.341, Attitude towards statistics (Affect) 0.502 and Statistics Anxiety (Self Concept) 0.323. As all these indicators were substantial for this study, they were examined further to see whether their elimination may increase AVE or CR. As it did not increase either of the two, the researcher decided to retain all three indicators. Thus, no indicators were dropped in the measurement model.

The next step taken was to examine the AVE of the constructs, where Statistical Literacy and Attitude towards Statistics produced AVE values above 0.5. However, the AVE for statistics anxiety was 0.407 but the convergent validity is still considered adequate as suggested by Fornell and Larcker (1981) that for AVE lower than 0.5, it is still accepted if the composite reliability is larger than 0.6, where for statistics anxiety in this study, the CR is high with the value 0.72. Hence, convergent validity was met in this study.

Next, for the internal consistency, although Cronbach's Alpha for Statistical Literacy and Statistics Anxiety did not reach 0.6, as Cronbach's alpha weights all indicators equally in a summated rating scale context; while in PLS-PM summated scale was not used, thus, the composite reliability is given more priority and recommended. As such, all three constructs showed high composite reliability (>0.7). Furthermore, Rho A which were high for the three constructs was also suggested for a better representation of internal consistency reliability (Dijkstra & Henseler, 2015). Thus, for this study, the internal consistency reliability was established. All the values for convergent validity assessment were presented in Table 1.

Table 1
Convergent Validity

Construct	Loading	Cronbach's Alpha	Rho A	Composite Reliability	AVE
Statistical Literacy		0.528	0.81	0.726	0.551
Level 1	0.663				
Level 2	0.719				
Level 3	0.746				
Level 4	0.341				
Attitude towards Statistics		0.69	0.812	0.81	0.527
Affect	0.502				
Cognitive Competence	0.920				
Difficulty	0.647				
Value	0.768				
Statistics Anxiety		0.528	0.556	0.72	0.407
Asking for Help	0.801				
Interpretation	0.862				
Self-Concept	0.323				
Worth of Statistics	0.845				

Discriminant Validity

Discriminant validity in this study was established using the multi- trait multi method matrix in the form of heterotrait monotrait ratio of correlations. Thus, discriminant validity was tested using the new suggested method, as the findings were presented in Table 2. As the HTMT values do not exceed HTMT 0.90 with the cut off value of 0.90 (Gold et al., 2001), it was ascertained that there was no problem of discriminant validity.

Table 2
Discriminant Validity Heterotrait Monotrait (HTMT) Ratio

	Statistics Anxiety	Attitude towards Statistics	Statistical Literacy
Statistics Anxiety			
Attitude towards Statistics	0.90		
Statistical Literacy	0.47	0.32	

The path coefficient analysis of the structural model was performed to conclude the hypothesis formulated. The values of these path coefficient were obtained through a bootstrapping procedure with a resample of 5000, allowing the calculation of an empirical value t to be performed (Hair et al., 2019). Path coefficient estimates (β) values are standardized on a range from +1 to -1, where values approaching +1 shows strong positive relationships while values closer to -1 indicating strong negative relationships. Empirical value of t greater than the critical value indicates that the path coefficient is significant to a certain degree of significance (Hair et al., 2019). Typically, the critical values used for the two-tailed test are 1.65 (significant level = 10%), 1.96 (significant level = 5%) and 2.57 (significant level = 1%) (Hair et al., 2019). Therefore, a critical value of 2.57 (significant level = 1% as suggested by Hair et al., (2019)) was used to evaluate the hypotheses in this study.

Three hypotheses were formulated to look at the relationships that exist between the study constructs. Then the test results were tabulated in Table 4.35, showing that one of the t- value in one hypothesis, H_{a1} was found as not significant, while the other two t values are significant at 1% level namely H_{a2} and H_{a3}. Based on the table, we can conclude that, the statistics anxiety has a negative significant relationship with statistical literacy (β = -0.347; t = 19.071), thus, H_{a2} was accepted. Statistics anxiety also has a significant negative relationship with attitudes toward statistics (β = -0.682; t = 4.441), which also means that Ha3 was also accepted. However, attitudes toward statistics have no significant relationship with statistical literacy (β = -0.019; t = 0.175), thus, H_{a1} is rejected. Conclusively, there was one unsupported path out of the three paths tested.

Table 3
Hypothesis Testing Summary

Hypothesis	Paths	Path Coefficient (β)	t Statistics	p Values	Results
H_{a1}	ATT → Statistical Literacy	-0.019	0.175	0.937	Not Supported
H_{a2}	ANX → Statistical Literacy	-0.347	19.071	0.00***	Supported
H_{a3}	ANX → ATT	-0.682	4.441	0.00***	Supported

***significant at p<0.01

Specifying the Structural Model

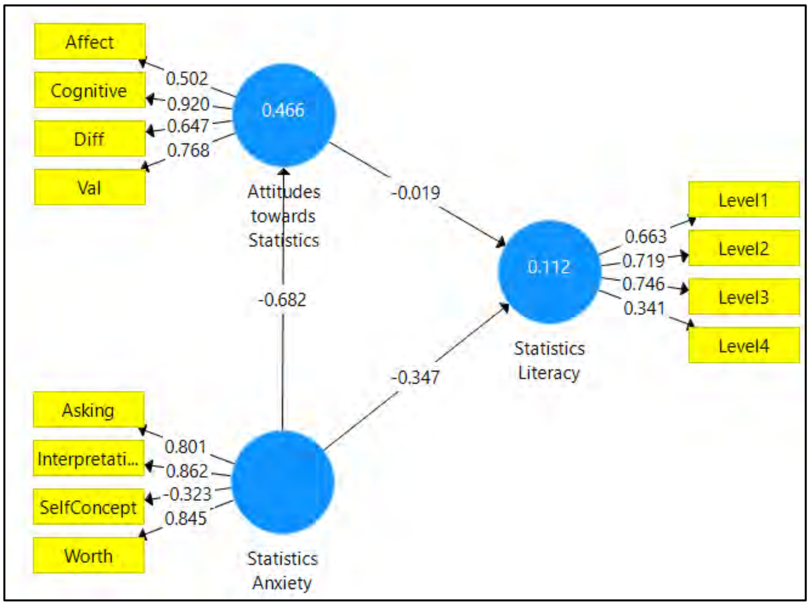

Figure 1: *Structural Model*

In Figure 1, statistical literacy consisted of Level 1 to 4 according to item difficulty level from very difficult, difficult, easy, and very easy level because of the best spread of item numbers in each level to be analysed using PLS-SEM. Analysis that is often used to measure structural models is the coefficient of determination R^2 or determinant coefficient which measures the accuracy of the model prediction. In short, the value of the R^2 represents the total variance described on the endogenous variable in the structural model (Hair et al., 2019). In this study, the endogenous construct is the construct of statistical literacy and attitude toward statistics that acts as a dependent variable. Figure 1 illustrates the structural model of the study.

To avoid too much reliance to R^2 value, cross-validated redundancy, Q^2 was also used to assess the inner model's predictive relevance. A greater value of Q^2 showed higher model's predictive accuracy and values greater than zero indicates the path predictive relevance but not on the quality of prediction (Hair et al., 2019). In addition to the basic measures, Hair et al. (2019) also suggested to report the effect size, or Cohen f^2 for each path, as it shows whether a path represents small (0.02), medium (0.15), and large (0.35) effect size. The variance inflation factor (VIF) values were also used to indicate whether there were issues on collinearity among the constructs, where VIF values close to 3 and lower is ideal to show that the model has no collinearity issues.

To assess the structural model in this study, all R^2, beta (β) and the t-values, the predictive relevance (Q^2) and the effect sizes (f^2) were reported. In reporting and interpreting the findings of this study, both the statistical significance (p-value) and substantive significance (effect size) were reported as seen in Table 4. This section describes the predictors for endogenous latent variable which is the statistical literacy. As illustrated in Table 4.36, it was estimated that the statistics anxiety negatively influenced statistical literacy, explaining 11.2% of variance. The strongest and only predictor for statistical literacy was statistics anxiety with a low effect size ($\beta = -0.347$, $p < 0.01$, $t = 19.071$, $f^2 = 0.073$). Q^2 of 0.061 indicates medium predictive relevance of the path model (Hair et al., 2019). Table 4 also depicts the results of predictor on attitudes toward statistics. For this model, 46.6% of the variance in attitudes toward statistics was explained by statistics anxiety with a high effect size ($\beta = -0.682$, $t = 4.441$, $p < 0.01$, $f^2 = 0.732$). This path also asserted Q^2 of 0.563 depicting large predictive relevance (Hair et al., 2019). Both Q^2 values in this model are larger than zero showing that the exogenous variable had predictive relevance on endogenous variables (Hair et al., 2017). All VIF values were lower than 3 showing that collinearity between constructs was not an issue. In conclusion, this model accounted for only 11.2% of the variance in statistical literacy and 46.6% of the variance in attitudes toward statistics.

Table 4
Summary Results of Structural Model

Construct	R^2	VIF	Q^2	f^2
ATT →Statistical Literacy	-	1.732		0.000
ANX →Statistical Literacy	0.112	1.732	0.061	0.073
ANX →ATT	0.466	1.00	0.563	0.732

DISCUSSION

Findings of this study supported Model of Statistical Literacy (Gal, 2003) which highlighted that knowledge and dispositional elements needed to be together while confirming to the AEM model (Onwuegbuzie et al., 2002) which highlighted that a cognitive variable such as statistical literacy and an affective variable such as anxiety are reciprocally correlated to each other. Furthermore, this study echoed several other empirical studies that statistics anxiety has a negative relationship to statistics achievement (Macher et al., 2013; Paechter et al., 2017; Ratanaolarn, 2016; Sesé et al., 2015). Although almost all education officers may be equipped with at least a basic statistics course (Reston et al., 2014), many still experienced statistics anxiety, particularly those in non-mathematics-oriented disciplines (Hsu et al., 2009) where the anxiousness has been shown to affect the ability to acquire the statistical literacy required to interpret and critique reports which is paramount in the education policy makers' workplace (Cui et al, 2019; Macher et al., 2013; Paechter et al., 2017). Suggested strategies in reducing and overcoming statistics anxiety includes training and courses that involves application of statistics pertaining real-world scenarios (Paechter et al.,2017), combined with facilitators attentiveness towards trainees' statistics anxiety (Hsu et al., 2009) and compulsory statistics course for all students including the non-mathematical students (Reston et al., 2014) to better prepare them to work life situations as little attention was given to statistics anxiety of working adults. The finding was also in line with Piaget's Cognitive Constructivism (Piaget, 1972) where adults develop their own statistical literacy ability through their environmental experiences, such as in the statistics classroom, attitudes, and beliefs. For a constructivist adult, handling statistics can be affected by their statistics anxiety; consequently, adults with bad experiences during school days in learning mathematics may have develop anxiousness towards their ability to solve statistical tasks (Gal & Ginsburg, 1994).

The strongest predictor for statistical literacy was statistics anxiety with significant negative relationship to statistical literacy, in low effect size but medium predictive relevance. This showed that statistics anxiety such as worry and rumination, low statistics self-efficacy and fear of failure reduces the education personnel cognitive capacity required for solving task involving statistical information, hence affecting their level of statistical literacy. This also indicates that their anxiousness towards statistics is more dominant than attitude towards statistics especially in the education policy makers workplace when involving high stakes decision-making that could affect the whole nation's education sector. Thus, to get more statistically literate policy makers, proper training and support on certain topics should be held regularly to boost confidence and reduce anxiousness towards data and statistics, helping to make better decision and policy making in their workplace. Properly planned interventions, highly structured with facilitated and collaborative approach might engaged participants in discussing data and statistics in different levels with standardized official reports and survey data visualized in graphs, tables, and charts to scaffold discussions (Onwuegbuzie et al., 2010).

Interestingly, attitude towards statistics was found to have no significant relationship on statistical literacy as this finding contradicted many prominent studies held previously (Gopal et al., 2018; Mira Khalisa & Siti Mistima, 2017; Nguyen et al., 2016; Ratanaolarn, 2016; Sesé et al., 2015). As almost all previous studies are related to students, results on working adults such as the current study may differ. This may be due to that even if the education policy makers have a positive attitude towards statistics, as they were already exposed to the awareness, importance, worth and values of statistics, especially in their workplace. However, positive feelings and attitude only does not guarantee a higher score of statistical literacy. To be more statistically literate might involve many other factors, such as statistics background and statistics self-efficacy. Thus, this may indicate a suggestion for future studies to investigate other predictors of statistical literacy other than attitude and anxiety. This study also provided the much-needed empirical evidence on working adults attitude towards statistics that may suggest some possible difference between adults and students' attitude towards statistics as Gal and Ograjensek (2017) have made a call to explore more on attitude of statistics of working adults handling statistics and invest extra efforts for statistics and realizing the usefulness of statistics. This finding may not support Gal's Model of Statistical Literacy as he posited that dispositional elements such as attitude and belief and knowledge elements work together dynamically and context-dependently in enabling statistically literate behaviour.

In addition, statistics anxiety showed a strong negative relationship with attitude towards statistics. This finding was compatible with the research done by Reeves and Chiang (2018) that teachers with less data anxiety held positive beliefs and effectiveness in practicing data-driven decision making in schools. This showed that deep or intense statistics anxiety including the trepidation, apprehension, and tension that the education policy makers feel while working with statistical information could inhibit the enactment of desired positive feelings and attitude towards statistics. They may feel that their statistics fear, worry and anxiety when forced to deal with complicated figures and formula can affect their refusal to engage in successful data use and interpretations comfortably and positively. This finding also suggested that attitude towards statistics may has an indirect effect towards statistical literacy through statistics anxiety. Thus, future studies on statistics anxiety as a mediator for the relationship between attitude towards statistics and statistical literacy should be considered.

From the two predictors hypothesized to be related to statistical literacy, statistics anxiety was the strongest predictor showing significant negative relationship with statistical literacy. Attitude towards statistics was found not significant in influencing statistical literacy but statistics anxiety strongly and negatively affected attitude towards statistics. Hence, the potential mediating role of statistics anxiety for the relationship between attitude towards statistics and statistical literacy in further studies was recommended.

CONCLUSION

The main theoretical implication would be strengthening of Model of Statistical Literacy (Gal, 2002), where dispositional elements including beliefs and attitude was addressed in the second stage of the study, by incorporating the prediction of attitude towards statistics and statistics anxiety effect on statistical literacy. The explanatory power of Model of Statistical Literacy was enhanced while examining the substantial predictors of statistical literacy. In this study, findings showed that statistics anxiety was a strong predictor of statistical literacy while also influencing attitude towards statistics. Findings from this study also provide insights for Anxiety Expectation Mediation Model (Onwuegbuzie et al., 2002) statistics anxiety showed negative significant effect towards statistical literacy, but attitude towards statistics does not affect statistical literacy significantly. Hence, the findings provide new insights that attitude towards statistics of a policy maker might be different from attitude of students as their awareness on the importance of statistics in making decision may influence their positive attitude towards statistics and the risk on making high stakes decision made statistics anxiety more prominent than the studies on students at schools and universities. This study could provide better understanding on direction and strength of these affective variables towards a cognitive variable, in this case, statistical literacy among management and professional working adults in the context of the current study.

REFERENCES

Abdul Hamid, H. S., & Sulaiman, M. K. (2015). Statistics anxiety and achievement in a statistics course among psychology students. *International Journal of Behavioral Science*, *9* (1), 55–66.

Adegboye, O. A., & Jawid, A. (2016). Multivariate multilevel models for attitudes toward statistics: multi-disciplinary settings in Afghanistan. *Journal of Applied Statistics*, *43* (1), 244–261. https://doi.org/10.1080/02664763.2015.1091445

Budgett, S., & Rose, D. (2017). Developing statistical literacy in the final school year. *Statistics Education Research Journal*, *16* (1), 139–162.

Callingham, R., & Watson, J. (2017). The development of statistical literacy at school. *Statistics Education Research Journal*, *16*(1), 181–201.

Ciftci, S. K., Karadag, E., & Akdal, P. (2014). Instruction of statistics via computer-based tools: Effects on statistics' anxiety, attitude and achievement. *Journal of Educational Computing Research*, *50* (1), 119–133. https://doi.org/10.2190/EC.50.1.f

Cimpoeru, S., & Roman, M. (2018). Statistical literacy and attitudes towards statistics of Romanian undergraduate students. *Munich Personal RePEc Archive*, *90452*, 1–22.

Chick, H., & Pierce, R. (2012). The statistical literacy needed to interpret school assessment data. *Mathematics Teacher Education & Development*, *15*(2), 1–19. https://login.ezproxy.utas.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eue&AN=94988608&site=eds-live

Chick, H., Pierce, R., & Wander, R. (2014). Sufficiently assessing teachers' statitistical literacy. *Proceedings of the Ninth International Conference on Teaching Statistics*, 1–6.

Cruise, R., Cash, R., & Bolton, D. (1985). Development and validation of an instrument to measure statistical anxiety. *ASA Proceedings of the Section on Statistical Education*, 92–97.

Cui, S., Zhang, J., Guan, D., Zhao, X., & Si, J. (2019). Antecedents of statistics anxiety: An integrated account. *Personality and Individual Differences*, *144*(March), 79–87. https://doi.org/10.1016/j.paid.2019.02.036

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly: Management Information Systems*, *39*(2), 297–316. https://doi.org/10.25300/MISQ/2015/39.2.02

Gal, I. (2002). Adults' statistical literacy: Meanings, components, responsibilities. *International Statistical Review*, *70*(1), 1–51.

Gal, I., & Ograjensek, I. (2017). Official statistics and statistics education: Bridging the gap. *Journal of Official Statistics*, *33*(1), 79–100.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems*, *18*(1), 185–214. https://doi.org/10.1080/07421222.2001.11045669

Gopal, K., Salim, N. R., & Ayub, A. F. M. (2018). Influence of self-efficacy and attitudes towards statistics on undergraduates' statistics engagement in a Malaysian public university. *Journal of Physics: Conference Series*, *1132*(1). https://doi.org/10.1088/1742-6596/1132/1/012042

Hair, Joe F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, Joseph F., Black, W. C., Babin, B. y J., & Anderson, R. E. (2018). *Multivariate Data Analysis* (8th ed.). Cengage Learning.

Hair, Joseph F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modelling (PLS-SEM). In *SAGE Publications Inc* (Second). Sage Publications.

Hair, Joseph F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*(January), 277–319. https://doi.org/10.1108/S1474-7979(2009)0000020014

Hiller, S. E., Kitsantas, A., Cheema, J. E., & Poulou, M. (2021). Mathematics anxiety and self-efficacy as predictors of mathematics literacy. *International Journal of Mathematical Education in Science and Technology*, 1–19. https://doi.org/10.1080/0020739X.2020.1868589

Joreskog, K. G. (1970). A general method for estimating a linear structural equation system. In *Structural Equation Models in the Social Sciences* (Vol. 53, Issue 9, pp. 255–284). Seminar Press.

Macher, D., Paechter, M., Papousek, I., Ruggeri, K., Freudenthaler, H. H., & Arendasy, M. (2013). Statistics anxiety, state anxiety during an examination, and academic achievement. *British Journal of Educational Psychology*, *83*, 535–549. https://doi.org/10.1111/j.2044-8279.2012.02081.x

Ministry of Education. (2013). Malaysia Education Blueprint 2013 - 2025. In *Ministry of Education* (Vol. 27, Issue 1). https://doi.org/10.1016/j.tate.2010.08.007

Mira Khalisa, R., & Siti Mistima, M. (2017). Attitude towards statistics and performance among post-graduate students. *Proceedings of the International Conference on Education*, *030004*, 1–6. https://doi.org/10.1063/1.4983881

Nguyen, T. U. H., Charity, I., & Robson, A. (2016). Students' perceptions of computer-based learning environments, their attitude towards business statistics, and their academic achievement: implications from a UK university. *Studies in Higher Education*, *41*(4), 734–755. https://doi.org/10.1080/03075079.2014.950562

Nielsen, T., & Kreiner, S. (2018). Measuring statistical anxiety and attitudes toward statistics: The development of a comprehensive Danish instrument (HFS-R). *Cogent Education*, *5*(1), 1–19. https://doi.org/10.1080/2331186X.2018.1521574

OECD. (2013). *Skilled for Life? Key Findings from the Survey of Adult Skills*. OECD.

Onwuegbuzie, A. J., Bailey, P., & Daley, C. E. (2002). The role of foreign language anxiety and students' expectations in foreign language learning. *Research in Schools*.

Onwuegbuzie, A. J., Da Ros, D., & Ryan, J. M. (1997). The components of statistics anxiety: A phenomenological study. *Focus on Learning Problems in Mathematics*, *19*(4), 11–35.

Paechter, M., Macher, D., Martskvishvili, K., & Wimmer, S. (2017). Mathematics anxiety and statistics anxiety. Shared but also unshared components and antagonistic contributions to performance in statistics. *Frontiers in Psychology*, *8*(July), 1–13. https://doi.org/10.3389/fpsyg.2017.01196

Piaget, J. (1972). *Psychology and Epistemology: Towards a Theory of Knowledge*. Grossman.

Pierce, R., Chick, H., Watson, J., Les, M., & Dalton, M. (2014). A statistical literacy hierarchy for interpreting educational system data. *Australian Journal of Education*, *58*(2), 195–217. https://doi.org/10.1177/0004944114530067

Reeves, T. D., & Chiang, J. L. (2018). Online interventions to promote teacher data-driven decision making: Optimizing design to maximize impact. *Studies in Educational Evaluation*, *59*(August), 256–269. https://doi.org/10.1016/j.stueduc.2018.09.006

Ringle, C.M., Wende, S. and Becker, J.-M. (2015). *SmartPLS3* (No. 3). SmartPLS.

Schau, C., Millar, M., & Petocz, P. (2012). Research on attitudes towards statistics. *Statistics Education Research Journal*, *11*(2), 2–5.

Schau, C., Stevens, J., Dauphinee, T. L., & Vecchio, A. del. (1995). The development and validation of the survey of attitudes toward statistics. *Educational and Psychological Measurement*, *55*(5), 868–875.

Sesé, A., Jiménez, R., Montaño, J. J., & Palmer, A. (2015). Can attitudes toward statistics and statistics anxiety explain students' performance? *Journal of Psychodidactics*, *20*(2), 285–304. https://doi.org/10.1387/revpsicodidact.13080

Sharma, S. (2017). Definitions and models of statistical literacy: A literature review. *Open Review of Educational Research*, *4*(1), 118–133. https://doi.org/10.1080/23265507.2017.1354313

UNESCO. (2018). *Handbook on Measuring Equity in Education*. UNESCO Institute for Statistics.

United Nations Economic Comission for Europe. (2012). Making data meaningful: A guide to improving statistical literacy. In *United Nations Economic Comission for Europe: Vol. Part 4*. https://doi.org/10.1111/j.1600-0897.1998.tb00338.x

Watson, J., & Callingham, R. (2020). COVID-19 and the need for statistical literacy. *Australian Mathematics Education Journal*, *2*(2), 20–25.