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Factors Influencing Students' Understanding of Basic Statistical Concepts

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Abstract

This study focused on modelling the influence of teaching practices, students' attitudes towards statistics, learning practices and perceived ability on students' understanding in basic statistical concepts using Structural Equation Modelling. A total of 416 students from four Malaysian public tertiary institutions made up the sample for this study. The results showed that students' perceived ability in statistics has a strong influence on students' understanding of basic statistical concepts (measured by performance) and students' attitudes toward statistics. Teaching practices also significantly affect students' learning practices. This study found that learning practices and teaching practices do not affect students' attitudes toward statistics and do not lead to an increase in students' understanding of basic statistical concepts as measured through their test performance.

Keywords: *Learning of statistics, conceptual understanding, basic concepts of statistics, structural equation modelling, teaching and learning*

INTRODUCTION

The conceptual understanding of statistical concepts is commonly recognized as one of the most significant elements of statistical knowledge. It refers to the ability to link understanding of statistical ideas and concepts into a network of interrelated propositions. Many researchers (e.g., Ben-Zvi & Garfield, 2004; Garfield, 1999; Rumsey, 2002; Watson, 2005) support the need to comprehend fundamental statistical concepts and terminology, including statistical symbols, as it is omnipresent and unavoidable in our day-to-day living. However, these researchers (as well as others) pointed out that understanding statistical concepts is not the same as understanding statistical mechanics; for example, plugging numbers into the correct formulae. In order to understand statistical concepts, the ability to read and use statistical tools – such as percentage, ratio, measures of spread, central tendency and variability, as well as tables, graphs and maps – is required. Crooks et al. (2019) added that conceptual understanding of statistics demands an understanding of the 'why' of statistics in addition to the 'how' of it. In addition to having procedural knowledge in solving a statistical problem, students must also have conceptual knowledge of statistics. "If students don't understand the important concepts, there's little value in knowing a set of procedures" (American Statistical Association, 2005, p.10).

Conceptual understanding has been characterized as knowledge that is rich in relationships, where discrete pieces of statistical knowledge, ideas and concepts are connected to construct a network of interrelated propositions (Broers, 2001; Hiebert & Lefevre, 1986). The construction of interrelated propositions can occur "between pieces of information already stored in the memory or between an existing piece of knowledge and one that is newly learned" (Hiebert & Lefevre, 1986, p. 3-4). Conceptual understanding, hence, is essential for the development of statistical reasoning and thinking. Without it, students would not be able to make connections and explain the relationships between the different statistical processes or discrete statistical knowledge (Ben-Zvi & Garfield, 2004, p.7).

Statistical concepts are the basis of learning statistics, and therefore, should be given due attention by every educational institution. Research on understanding basic concepts of statistics that has been conducted includes the following three areas: (1) reasoning about distributions and graphical representations of distributions (Bakker & Gravemeijer, 2004; Ben-Zvi, 2004; Hammerman & Rubin, 2004; Whitaker & Jacobbe, 2017); (2) understanding concepts related to statistical variation, such as measures of variability (DelMas & Liu, 2005; Mathews & Clark, 1997; Turegun & Reeder, 2011); and (3) sampling distributions (Braham & Ben-Zvi, 2017; delMas et al., 1999; Findley & Lyford, 2019; Saldanha & Thompson, 2001).

There are many factors that contribute to students' understanding of basic statistical concepts and their success in statistics courses. Deep concerns have been raised by educators on the poor performance of students in these courses; thus, it is important to identify the causes of students' poor understanding of the basics concepts to improve the teaching and learning of statistics. Since the classroom is a learning environment where interactions occur among students and instructors, students' perceptions of their classroom learning environments and the factors associated with their perceptions may help us to find or devise some alternative ways to enhance student learning. Specifically, these factors include lecturers' instructional practices, the students' own learning practices, and their attitudes towards statistics, as well as their perceived ability or self efficacy in learning statistics.

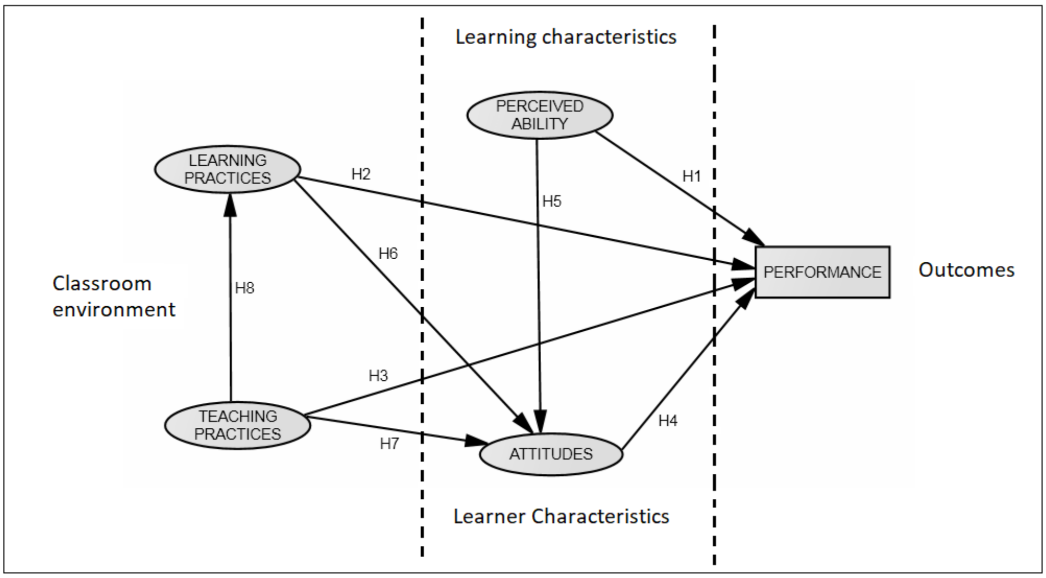
Research Hypotheses and Proposed Model

Hence, in this study, these variables were investigated whereby a structural model was developed to examine the causal relationships between them, given their significant roles in students' successful learning of statistics. The hypotheses tested were as follows:

H1: Students' perceived ability will have a direct effect on students' performance.
H2: Students' learning practices will have a direct effect on students' performance.
H3: Instructors' teaching practices will have a direct effect on students' performance.
H4: Students' attitudes toward statistics will have a direct effect on students' performance.
H5: Students' perceived ability will have a direct effect on students' attitudes toward statistics.
H6: Students' learning practices will have a direct effect on students' attitudes toward statistics.
H7: Instructors' teaching practices will have direct effect on students' attitudes toward statistics.
H8: Instructors' teaching practices will have direct effect on students' learning practices.

Figure 1 displays the proposed model showing the relationships among the variables guided by the proposed hypotheses of the study.

Figure 1
Structural model tested in the study



LITERATURE REVIEW

Students' Statistical Competencies and Conceptual Understanding

Statistical competencies, according to Rumsey (2002), underlie statistical reasoning and thinking. Without statistical competencies, statistical reasoning and thinking cannot be developed. Statistical competencies include data awareness, knowledge of certain basic statistical concepts and terminology, knowledge of the basics of collecting data and generating descriptive statistics, basic interpretation skills (i.e., the ability to describe what the results mean in the context of the problem) and basic communication skills (i.e., being able to explain the results to someone else) (Rumsey, 2002).

Huberty et al. (1993) argue that factors that appear to underlie statistical comptence include: computational aptitude, propositional knowledge, and conceptual understanding. Computational aptitude is the ability to understand and use mathematical formulae while propositional knowledge and conceptual understanding relate respectively to the knowledge of statistical concepts and their interrelationships (Leppink, 2016). The process begins by developing a basic foundation of knowledge of statistical concepts and ideas (i.e., statistical competencies) where statistical competencies promote and develop skills in data awareness, production, understanding, interpretation, and communication.

Conceptual understanding, on the other hand, is knowing the procedural steps in solving a problem and at the same time, understanding why it works. Students who lack conceptual understanding may underperform due to their tendency to misconceive and misinterpret statistical concepts and statistical analysis. Hence, a major and an important goal of statistics education is to focus on developing a deep conceptual understanding of basic statistical concepts and statistical competencies in students. With good conceptual understanding and statistical competence, students would be able to make connections and explain the relationships between discrete statistical knowledge (Ben-Zvi & Garfield, 2004, p.7).

Conceptual understanding and statistical competencies are essential for the development of statistical literacy, reasoning and thinking (Mahmud et al., 2018). According to Ben-Zvi and Garfield (2004), statistical literacy includes "basic and important skills that may be used in understanding statistical information or research results" (p. 7). In addition, to be statistically literate in the proper meaning of the term, students must be able to extract, understand, and explain different representations of data (Gal, 2002; Garfield, 1999).

Statistical reasoning, on the other hand, refers to the way people reason with statistical ideas by means of interpreting and making inferences of the statistical results based on the sets of data, graphical representations and statistical summaries, such as distribution, centre, spread, association, uncertainty, randomness and sampling (Garfield, 2002). Ben-Zvi and Garfield (2004) define statistical reasoning as "the way people reason with statistical ideas and make sense of statistical information" (p. 7).

Statistical thinking involves an understanding of why and how statistical investigations are conducted and the 'big ideas' that underlie statistical investigations (Ben-Zvi & Garfield, 2004). This includes recognizing and understanding the entire investigative process, how models are used to simulate random phenomena, how data are produced to estimate probabilities; how, when, and why existing inferential tools can be used, and utilizing the context of a problem to plan and evaluate investigations (delMas et al., 2007). One crucial aspect of statistical thinking is the ability to critique and evaluate statistical studies (Ben-Zvi & Garfield, 2004).

In summary, statistical literacy is the ability to understand and use the basic language and tools of statistics (i.e., identifying, describing, rephrasing, translating, interpreting, and reading). Statistical reasoning is the ability to choose, generate, and properly interpret appropriate descriptive and inferential methods and the ability to make inferences and justify conclusions (i.e., explaining the why and how of the process). Statistical thinking is the ability to understand why and how statistical investigations are conducted and knowing when and how to apply statistical knowledge and procedures (i.e., applying, critiquing, evaluating, and generalizing) (Mahmud et al., 2018).

Most research suggests that before any effort to educate students about statistical methods, instructors must first work on developing their statistical literacy, thinking, and reasoning. This must come first before teaching students appropriate statistical methods as basic knowledge in statistical literacy, reasoning, and thinking is needed for understanding published research (delMas et al., 2007), which is a critical skill that students need to have in order to conduct a good literature review.

In short, introductory statistics courses should focus on the basic foundation of statistical concepts and ideas where statistical literacy, reasoning and thinking are developed throughout the course. Students will then reinforce their understanding of statistical terms and concepts, and statistical literacy, reasoning and thinking skills along the process.

Factors Influencing Students' Performance in Statistics Courses

Students' performance in statistics courses at the undergraduate level has been of interest to researchers for many years. Many efforts have been made to investigate factors that affect a student's performance in a statistics course. These factors include instructors' knowledge (Callingham et al., 2016), the teaching and learning environment (Semukono et al., 2013), attitude (Naccache, 2012; Rochelle & Dotterweich, 2007), anxiety (Hoegler & Nelson, 2018; Hedges, 2017; Abd Hamid & Sulaiman, 2014), perceived ability or self-efficacy (Hoegler & Nelson, 2018; Lane et al., 2004), learning practices (Ariffin et al., 2014), learning behaviour (Luc Bude et al., 2007), teaching practices (Gundlach et al., 2015; Wilson, 2013), use of technology in learning (Tchantchane et al., 2012), gender (Monroe et al., 2011) and age (Dutton & Dutton, 2005).

In previous studies, a number of models were developed to predict and measure students' performance (Skaalvik et al., 2015; Badiee et al., 2014; Yurt & Sunbul, 2014; Emmioğlu, 2011; Onwuegbuzie, 2003). For example, Alyani and Nurafni (2019) presented a model where gender, age and educational background were predictors of a student's GPA. Brezavšček et al. (2020), using the same approach, examined the relationships among the factors influencing students' mathematics achievement which included attitude towards mathematics and math anxiety, engagement in learning activities, and attitude towards the use of technology in learning mathematics. Garfield et al. (2002) suggested that the desired outcomes of introductory statistics courses should include not only statistical learning and understanding, but also the willingness of students to persist in their learning and application of skills, as well as positive attitudes and beliefs about statistics.

As students are part of the teaching and learning environment, their voices and perspectives are of a great significance and need to be investigated in order to improve the process of teaching and learning statistics. It is also important to examine the relationship between statistics teaching and learning and the factors that influence students' conceptual understanding of statistical concepts. While there are numerous factors that affect the performance of students in statistics, as evident in the existing literature, this research aims to explore student attitudes, perceived ability, learning practices and teaching practices which are considered important variables that contribute to students' understanding of basic statistical concepts and key factors to succeed in statistics courses.

Influence of students' perceived ability on their performance and attitudes toward statistics

Students' perceived ability may have a profound influence on their learning outcomes and attitudes towards statistics. Perceived ability or self-efficacy as one of the concepts under the Social Learning Theory by Bandura (1997) has served as a basis to further understand an individual's motivation to learn and their learning pursuits as it is one of the predictors of academic success. Self-efficacy is defined as self-beliefs or self-judgement that students perceive about their ability to successfully complete a specific task (Bandura, 1997). It is considered as one of the fundamental factors in learning basic statistical concepts in terms of attitudes, where it determines the feeling, thinking, motivation and behaviour of the student.

Finney and Schraw (2003) defined statistics self-efficacy as the "confidence in one's abilities to solve specific tasks related to statistics" (p. 164). They developed measures to assess self-efficacy in statistics that comprise students' current self-efficacy in statistics (CSSE) and self-efficacy to learn statistics (SELS). They investigated whether self-efficacy affected students' performance in a statistics course and found that students' statistical achievement and their self-efficacy were positively related. Other researchers have also found a significant relationship between self-efficacy and academic achievement (Awang-Hashim et al., 2002; Finney & Schraw, 2003; Goulão, 2014; Lampert, 2007; Lane et al., 2004; Onyeizugbo, 2010).

It is unfortunate that many students perceive statistics as a difficult subject even before studying statistics (Baharun & Porter, 2009). Perceived level of difficulty or perceived ability can affect students' attitudes toward learning statistics (Estrada et al., 2005) and the primary concern is that a perception of difficulty will lead to avoidance or lack of learning engagement, if given a choice (Fitzmaurice et al., 2014).

Influence of students' learning practices on their performance and attitudes toward statistics

Learning practices also play a role in optimising academic performance (Diseth et al., 2010; Kizilgunes et al., 2009; Purdie & Hattie, 1996; Rautopuro & Väisänen, 2003). Learning practices are methods that a learner uses to improve their understanding, integration, and retention of new information in the learning process (Cross & Steadman, 1996). High achievers report a greater use of learning strategies than low achievers (Andrews, 1990; Dunn et al., 1995; John & Michael, 2018; Klavas, 1994; Pintrich & Schrauben, 1992), although these practices may vary among students (Ablard & Lipschultz, 1998). The use of certain learning practices is said to be related to interest in learning, and thus would improve students' understanding or performance (Brush, 1997; Christou & Dinov, 2010; House, 2003, 2005).

Several research findings which analyze the association between learning practices and performance show that there exists a significant relationship between them (Christou & Dinov, 2010; Hassanbeigi et al., 2011; Montaque & ve Bos, 1990). Zimmerman (1989, 1990) listed some of the self-regulated learning practices which are related to students' academic performance:

1) self-evaluating, i.e., students assessing the quality of their own work
2) organizing and transforming, i.e., students manipulating content to improve their learning
3) goal setting, i.e., students setting large and small related objectives and mapping out a process to achieve them
4) information seeking, i.e., students finding information from academic sources rather than from social resources.

Schau (2003) developed the Survey-of-Attitudes-toward-Statistics (SATS-36) scale to capture and examine students' attitudes towards learning statistics in a course. SATS-36 enables educators to assess which component of students' attitudes would need attention and require improvement. One of the six components, named "effort" consisting of 4 items, measures the amount of time students put in to learn statistics.

Eccles and colleagues (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000; Wigfield et al., 2006), in relation to the expectancy-value theory, too suggest that an individual's expectations for success and subjective task values will influence performance choices, directly or indirectly. Subjective task values refer to the "quality of the task that contributes to the increasing or decreasing probability that an individual will select it" (Eccles, 2005, p. 109). Moreover, if students "have high expectations of success but do not value a task at all (mentally assigning it a "0" value), then [they] will not feel motivated at all. Likewise, if [students] value a task highly but have no expectation of success about completing it (assigning it a "0" expectancy), then [they] also will not feel motivated at all" (Expectancy-Value Theory, n.d.).

Hence, learning practices do have significant influence on students' attitudes towards the lesson which also affect their performance (Çalışkan & Kılınç, 2012; Habók & Magyar, 2018; Sirmaci, 2010; Çetingöz & Özkal, 2009).

A total of 596 students at a Malaysia public university participated in the study voluntarily. The respondents were systematically split into two random halves. The first sub-sample (n_1 = 298) comprised 85% undergraduate students. This sub-sample was used to identify the underlying facets of *sejahtera* living. The second sub-sample (n_2 = 298), also consisting of mainly undergraduate students (79%) was used for cross-validation. The procedure tested the stability and replicability of the underlying factors extracted from the first sub-sample. Cross-validation reduces the prospect of capitalizing on chance in the extraction of reliable and stable factors. The sample size of 298 for each analysis was deemed adequate for an exploratory factor analysis since the number of observations per item exceeded the threshold of 5:1.

Influence of instructors' teaching practices on students' performance, attitudes toward statistics and learning practices.

Past research has demonstrated that students' academic performance is not only influenced by their learning practices but also by the teaching practices of their instructors throughout the course. A number of research has shown that instructors have a substantial impact on students' performance (Chetty et al., 2014; Ganyaupfu, 2013; Yousef, 2017). Teaching practices vary across lecturers—some instructors may prefer direct instructional methods (i.e., lecturing, demonstrating and chalk-and-talk), while others may choose to employ strategies that are more student-centred (i.e., discussion, peer teaching, cooperative learning, etc.). Some instructors may be prone to employing rote learning (i.e., memorizing information), while others may emphasize understanding and the application of knowledge. Research has found that teaching practices both have a positive effect on student performance (Kennedy & Tay, 1994) and are a significant positive correlate of the construct (Onn, 1999).

Teaching basic statistical concepts is indeed a great challenge for many instructors as they need to be able to deliver the concepts in a way that their students can understand, especially at the undergraduate introductory level. A majority of students are exam-oriented; hence, instructors need to explicate the rationale of learning statistics to increase students' motivation to master the knowledge and not only to satisfy the university or course requirements. Instructors should also prioritize the setting of clear objectives around which coherent lessons can be developed so that their teaching can be more effective (Umugiraneza et al., 2018). It is vital that the teaching practices used help students to understand statistical concepts well, so that not only can they perform well in their statistics courses, but they can also develop sound statistical literacy.

Active learning strategies have been shown to develop statistical reasoning in students. These strategies include group projects that require students to design a study, collect and analyze data, interpret their results, write a coherent and well-argued report, and share their findings in an oral presentation (Smith, 1998). It is commonly accepted that students always learn best when they are actively engaged in working on real-world problems (Sole & Weinberg, 2017).

Onwuegbuzie (2000) voiced a valid concern that non-cognitive variables such as students' attitudes, feelings, beliefs and perceptions may counteract the learning atmosphere that statistics instructors attempt to create. Instructors' attention to students' perspectives is needed to make statistics an interesting subject. Ncube and Moroke (2015) listed some recommendations to develop students' learning interest and help them perform better in a statistics course. These include more exercises after each chapter, group assignments and presentations on how statistics can be integrated or applied in a job setting, use of statistical software to solve practical questions, and quizzes. Schau (2003) also noted the importance of student motivation and the need to use statistical thinking and statistical knowledge appropriately. It is very important to instill interest in learning statistics and make students understand statistics thoroughly so that they can perform well. Teaching practices have been found to exert a significant effect on students' attitudes in several studies (Hannafin & Scott, 2001; Kreijns et al., 2007; Meletiou-Mavrotheris et al., 2007). Apart from that, instructors' instructional practices also have been found to affect students' learning practices (Andrews, 1990; Dunn et al., 1995; Klavas, 1994). Felder (1993) established that the alignment between students' learning practices and the instructor's teaching practices leads to better recall and understanding.

Influence of students' attitudes toward statistics on their performance

The attitudes that students show towards learning a subject also have a major impact on their performance (Christou & Dinov, 2010; Evans, 2007). Attitudes as defined by Eagly and Chaiken (2007) is "an individual's propensity to evaluate a particular entity with some degree of favorability or unfavorability" (p. 2). In 1980, Roberts and Bilderback developed the Statistics-Attitudes-Survey (SAS) followed by Wise (1985) who developed the Attitudes-Toward-Statistics (ATS) survey. Both surveys were developed to measure students' attitudes towards statistics. To date, the most widely and commonly used instruments are the SATS-28 and SATS-36 by Schau et. al. (1995) and Schau (2003). The SATS-28 consists of a four-component structure that measures affect, cognitive competence, value, and difficulty. Later two more components were added, which are effort and interest, in the SATS-36.

There is an increasing body of evidence to support the conviction that students' attitudes toward statistics affect their course enrolment, persistence, performance and the overall environment in the class (Hilton et al., 2004). Schau (2003) discovered that students' attitudes toward statistics were positively related to their performance in statistics. Since students' attitudes toward statistics have been shown to be related to student performance in statistics courses (Rosli & Maat, 2017; Saidi & Siew, 2019; Schau et al., 2012; Shultz & Koshino, 1998), it is hence believed that students' negative attitudes toward statistics would present a significant obstacle for their effective learning of statistical content and skills (Mills, 2004).

According to Gal et al. (1997), students' attitudes toward statistics may affect the extent to which they will develop useful statistical thinking skills and apply what they have learned outside the classroom. Presumably, poor attitudes will lead to poor skills. Baker (1988) also argued that in any learning situation, attitudes are considered to be a fundamental or an input variable, as well as an output or outcome variable. Therefore, it is important for researchers to thoroughly study the attitudes students have toward statistics and their relationship with performance so that interventions can be taken to increase their learning of this important course.

METHODOLOGY

Survey Respondents

First year students enrolled in introductory statistical courses from five Malaysian public universities participated in the study. The courses were similar in terms of the syllabus content, and all respondents were exposed to the same basic statistical concepts, with a slight variation in the treatment of the concepts. Students' learning dissimilar concepts were excluded from being included in this study. Subsequently, a total of 416 students from four tertiary institutions made up the sample for this study (UiTM=113, UPM=144, UIA=81, USM=78). Kline (2011) stated that a sample size of 200 or more is necessary to obtain trustworthy results when structural equation modeling (SEM) is used in data analysis. Also the total of 416 students exceeded the recommended sample size for advanced multivariate statistical techniques, such as SEM (Tabachnick & Fidell, 2007).

Research Instruments

This study used five survey instruments that were developed in three phases: (1) item generation and theme development, (2) respondents' feedback and (3) pilot testing. The instruments used are summarized in Table 1:

Table 1
Research Instruments

Instrument	Construct	No of Items	Scaling
1) Students' Perceived Ability in Selected Basic Statistical Concepts Questionnaire (PASQ)	Students' beliefs in their ability to understand and answer questions on statistical concepts	30	5-point agreement scale ranging from Strongly Disagree (1) to Strongly Agree (5).
2) Survey of Attitudes towards Statistics adopted from Schau et al. Vecchio (1995) (SATS)	Students' attitudes towards statistics in four components	28	
3) Instructors' Teaching Practices in Statistics Questionnaire (TPSQ)	Instructor's teaching practices that develop students' conceptual understanding in Statistics	26	
4) Students' Learning Practices in Statistics Questionnaire (LPSQ)	Students' learning practices throughout the statistics course	10	
5) Multiple Choice Questions on statistical concepts (adapted from DelMas et al., 2007) (MCQ30)	Students' statistical competency and conceptual knowledge and understanding of basic statistical concepts.	30	

Data Collection

Permission was sought from the relevant heads of the departments offering the introductory statistics courses. However, only six instructors from four institutions agreed to allow their students to participate in the study, namely Universiti Teknologi MARA Malaysia (UiTM), Universiti Sains Malaysia (USM), Universiti Putra Malaysia (UPM) and the International Islamic University Malaysia (IIUM). The final sample comprised students who enrolled in the following courses: ECON 1140 Statistical Methods (IIUM), MGM3162 Business Statistics (UPM), ACT3111 Statistics for Accounting and Finance (UPM), QMT 181 Introduction to Statistics (UiTM) and MAT 161 Elementary Statistics (USM). These courses included all of the topics tested in the MCQ30—the instrument used in the study to measure students' understanding of statistical concepts (i.e., student performance).

The SATS questionnaire was distributed at the beginning of week 1 of the semester. Students were given 10 minutes to complete the SATS. The PASQ and MCQ30 were distributed in week 7 of the semester, after all the topics had been taught by the instructors. The PASQ and the MCQ30 were administered separately to ensure that neither one influenced students' responses to the other. The PASQ questionnaire was administered first before the test (MCQ30). The total time given for students to complete the questionnaire and the MCQ30 was 40 minutes. The TPSQ and LPSQ were distributed towards the end of the semester at the end of the lesson and the time given was 10 minutes.

Data Analysis Procedure

The MCQ 30 test was measured by the total raw scores based on each correct answer (i.e. 1 mark for a correct answer and 0 mark for an incorrect answer), which were subsequently transformed into interval-scaled person measures using the basic Rasch Model, as implemented by Winsteps version 3.63.

The factorial validity of the model (Figure 1) was established by testing the fit of the measurement model to the data based on goodness-of-fit indices. Three statistical software (SPSS 18.0, AMOS 18.0, and WINSTEPS 3.63.0) were used in the data analysis process. SPSS18.0 was used to analyze the preliminary data and provide demographic information. AMOS 18.0 was used to test the measurement model through Confirmatory Factor Analysis (CFA) and to test the structural model. Each student's responses to the test and questionnaires were checked to make sure that there were no missing values during data entry in SPSS 18.0. Winsteps 3.63.0, a Rasch Model software was used to assess the reliability and validity of the instruments and to generate linear measures in logits (log odd units) to fit the proposed model. Interval scaled person measures were used for all the constructs.

RESULTS

Confirmatory Factor Analysis of the Scales

The Confirmatory Factor Analysis (CFA) for each scale (perceived ability, attitudes, learning practices and teaching practices), shows that the model fit measures of CFI, TLI, GFI, AGFI and RMSEA for *Perceived Ability* and *Attitudes* fail to meet the criteria for good fit (Table 3). Modifications were then made based on the modification index resulted from AMOS. For *Perceived Ability*, the items from *types of data* and *data representation* were combined into one construct, named *data presentations*. For *Attitudes*, item 20 and item 23 (*cognitive competence* items) and item 17 (*difficulty* item) were deleted and the remaining items from *affect* and *cognitive competence* were combined into a single construct, named *affect_cognitive.*

Table 3

Goodness of fit measures for perceived ability, attitudes, learning practices and teaching practices

Goodness of Fit Measures	**P value ($P \geq 0.05$)**	**Ratio (2 or less)**	**CFI (0.90 and above)**	**TLI (0.90 and above)**	**GFI (0.95 and above)**	**AGFI (0.90 and above)**	**RMSEA (0.08 or less)**	**AIC (Smaller values suggest a good fitting)**
Perceived Ability	0.000	10.231	0.987	0.962	0.975	0.873	0.149	36.461
Attitudes	0.000	71.801	0.949	0.848	0.854	0.270	0.413	159.602
Teaching Practices	0.172	1.760	0.999	0.998	0.996	0.979	0.043	19.519
Learning Practices	0.881	0.022	1.000	1.006	1.000	1.000	0.000	10.022

Notes: **Criteria for Fit:** Chi-Square test $P \geq 0.05$; GFI ≥ 0.95; RMSEA ≤ 0.08; AGFI$\geq$ 0.90; CFI$\geq$ 0.90; TLI$\geq$0.90; Relative Chi-Square ≤ 2; AIC -Smaller values suggest a good fitting model

The *Perceived Ability* CFA model and the *Attitudes* CFA model based on the newly modified constructs suggest that both models fit the data well and that the models fail to be rejected. The revised CFA model yielded goodness of fit measures with lower AIC compared to the initial CFA model for both constructs (Table 4). The AIC which is a comparative measure of fit with lower values indicates a better fit and thus, the re-specified model is considered a better model compared to the initial model (Schermelleh-Engel, Moosbrugger & Müller, 2003).

Table 4

Goodness of fit measures for perceived ability and attitudes after modifications

Goodness of Fit Measures	**P value ($P \geq 0.05$)**	**Ratio (2 or less)**	**CFI (0.90 and above)**	**TLI (0.90 and above)**	**GFI (0.95 and above)**	**AGFI (0.90 and above)**	**RMSEA (0.08 or less)**	**AIC (Smaller values suggest a good fitting)**
Perceived Ability	0.529	0.396	1.000	1.002	0.999	0.996	0.000	10.396
Attitudes	0.912	0.012	1.000	1.002	1.000	1.000	0.000	10.012

Having established the best fitting measurement models for all the constructs, the convergent and discriminant validity were calculated to quantify construct validity. Convergent validity of each factor was tested by examining the standardized factor loadings (Table 5). According to Hair et al. (2010), factor loading values more than 0.5 and above 0.7 are considered good for a construct. All the constructs were deemed valid and reliable as they meet the above-given criteria for factor loadings. As all items produced values greater than 0.5 in the analyses conducted (i.e., convergence was achieved), the covariance matrix was assumed to be non-singular and free from multicollinearity.

Convergent validity can also be calculated using the Average Variance Extracted (AVE) as proposed by Fornell and Larcker (1981), where the total of squared multiple correlations are divided by the number of subscales. The guideline is that the AVE value should be greater than 0.5, meaning more than half of the variances are observed (Hair et al., 2010). Examining the AVE values in Table 6, it was found that all of these values are over 0.50. Hence, based on the standardized factor loadings and the AVE calculation, convergent validity was confirmed.

Table 5

Standardized factor loadings and Average variance extracted (AVE) for perceived ability, attitudes, teaching practices and learning practices

Constructs	Items	Standardized Regression Weight (Loadings)	Squared Multiple Correlation	Total Squared Multiple Correlation	Average Variance Extracted (AVE)
Perceived Ability	Data Presentations	0.893	0.798	2.502	0.834
	Measures of Center	0.933	0.870		
	Measures of Spread	0.913	0.834		
Attitudes	Affect_Cognitive	0.981	0.963	2.853	0.951
	Value	0.961	0.923		
	Difficulty	0.983	0.967		
Teaching Practices	Pedagogical Approach	0.948	0.900	3.324	0.831
	Engaging Students in Learning 1	0.957	0.915		
	Engaging Students in Learning 2	0.762	0.580		
	Use of Technology	0.964	0.929		
Learning Practices	Regular Practices	0.905	0.819	1.86	0.62
	Self-Determination	0.645	0.416		
	Source of Reference	0.790	0.625		

The discriminant validity for the four scales was evident as the AVEs were found to be greater than the squared correlations between any two dimensions (Table 6). The squared correlations between *Attitudes* and *Learning Practices* produced a value which is relatively close to the AVE value of *Attitudes* and AVE value of *Learning Practices*, but it is still below the threshold limit. Thus, the discriminant validity for the four scales is supported.

Table 6

Discriminant validity for perceived ability, attitudes, teaching practices and learning practices

Scales	Perceived Ability	Attitudes	Teaching Practices	Learning Practices
Perceived Ability	0.8340			
Attitudes	0.0529	0.9510		
Teaching Practices	0.0010	0.0018	0.8310	
Learning Practices	0.0004	0.5184	0.0135	0.6200

Note: Diagonal values are AVE and off-diagonal values are squared correlations

Assessment of the Assumption of Normality

To test the assumption of normality, the univariate skew and kurtosis were examined using the suggested cut-offs of |3.0| and |10.0|, respectively. The skewness of the items ranged from –0.771 to 0.635 and the values for kurtosis ranged from 0.064 to 4.687. Kline's (2011) suggestion that only variables with skew index absolute values greater than 3 and kurtosis index absolute values greater than 10 are of concern, none of the variables in this analysis has problematic levels of skewness or kurtosis. Thus, the data were sufficiently univariate normally distributed. West, Finch and Curran (1995) recommended concern if skewness is more than 2 and kurtosis is more than 7. If the univariate distributions are nonnormal, then the multivariate distribution will be nonnormal. From the analysis, the univariate skewnesses and kurtoses fall into acceptable ranges of normality (Harlow, 1985).

A Bollen-Stine bootstrap was run in AMOS 16.0 to confirm that the overall model worked satisfactorily. For non-normal data, Bollen-Stine bootstrap can provide the correct p-values for the chi-square statistic to asses overall model fit, rather than the usual maximum likelihood-based p-value to assess overall model fit. Using a conventional significance level of 0.05, the model will be rejected if the p-value is smaller than 0.05. If the p-value is larger than 0.05, the model will not be rejected (the model is accepted, and thus conclusion can be made that the model fit the data well) (Bollen & Long, 1993; Bollen & Stine, 1992). Testing the null hypothesis that the model is correct, using number of bootstrap samples of 500 (Cheung & Lau, 2008), the results yielded Bollen-Stine bootstrap, $p = 0.369$ (Figure 2). This result confirmed that the model was correct and would not be rejected.

Figure 2
Bollen-Stine bootstrap

Bollen-Stine Bootstrap (Default model)

Testing the null hypothesis that the model is correct, Bollen-Stine bootstrap p = .369

Summary of Bootstrap Iterations (Default model)

Iterations	Method 0	Method 1	Method 2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	1	0
5	0	42	0
6	0	198	0
7	0	191	0
8	0	54	0
9	0	14	0
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
Total	0	500	0

0 bootstrap samples were unused because of a singular covariance matrix.
0 bootstrap samples were unused because a solution was not found.
500 usable bootstrap samples were obtained.

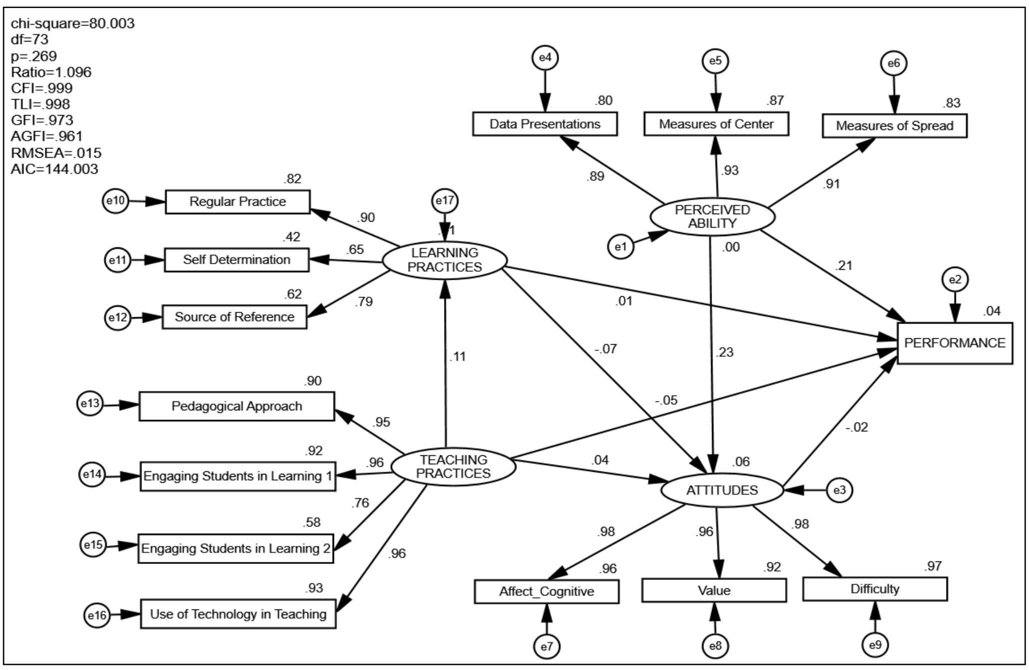
Bootstrap Distributions (Default model)
ML discrepancy (implied vs sample) (Default model)

```
                              |--------------------
                     39.482   |*
                     45.519   |*
                     51.555   |****
                     57.591   |***********
                     63.628   |**************
                     69.664   |****************
                     75.700   |*****************
N = 500              81.737   |************
Mean = 76.755        87.773   |***********
S. e. = .675         93.810   |********
                     99.846   |*****
                    105.882   |****
                    111.919   |***
                    117.955   |*
                    123.992   |*
                              |--------------------
```

Estimation of the Hypothesized Structural Model

Next, the structural model based on the hypotheses was tested. The specified structural model produced a good fit to the data as indicated by the goodness of fit indices (Figure 3). Model fit measures of CFI=0.999, TLI=0.998, GFI=0.973 and the RMSEA=0.015 meet the criteria for fit with p-value equal 0.269. The value of the relative Chi-square (χ^2 /df) equals 1.096 which is less than 2, and the value of the adjusted goodness-of-fit index (AGFI) equals 0.961, which is more than 0.95, also indicated that the model fitted the data well and that the model failed to be rejected.

Figure 3
Structural model (Standardized factor loadings and regression estimates with selected fit indices)



The summary of the hypotheses testing results are shown in Table 7 and the detailed results of the R^2 values (effect size) are shown in Table 8.

The hypotheses being tested in numerical order are the effects of: *Perceived Ability* on *Performance*; *Learning Practices* on *Performance*; *Teaching Practices* on *Performance*; *Attitudes* on *Performance*; *Perceived Ability* on *Attitudes*; *Learning Practices* on *Attitudes*; *Teaching Practices* on *Attitudes*; *Teaching Practices* on *Learning Practices*.

Based on the results in Table 7, it is evident that students' *Perceived Ability* in statistics has a direct effect on students' *Performance* and a direct effect on students' *Attitudes* toward statistics. Instructors' *Teaching Practices* is also positively related to the students' *Learning Practices*. The confidence intervals for these paths do not contain the value zero (Hair et al., 2017). Furthermore, the results of the effect size (Table 8), suggest that *perceived ability* exhibited an acceptable effect size on *Performance* (f^2 =0.0449) and on *Attitudes* (f^2 =0.0541). So does the effect size of *Teaching Practices* on *Learning Practices* (f^2 = 0.0132). These values are all above 0.002.

Cohen (1988) established that the effect size, f^2 values of 0.02, 0.15 and 0.35 are to be classified as small, medium and large. However, Aguinis, Beaty, Boik, and Pierce (2005) identified a median effect size of .002 and has also shown that the average effect size in tests of moderation is only 0.009. Whereas, Kenny (2015) suggests a more realistic but still optimistic standard for effect sizes might be 0.005, 0.01, and 0.025 for small, medium, and large, respectively, given the Aguinis et al. (2005) review. Chin, Marcolin, and Newsted (2003) supported that small effect size is important and can be meaningful. The effect sizes in moderation tests are, on average, lower than those indicated by Cohen (1988), hence the most conservative choice is to use lower effect sizes than expected (Aguinis et al., 2005; Perugini, Gallucci, & Costantini, 2018).

There exists no relationship between students' *Learning Practices* and students' *Attitudes* toward statistics. Instructors' *Teaching Practices* were also found to have no direct effect on students' *Attitudes* toward statistics. The results of confidence intervals, based on the bootstrapping method (subsamples 500) used to analyze the path coefficient significance further confirm on the findings (Davison & Hinkley, 1997; Efron & Tibshirani, 1993; Hair et al., 2017).

Table 7

Results of Hypothesis Testing

Hypothesis	Structural Relation	Standard Regression Weights	t-value	Confidence Intervals		p-value
				2.5%	97.5%	
H1	Performance ← Perceived Ability*	0.206	4.023	0.105	0.287	0.000
H2	Performance ← Learning Practices	0.007	0.137	-0.093	0.096	0.891
H3	Performance ← Teaching Practices	-0.047	-0.958	-0.143	0.088	0.338
H4	Performance ← Attitudes	-0.019	-0.381	-0.103	0.077	0.704
H5	Attitudes ←Perceived Ability**	0.228	4.589	0.122	0.32	0.000
H6	Attitudes ←Learning Practices	-0.068	-1.306	-0.15	0.045	0.192
H7	Attitudes ←Teaching Practices	0.041	0.832	-0.054	0.137	0.405
H8	Learning Practices ←Teaching Practices *	0.114	2.140	0.018	0.214	0.032

Note: t-value >2.58 (p-value <0.01**), t-value >1.96 (p-value <0.05*)

Table 8
Effect Size

Structural Relation	R^2 included	R^2 excluded	f^2	f^2 (Cohen, 1988)	f^2 (Aguinis et al., 2005)	f^2 (Kenny, 2015)
Performance ← Perceived Ability	0.043	0.000	0.0449	Small	Medium	Large
Performance ← Learning Practices	0.043	0.043	0.0000	None	None	None
Performance ← Teaching Practices	0.043	0.040	0.0031	None	None	None
Performance ← Attitudes	0.043	0.043	0.0000	None	None	None
Attitudes ←Perceived Ability	0.058	0.007	0.0541	Small	Medium	Large
Attitudes ←Learning Practices	0.058	0.054	0.0042	None	None	None
Attitudes ←Teaching Practices	0.058	0.057	0.0011	None	None	None
Learning Practices ←Teaching Practices	0.013	0.000	0.0132	None	Medium	Medium

DISCUSSION

There are many studies that focused on the teaching and learning of statistics over the years as statistics education is fast becoming a research area of increasing interest among researchers. The importance of developing students' statistical literacy at the undergraduate level remained the primary issue discussed across the globe. This study, sought to determine the influence of students' learning practices, lecturers' teaching practices, students' perceived ability, students' attitudes towards statistics on students' conceptual understanding of basic statistical concepts as measured by their performance on a 30-item MCQ test.

The results of analysis showed that students' perceived ability has a direct and positive effect on students' performance in basic statistical concepts. Several studies support this finding, which showed that students' perceived ability is associated with performance (House, 2006; Jaiswal & Choudhuri, 2017; Lenaburg, 2007; Lynch, 2002; Obilor, 2012; Tenaw, 2013). Students' perceived ability or self-efficacy influences the tasks students choose to learn and the goals they set for themselves. Perceived ability also affects students' level of effort and persistence when learning difficult tasks. If they hold the belief that they are able to accomplish a particular task, they will be more likely to attempt and persist in that task (Schmidt & Shumow, 2011).

Students' perceived ability was also found to have a direct effect on students' attitudes towards statistics. This finding coincides with the studies by Dempster and McCorry (2009), and Kloosterman et al. (1996) who found strong support for the relationship between students' perceived ability and their attitudes where there exists a relation between students' attitude and their perceived ability at the beginning of the course and that certain beliefs do motivate or demotivate students. Hence, students' perceived ability has implications on their motivation levels and performance.

Self-efficacy or perceived ability and attitudes are factors that have been found to be related to students' performance. Conversely, in this study, attitudes have no direct relationship with students' performance in understanding basic statistical concepts. The finding concerning the relationship of attitudes and performance were contrary to the findings of some previous studies (Chiesi & Primi, 2010; Christou & Dinov, 2010; Sorge & Schau, 2002; Tremblay, Gardner, & Heipel, 2000). Conflicting results might be due to differences in the population of interest (i.e. American sample would produce different findings from an Asian sample).

Learning practices include effort regulation, help seeking, and peer learning (Nisbet & Shucksmith, 1986; Pintrich, 2000) as well as task absorption (Elliot, Murayama, & Pekrun, 2011) to enhance student learning. According to the empirical data garnered in this study, learning practices are not directly related to students' attitudes towards students' performance in basic statistical concepts. This finding is also contrary to the findings of previous studies by Brush (1997) and House (2003, 2005). In few studies, learning practices has been found to be positively related to performance (Christou & Dinov, 2010; Diseth et al., 2010; Hassanbeigi et al., 2011; Pintrich, Smith, Garcia, & McKeachie, 1993). Onwuegbuzie (2001) discovered that learning practices does affect students' performance where students who prefer to learn in a co-operative learning groups do not perform well compared to their counterparts. However, from this study, students' learning practices were found to have no direct influence on students' performance in basic statistical concepts which was in line with studies conducted by Rautopuro and Väisänen (2003), Awang, Abd Samad, Mohd Faiz, Roddin, and Kankia (2017) and Gappi (2013). Different instrumentation and differences in the way variables are measured for the learning practices would have caused the difference in the findings.

Results from the analysis also showed that teaching practices do not have a direct influence on students' attitudes and their performance in basic statistical concepts. This contradicts previous studies by Yousef (2017), Ganyaupfu (2013), Brush (1997), Diseth, Pallesen, Brunborg, and Larsen (2010), and Onn (1999) where there exists a relationship between teaching practices and performance. Teaching practices was also found to have no effect on students' attitudes and were contrary to the findings of previous studies (Hannafin & Scott, 2001; Kreijns et al., 2007; Meletiou-Mavrotheris et al., 2007). The differences in respondents' characteristics, settings and research instruments are postulated to play a role to the differing findings. Nonetheless, it was found that teaching practices do affect students' learning practices. Previous research also shows that teaching practices that match students' learning practices can improve their performance significantly while a mismatch can result in poor students' performance (Andrews, 1990; Dunn, Griggs, Olson, Gorman, & Beasley, 1995; Giordano & Rochford, 2005; Klavas, 1994).

Future research should consider examining the impact of learning practices on students' perceived ability and the impact of teaching practices on students' perceived ability, as perceived ability is related to both attitudes and performance.

CONCLUSION

In recent years, there has been extensive research regarding students' understanding of basic statistical concepts for the development of statistical thinking, statistical literacy and statistical reasoning (Chance, DelMas & Garfield, 2004; Chance, 2002; DelMas, 2002; Gal, 2002; Garfield, 1995, 1999; Wild & Pfannkuch, 1999). This study examined the influence of students' learning practices, lecturers' teaching practices, students' perceived ability, and students' attitudes towards statistics on their understanding of basic statistical concepts. Results from the analysis provide some empirical evidence that students' understanding in basic statistical concepts is mainly associated with their perceived ability, rather than their attitudes, learning practices and instructors' teaching practices. In other words, students with low self-efficacy levels had low test scores; while students with high self-efficacy levels performed better on the test. Students' attitudes are influenced by their perceived ability while teaching practices do affect learning practices. Students who perceived greater ability, have a higher sense of their own competency in the task given and have more positive attitudes toward learning statistics.

Nonetheless, further understanding of students' learning practices and instructors' teaching practices are needed to improve students' understanding of basic statistical concepts and their performance in statistics, particularly. Future research should examine students' perceived attitude, understanding and ability in introductory statistical concepts through a longitudinal study, to better understand the relationships between these constructs. It is also recommended that the instruments used in this study – MCQ30, PASQ, LPSQ and TPSQ – be administered to other similar populations to determine the generalizability of the instruments in measuring the target constructs. Future research should also include qualitative data collection methods to enhance the quantitative findings as qualitative approaches would give a complementary view of the learning and teaching of statistics.

REFERENCES

Abd Hamid, H. S., & Sulaiman, M. K. (2014). Statistics anxiety and achievement in a statistics course among psychology students. *International Journal of Behavioral Science*, *9*(1), 55–66.

Ablard, K., & Lipschultz, R. E. (1998). Self-regulated learning in high-achieving students: relations to advanced reasoning, achievement goals, and gender. *Journal of Educational Psychology*, *90*(1), 94–101.

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect Size and Power in Assessing Moderating Effects of Categorical Variables Using Multiple Regression: A 30-Year Review. *Journal of Applied Psychology*, *90*(1), 94–107. https://doi.org/https://doi.org/10.1037/0021-9010.90.1.94

American Statistical Association. (2005). *Guidelines for Assessment and Instruction in Statistics Education College Report*. *GAISE College Report*. Retrieved from http://www.amstat.org/education/gaise/

Andrews, R. H. (1990). The development of a learning styles program in a low socioeconomic, underachieving North Carolina elementary school. *Journal of Reading, Writing, and Learning Disabilities International*, *6*, 307–314.

Araki, L. T., & Shultz, K. S. (1995). *Student attitudes toward statistics and their retention of statistical concepts*. Paper presented at the annual meeting of the Western Psychological Association, Los Angeles.

Ariffin, I., Solemon, B., Md. Din, M., & Md. Anwar, R. (2014). Learning Style and Course Performance: An Empirical Study of Uniten it Students. *International Journal of Asian Social Science, Asian Economic and Social Society*, *4*(2), 208–216.

Awang-Hashim, R., O'Neil Jr, H. F., & Hocevar, D. (2002). Ethnicity, effort, self-efficacy, worry, and statistics achievement in Malaysia: A construct validation of the state-trait motivation model. *Educational Assessment*, *8*(4), 341–364. https://doi.org/10.1207/S15326977EA0804_3

Awang, H., Abd Samad, N., Mohd Faiz, N. S., Roddin, R., & Kankia, J. D. (2017). Relationship between the Learning Styles Preferences and Academic Achievement. In *IOP Conf. Series: Materials Science and Engineering*. Retrieved from http://iopscience.iop.org/article/10.1088/1757-899X/226/1/012193/pdf

Baker, C. (1988). *Key Issues in Bilingualism and Bilingual Education*. Clevedon: Multilingual Matters.

Bakker, A. and Gravemeijer, K. (2004). Learning to reason about distribution. In D. Ben-Zvi and J. Garfield (Ed.), *The Challenge of Developing Statistical Literacy, Reasoning, and Thinking* (pp. 147–168). Dordrecht, The Netherlands: Kluwer.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: W. H. Freeman.

Ben-Zvi, D. (2004). Reasoning about data analysis. In D. Ben-Zvi and J. Garfield (Ed.), *The Challenge of Developing Statistical Literacy, Reasoning, and Thinking* (pp. 121–146). Dordrecht, Netherlands: Kluwer.

Ben-Zvi, D., & Garfield, J. (Eds.). (2004). Goals, Definitions, And Challenges. In D. Ben-Zvi & J. Garfield (Eds.), *The challenge of developing statistical literacy, reasoning and thinking*. Dordrecht, The Netherlands: Dordrecht, The Netherlands: Kluwer Academic Publishers.

Bollen, K. A., & Long, J. S. (1993). *Testing structural equation models*. Newbury Park, California: Sage.

Bollen, K. A., & Stine, R. A. (1992). Bootstrapping goodness-of-fit measures in structural equation models. *Sociological Methods and Research, 21,* 205–229.

Braham, H. M., & Ben-Zvi, D. (2017). Students' emergent articulations of statistical models and modeling in making informal statistical inferences. *Statistics Education Research Journal*, *16*(2), 116–143. Retrieved from https://iase-web.org/documents/SERJ/SERJ16(2)_ManorBraham.pdf

Broers, N. J. (2001). Analyzing Propositions Underlying the Theory of Statistics. *Journal of Statistics Education V*, *9*(3).

Brush, T. A. (1997). The effects on student achievement and attitudes when using integrated learning systems with cooperative pairs. *Educational Technology Research and Development*, *45*, 51–64.

Bude, L. (2006). Assessing students' understanding of statistics. In A. Rossman and B. Chance (Ed.), *Proceedings of the Seventh International Conference on Teaching Statistics*. Voorburg, The Netherlands: International Statistical Institute.

Bude, Luc, Wiel, V. De, J., M. W., Imbos, T., Candel, M. J. J. M., Broers, N. J., & Berger, M. P. F. (2007). Students' Achievements in a Statistics Course in Relation to Motivational Aspects and Study Behaviour Statistics Education Research Journal, v6 n1 p5-21 May 2007. *Statistics Education Research Journal*, *6*(1).

Çalışkan, H., & Kılınç, G. (2012). The Relationship Between the Learning Styles of Students and Their Attitudes Towards Social Studies Course. *Procedia - Social and Behavioral Sciences*, *55*, 47–56. https://doi.org/10.1016/j.sbspro.2012.09.476

Callingham, R., Carmichael, C., & Watson, J. M. (2016). Explaining Student Achievement: the Influence of Teachers' Pedagogical Content Knowledge in Statistics. *Int J of Sci and Math Educ*, *14*, 1339–1357. https://doi.org/https://doi.org/10.1007/s10763-015-9653-2

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, *56*, 81–105.

Çetingöz, D., & Özkal, N. (2009). Learning strategies used by unsuccessful students according to their attitudes towards social studies courses. *Procedia Social and Behavioral Sciences, 1*, 1905–1913.

Chance, B., DelMas, R., & Garfield, J. (2004). Reasoning about sampling distributions. In D. Ben-Zvi & J. Garfield (Eds.), *The Challenge of Developing Statistical Literacy, Reasoning, and Thinking* (pp. 295–323). Dordrecht, The Netherlands: Kluwer.

Chance, B. L. (2002). Components of Statistical Thinking and Implications for Instruction and Assessment. *Journal of Statistics Education*, *10*(3).

Cheung, G. W., & Lau, R. S. (2008). Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organizational Research Methods*, *11*(2), 296–325.

Chiesi, F., & Primi, C. (2010). Cognitive and non-cognitive factors related to students' statistics achievement. *Statistics Education Research Journal*, *9*(1), 6–26. Retrieved from http://www.stat.auckland.ac.nz/~iase/serj/SERJ9(1)_Chiesi_Primi.pdf

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189–217.

Christou, N., & Dinov, I. D. (2010). A Study of Students' Learning Styles, Discipline Attitudes and Knowledge Acquisition in Technology-Enhanced Probability and Statistics Education. *MERLOT Journal of Online Learning and Teaching*, *6*(3).

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Colman, A. M., Norris, C. E., & Preston, C. C. (1997). Comparing rating scales of different lengths: Equivalence of scores from 5-point and 7-point scales. *Psychological Reports*, *80*, 355–362.

Crooks, N. M., Bartel, A. N., & Alibali, M. W. (2019). Conceptual knowledge of confidence intervals in psychology undergraduate and graduate students. *Statistics Education Research Journal*, *18*(1), 46–62.

Cross, R. C., & Steadman, M. H. (1996). *Classroom research: Implementing the scholarship of teaching*. San Francisco: Jossey-Bass Publishers.

Dauphinee, T. L., Schau, C., and Stevens, J. J. (1997). Survey of attitudes toward statistics: Factor structure and factorial invariance for women and men. *Structural Equation Modeling*, *4*, 129–141.

Davison, A. C., & Hinkley, D. V. (1997). *Bootstrap Methods and Their Application*. Cambridge University Press: Cambridge.

delMas, R., Garfield, J., and Chance, B. (1999). A model of classroom research in action: Developing simulation activities to improve students' statistical reasoning. *Journal of Statistics Education*, *7*(3). Retrieved from http://www.amstat.org/publications /jse/secure/v7n3/delmas.cfm

DelMas, R. C. (2002). Statistical Literacy, Reasoning, and Learning. *Journal of Statistics Education*, *10*(3).

DelMas, R. C., Garfield, J., Ooms, A., & Chance, B. (2007). Assessing students' conceptual understanding after a first course in statistics. *Statistics Education Research Journal*, *6*(2), 28–58.

DelMas, R., & Liu, Y. (2005). Exploring students' conceptions of the standard deviation. *Statistics Education Research Journal*, *4*(1), 55–82. Retrieved from http://www.stat. auckland.ac.nz/~iase/serj/SERJ4(1)_delMas_Liu.pdf

Dempster, M., & McCorry, N. K. (2009). The role of previous experience and attitudes toward statistics in statistics assessment outcomes among undergraduate psychology students. *Journal of Statistics Education*, *17*(2). Retrieved from http://www.amstat.org /publications/jse/v17n2/dempster.html

Dillman, D. A., Smyth, J. D. & Christian, L. M. (2009). *Internet, mail and mixed-mode surveys: The tailored design method*. Hoboken, N.J.: John Wiley & Sons.

Diseth, Ã., Pallesen, S., Brunborg, G., and Larsen, S. (2010). Academic achievement among first semester undergraduate psychology students: the role of course experience, effort, motives and learning strategies. *Higher Education*, *59*(3).

Dunn, R., Griggs, S. A., Olson, J., Gorman, B., & Beasley, M. (1995). A meta-analytic validation of the Dunn and Dunn model of learning-style preferences. *Journal of Educational Research*, *88*, 353–361.

Dutton, J., & Dutton, M. (2005). Characteristics and Performance of Students in an Online Section of Business Statistics. *Journal of Statistics Education*, *13*(3). https://doi.org/ 10.1080/10691898.2005.11910564

Eccles, J. S. (2005). Subjective task values and the Eccles et al. model of achievement related choices. In A. J. Elliott & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105–121). New York: Guilford.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*, 109–132.

Efron, B., & Tibshirani, R. J. (1993). *An Introduction to the Bootstrap*. Chapman Hall: New York.

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3 × 2 Achievement Goal Model. *Journal of Educational Psychology, 103*, 632–648.

Elmore, P. B., Lewis, E. L., & Bay, M. L. G. (1993). *Statistics achievement: A function of attitudes and related experiences*. Paper presented at the annual meeting of the American Educational Research Association, Atlanta, GA.

Emmioğlu, E. (2011). *The relationship between mathematics achievement, attitudes toward statistics,and statistics outcomes: A structural equation model analysis*. Unpublished doctoral dissertation. Middle East Technical University.

Estrada, A., Batanero, C., Fortuny, J. M., & Diaz, C. (2005). A structural study of future teachers' attitudes towards statistics. In *Proceedings of the 4th Conference of the European Society for Research in Mathematics Education*.

Evans, B. (2007). Student Attitudes, Conceptions, and Achievement in Introductory Undergraduate College Statistics. *The Mathematics Educator 2007*, *17*(2), 24–30.

Expectancy-Value Theory. (n.d.). Retrieved from https://courses.lumenlearning.com/edpsy/ chapter/expectancy-value-theory/

Felder, R. M. (1993). Reaching the second tier: Learning and teaching styles in college science education. *Journal of College Science Teaching*, *23*(5), 286 – 290.

Findley, K., & Lyford, A. (2019). Investigating Students' Reasoning about Sampling Distributions Through a Resource Perspective. *Statistics Education Research Journal*, *18*(1), 26–45. Retrieved from http://iase-web.org/documents/SERJ/SERJ18(1)_Findley.pdf?1558844313

Finney, S. J., & Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary Educational Psychology*, *28*, 161–186.

Fitzmaurice, O., Leavy, A. M., & Hannigan, A. (2014). Why is statistics perceived as difficult and can practice during training change perceptions? Insights from a prospective mathematics teacher. *Teaching Mathematics and Its Applications*, *33*(4). https://doi.org/10.1093/teamat/hru010

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

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

Gal, I., Ginsburg, L., & Schau, C. (1997). Monitoring attitudes and beliefs in statistics education. In I. Gal & J. B. Garfield (Eds.), *The assessment challenge in statistics education* (pp. 37–51). Voorburg, Netherlands: IOS Press.

Ganyaupfu, E. M. (2013). Factors influencing academic achievement in quantitative courses among business students of private higher education institutions Journal of Education and Practice, Vol. 4 No. 15, pp. 57-65. *Journal of Education and Practice*, *4*(15), 57–65.

Gappi, L. L. (2013). Relationships Between Learning Style Preference and Academic Performance of Students. *International Journal of Educational Research and Technology*, *4*(2), 70–76.

Garfield, J. (1995). How students learn statistics. *International Statistical Review*, *63*, 25–34.

Garfield, J. (1999). Thinking about Statistical Reasoning, Thinking, and Literacy. In *Paper presented at First Annual Roundtable on Statistical Thinking, Reasoning, and Literacy*.

Garfield, J. (2002). The Challenge of Developing Statistical Reasoning. *Journal of Statistics Education*, *10*(3). Retrieved from www.amstat.org/publications/jse/v10n3/garfield.html

Garfield, J., Hogg, B., Schau, C., & Whittinghill, D. (2002). First Courses in Statistical Science: The Status of Educational Reform Efforts. *Journal of Statistics Education, 10*(2).

Giordano, J., & Rochford, R. A. (2005). Understanding Business Majors' Learning Styles. *The Community College Enterprise*, *11*(2), 21–39.

Goulão, M. F. (2014). The relationship between self-efficacy and academic achievement in adult' learners. *Athens Journal of Education*, *1*(3), 237–246.

Gundlach, E., Andrew, K., Richards, R., Nelson, D., & Levesque-Bristol, C. (2015). A Comparison of Student Attitudes, Statistical Reasoning, Performance, and Perceptions for Web-Augmented Traditional, Fully Online, and Flipped Sections of a Statistical Literacy Class. *Journal of Statistics Education*, *23*(1). https://doi.org/10.1080/10691898.2015.11889723

Habók, A., & Magyar, A. (2018). The effect of language learning strategies on proficiency, attitudes and school achievement doi: 10.3389/fpsyg.2017.02358. *Frontiers in Psychology*, *8*(2358). https://doi.org/https://doi.org/10.3389/fpsyg.2017.02358

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis* (7th ed.). New York: Pearson.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (Second). Sage: Thousand Oaks.

Hammerman, J. K., & Rubin, A. (2004). Strategies for managing statistical complexity with new software tools. *Statistics Education Research Journal*, *3*(2), 17–41.

Hannafin, R. D., & Scott, B. N. (2001). Teaching and learning with dynamic geometry programs in student-centered learning environments: A mixed method inquiry. *Computers in the Schools, 17*, 121–141.

Harlow, L. L. (1985). *Behavior of Some Elliptical Theory Estimators with Non-Normality Data in a Covariance Structures Framework: A Monte Carlo Study*. PhD dissertation. University of California, Los Angeles.

Harvey, A. L., Plake, B. S., & Wise, S. L. (1985). *The validity of six beliefs about factors related to statistics achievement*. Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Hassanbeigi, A., Askari, J., Nakhjavani, M., Shirkhoda, S., Barzegar, K., Mozayyan, M. R., & Fallahzadeh, H. (2011). The relationship between study skills and academic performance of university students. *Procedia-Social and Behavioral Sciences*, *30*, 1416 – 1424.

Hedges, S. (2017). Statistics Student Performance and Anxiety: Comparisons in Course Delivery and Student Characteristics. *Statistics Education Research Journal*, *16*(1), 320–336.

Hiebert, J., & Lefevre, P. (1986). Conceptual and Procedural Knowledge in Mathematics: An Introductory Analysis. In J. Hiebert (Ed.)*, in Conceptual and Procedural Knowledge: The Case of Mathematics* (pp. 1–27). Hillsdale: NJ: Lawrence Erlbaum Associates.

Hoegler, S., & Nelson, M. (2018). The Influence of Anxiety and Self-Efficacy on Statistics Performance: A Path Analysis. *Journal of Psychological Research*, *23*(5), 364–375. https://doi.org/10.24839/2325-7342.JN23.5.364

House, J. D. (2003). The motivational effects of specific instructional strategies and computer use for mathematics learning in Japan: Findings from the Third International Mathematics and Science Study (TIMSS). *International Journal of Instructional Media*, *30*, 77–95.

House, J. D. (2005). Motivational qualities of instructional strategies and computer use for mathematics teaching in Japan and the United States: Results from the TIMSS 1999 assessment. *International Journal of Instructional Media*, *32*, 89–104.

House, J. D. (2006). Mathematics Beliefs and Achievement of Elementary School Students in Japan and the United States: Results From the Third International Mathematics and Science Study. *The Journal of Genetic Psychology*, *167*(1), 31–45.

Huberty, C. J., Dresden, J., & Bak, B. (1993). Relations among dimensions of statistical knowledge. *Educational and Psychological Measurement*, *53*, 523–532.

Jaiswal, S. K., & Choudhuri, R. (2017). Academic Self Concept and Academic Achievement of Secondary School Students. *American Journal of Educational Research*, *5*(10), 1108–1113. Retrieved from https://www.researchgate.net/publication/321215133_Academic_Self_Concept_and_Academic_Achievement_of_Secondary_School_Students

Kennedy, P., & Tay, R. (1994). Students' performance in economics: Does the norm hold across cultural and institutional settings? *Journal of Economic Education, 25*(4), 291–301.

Kenny, D. A. (2015). Moderation.

Kizilgunes, B., Tekkaya, C., & Sungur, S. (2009). Modeling the relations among students' epistemological beliefs, motivation, learning approach and achievement , 243-2. *The Journal of Educational Research*, *102*, 243–256.

Klavas, A. (1994). In Greensboro, North Carolina: Learning style program boosts achievement and test scores. *The Clearing House*, *67*, 149–151.

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (Third). New York: The Guilford Press.

Kloosterman, P., Raymond, A., & Emenaker, C. (1996). Students' beliefs about mathematics: A Three Year Study. *The Elementary School Journal*, *97*, 40–56.

Konold, C., & Higgins, T. L. (2003). Reasoning about data. In J. Kilpatrick, W. G. Martin, & D. Schifter (Eds.), *A research companion to Principles and Standards for School Mathematics* (pp. 193–215). Reston, VA: National Council of Teachers of Mathematics.

Kreijns, K., Kirschner, P. A., Jochems, W., & van Buuren, H. (2007). Measuring perceived sociability of computer-supported collaborative learning environments. *Computers & Education*, *49*, 176–192.

Lampert, J. N. (2007). *The Relationship Of Self-Efficacy and Self-Concept To Academic Performance In A College Sample: Testing Competing Models and Measures (Master's thesis, Pacific University)*. Retrieved from https://common s.pacificu.edu/spp/86%0A

Lane, A. M., Hall, R., & Lane, J. (2004). Self-efficacy and statistics performance among Sport Studies students. *Teaching in Higher Education, 9*(4), 435–448. https://doi.org/DOI: 10.1080/1356251042000252372

Lenaburg, L. A. (2007). *Predicting student performance in introductory statistics using a measure of perception of cognitive competence in statistics: An analysis using Bayesian networks*. Doctoral dissertation. Uniersity of California, Santa Barbara.

Leppink, J. (2016). Helping medical students in their study of statistics: A flexible approach. *Journal of Taibah University Medical Sciences*. Retrieved from https://reader.elsevier.com/reader/sd/pii/S1658361216300816?token=664C89780823CEFC8E4B93807B4F6B37E8B0573E8840DEBD0F2151E665269290C8B0AA76B63A4650CD4018D094116A89

Linacre, J. M. (2006). *A User's Guide to WINSTEPS Rasch-Model Computer Programs*. Chicago: MESA Press.

Lynch, J. (2002). Parents' self-efficacy beliefs, parents' gender, children's reader self-perceptions, reading achievement, and gender. *Journal of Research in Reading*, *25*, 54–67.

Mahmud, Z., Ismail, N. Z., Kassim, N. L., & Zainol, M. S. (2018). The Effects of Attitudes towards Statistics, Perceived Ability, Learning Practices and Teaching Practices on Students' Performance in Statistics: A Review. *Journal of the International Institute of Islamic Thought and Civilization*, *24*(1), 71–98.

Malhotra, N. K. (2004). *Marketing research: An applied orientation* (4th ed.). Upper Saddle River, NJ: Prentice Hall.

Mathews, D., & Clark, J. (1997). Successful students' conceptions of mean, standard deviation, and the Central Limit Theorem. In *Paper presented at the Midwest Conference on Teaching Statistics*. Oshkosh, WI.

Meletiou-Mavrotheris, M., Lee, C., & Fouladi, R. T. (2007). Introductory statistics, college student attitudes and knowledge a a qualitative analysis of the impact of technology-based instruction. *International Journal of Mathematical Education in Science and Technology*, *38*, 65–83.

Mills, J. (2004). Students' attitudes toward statistics: Implications for the future. *College Student Journal*, *38*(3), 349–362.

Monroe, S, Moreno, A., and Segall, M. (2011). Student Performance Determinants in a Business Statistics Course at a Large Urban Institution. In *he Academic and Business Research Institute Conference Proceedings*. Las Vegas, NV.

Montaque, M., & ve Bos, C. (1990). Cognitive and metacognitive characteristics of eight grade student's mathematical problem solving. *Learning and Individual Differences*, *2*, 371–388.

Naccache, H. S. (2012). *Factors Related to Student Performance in Statistics Courses in Lebanon*. The University of Southern Mississippi.

Ncube, B., & Moroke, N. D. (2015). Students' Perceptions and Attitudes Towards Statistics in South African University: An Exploratory Factor Analysis Approach. *Journal of Governance and Regulation*, *4*(3). Retrieved from https://repository.nwu.ac.za/bitstream/handle/10394/25999/2015Students_perceptions.pdf?sequence=1&isAllowed=y

Nisbet, J., & Shucksmith, J. (1986). *Learning Strategies*. London: Routledge Education Books.

Norhayati Baharun, & Porter, A. (2009). Removing the angst from statistics. In *Paper presented at the 5th Asian Mathematical Conference 2009*. Kuala Lumpur, Malaysia.

Obilor, I. E. (2012). Relationship Between Self-Concept and Mathematics Achievement of Senior Secondary Students in Port Harcourt. *Journal Plus Education*, *8*(1). Retrieved from http://www.uav.ro/jour/index.php/jpe/article/download/928/988

Onn, A. (1999). *A study of factors affecting students' performance in 6th form accounting paper*. Master thesis. University of Malaya.

Onwuegbuzie, A. J. (2000). Statistics anxiety and the role of self-perception. *Journal of Educational Research*, *93*, 323–335.

Onwuegbuzie, A. J. (2001). Relationship Between Peer Orientation and Achievement in Cooperative Learning. *Journal of Educational Research*, *94*(3), 164–170.

Onwuegbuzie, A. J. (2003). Modeling Statistics achievement among graduate students. *Educational and Psychological Measurement*, *63*(6), 1020–1038.

Onyeizugbo, E. U. (2010). Self-Efficacy and test anxiety as correlates of academic performance. *Educational Research*, 477–480. Retrieved from http://www.interes journals.org/ER%0A

Pagani, L., & Seghieri, C. (2002). A statistical analysis of teaching effectiveness from students' point of view. *Metodološki Zvezki - Advances in Methodology and Statistics*, *17*.

Perugini, M., Gallucci, M., & Costantini, G. (2018). A Practical Primer To Power Analysis for Simple Experimental Designs. *International Review of Social Psychology*, *31(1)*(20), 1–23,. https://doi.org/DOI: https://doi.org/10.5334/irsp.181

Pintrich, P. R. (2000). The Role of Goal-Orientation in Self-Regulated Learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451–502). San Diego, CA: Academic Press.

Pintrich, P. R., & Schrauben, B. (1992). Students' motivational beliefs and their cognitive engagement in classroom tasks. In D. H. Schunk & J. Meece (Eds.), *Student perceptions in the classroom: Causes and consequences* (pp. 149–183). Hillsdale, NJ: Lawrence Erlbaum Associates.

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and Predictive Validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*, 801–813.

Purdie, N., & Hattie, J. (1996). Cultural differences in the use of strategies for self-regulated learning. *American Educational Research Journal*, *33*(4), 845–871.

Radhakrishna, R. B. (2007). Tips for developing and testing questionnaires/instruments. *Journal of Extension*, *45*(1).

Rautopuro, J., & Väisänen, P. (2003). "I did it my way". The impact of learning styles and strategies on students' success in quantitative research methods in educational sciences. In *European Conference on Educational Research*. University of Hamburg.

Reid, J. M. (1987). The learning style preferences of ESL students. *TESOL Quarterly*, *21*, 87–111.

Roberts, D. M., & Bilderback, E. W. (1980). Reliability and validity of a statistics attitude survey. *Educational and Psychological Measurement*, *40*(1), 235–238.

Rochelle, C. F., & Dotterweich, D. (2007). Student success in business statistics. *Journal of Economics and Finance Education, Vol. 6, No. 1, Pp. 19-24.*

Rosli, M. K., & Maat, S. M. (2017). Attitude towards statistics and performance among post-graduate students. In *Proceedings of the International Conference on Education, Mathematics and Science 2016, ICEMS 2016, in conjunction with 4th International Postgraduate Conference on Science and Mathematics 2016, IPCSM2016*. American Institute of Physics Inc.

Rumsey, D. J. (2002). Statistical Literacy as a Goal for Introductory Statistics Courses. *Journal of Statistics Education.*, *10*(3).

Saidi, S. S., & Siew, N. M. (2019). Assessing Students' Understanding of the Measures of Central Tendency and Attitude towards Statistics in Rural Secondary Schools. *International Electronic Journal of Mathematics Education*, *14*(1), 73–86.

Saldanha, L. A. and Thompson, F. W. (2001). Students' reasoning about sampling distributions and statistical inference. In R. S. & C. Maher (Ed.), *Proceedings of The Twenty-Third Annual Meeting of the North American Chapter of the International Group for the Psychology of Mathematics Education* (pp. 449–454). Snowbird, Utah. Columbus, Ohio: ERIC Clearinghouse.

Schau, C., Stevens, J., Dauphinee, T., & Del Vecchio, A. (1995). The development and validation of the Survey of Attitudes Toward Statistics. *Educational & Psychological Measurement*, *55*(5), 868–876.

Schau, C. (1999). Survey of Attitudes Toward Statistics (SATS). Retrieved from http://www.evaluationandstatistics.com/sitebuildercontent/sitebuilderfiles/sats28pre.pdf

Schau, C. (2003). Students' attitudes: The "other" Important outcome in statistics education. In *2003 ASA Proceedings:Papers presented at the American Statistical Association Joints Statistical Meetings.* Alexandria, VA: American Statistical Association, Section on Statistical Education.

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

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research Online*, *8*(2), 23–74.

Schmidt, J. A., & Shumow, L. (2011). *Perceived Competence and Subjective Experience of Ninth Graders vs. Other High School Students in Science*. Paper presented at the annual meetings of the American Educational Research Association. New Orleans, LA.

Semukono, F., Orobia, L. A., & Arinaitwe, A. (2013). Learning Environment, Students' Attitude and Performance in Quantitative Course Units: A Focus on Business Students. *Journal of Education and Vocational Research*, *4*(8), 238–245.

Shultz, K. S., & Koshino, H. (1998). Evidence of reliability and validity for Wise's attitude toward statistics scale. *Educational and Psychological Measurement*, *82*(1), 27–31.

Sirmaci, N. (2010). The relationship between the attitudes towards mathematics and learning styles. *Procedia Social and Behavioral Sciences*, *9*, 644–648.

Smith, G. (1998). Learning Statistics by Doing Statistics. *Journal of Statistics Education*, *6*(3). https://doi.org/10.1080/10691898.1998.11910623

Sole, M. A., & Weinberg, S. L. (2017). What's Brewing? A Statistics Education Discovery Project. *Journal of Statistics Education*, *25*(3), 137–144. https://doi.org/10.1080/10691898.2017.1395302

Sorge, C., & Schau, C. (2002). Impact of Engineering Students' Attitudes on Achievement in Statistics: A Structural Model. In *American Educational Research Association*. New Orleans. Retrieved from http://evaluationandstatistics.com/AERA2002.pdf

Tabachnick, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics* (5th ed.). New York: Allyn and Bacon.

Tchantchane, A., Fortes, P., & Koshy, S. (2012). An Evaluation of Technology Integration in Teaching Statistics: A Multivariate Survey Analysis. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, *7*(2), 16–27. https://doi.org/10.4018/jwltt.2012040102

Tenaw, Y. A. (2013). Relationship Between Self-Efficacy, Academic Achievement and Gender in Analytical Chemistry at Debre Markos College of Teacher Education. *African Journal of Chemical Education*, *3*(1). Retrieved from https://www.ajol.info/index.php/ajce/article/ viewFile/84850/74836

Tremblay, P. F., Gardner, R. C., & Heipel, G. (2000). A model of the relationships among measures of affect, aptitude, and performance in introductory statistics. *Canadian Journal of Behavioural Science*, *32*(1), 40–48.

Turegun, M., & Reeder, S. (2011). Community College Students' Conceptual Understanding of Statistical Measures of Spread. *Community College Journal of Research and Practice*, *35*(5). https://doi.org/https://doi.org/10.1080/10668920903381854

Umugiraneza, O., Bansilal, S., & North, D. (2018). Investigating teachers' formulations of learning objectives and introductory approaches in teaching mathematics and statistics. *International Journal of Mathematical Education in Science and Technology*, *49*(8), 1148–1164. https://doi.org/10.1080/0020739X.2018.1447150

Wallman, K. (1993). Enhancing Statistical Literacy: Enriching Our Society. *Journal of the American Statistical Association*, *88*(421).

Watson, J. M. (2005). Is statistical Literacy Relevant for Middle School Students? *Vinculum*, *42*(1).

West, S.G., Finch, J.F. and Curran, P. J. (1995). Structural equation models with non-normal variables: Problems and Remedies. In R. H. Hoyle (Ed.), *Structural Equation Modeling: Concepts, Issues and Applications*. Thousand Oaks CA: Sage Publications.

Whitaker, D., & Jacobbe, T. (2017). Students' Understanding of Bar Graphs and Histograms: Results From the LOCUS Assessments. *Journal of Statistics Education*, *25*(2). https://doi.org/https://doi.org/10.1080/10691898.2017.1321974

Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology*, *25*, 68–81.

Wigfield, A., Eccles, J. S., Schiefele, U., Roeser, R., & Davis-Kean, P. (2006). Development of achievement motivation. In W. Damon & N. Eisenberg (Eds.), *Handbook of child psychology* (6th ed.). Hoboken, NJ: Wiley.

Wild, C. J., & Pfannkuch, M. (1999). Statistical thinking in empirical enquiry. *International Statistical Review*, *67*(3), 223–265.

Wilson, S. G. (2013). The Flipped Class: A Method to Address the Challenges of an Undergraduate Statistics Course. *Teaching of Psychology*, *40*(3), 193–199. https://doi.org/https://doi.org/10.1177/0098628313487461

Wise, S. L. (1985). The development and validity of a scale measuring attitudes towards statistics. *Educational and Psychological Measurement*, *45*(2), 401–405.

Yousef, D. A. (2017). Factors influencing academic performance in quantitative courses among undergraduate business students of a public higher education institution. *Journal of International Education in Business*, *10*(1). Retrieved from https://www.researchgate.net/publication/315635093_Factors_Influencing_Academic_Performance_in_Quantitative_Courses_among_Undergraduate_Business_Students_of_a_Public_Higher_Education_Institution

Zieffler, A., Park, J., Garfield, J., delMas, R., & Bjornsdottir, A. (2012). The Statistics Teaching Inventory: A Survey on Statistics Teachers' Classroom Practices and Beliefs. *Journal of Statistics Education*, *20*(1). https://doi.org/10.1080/10691898.2012.11889632

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, *81*(3), 329–339.

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3–17.