International Journal of Business, Law, and Education
E-ISSN : 2747-139X
Publisher: IJBLE Scientific Publications Community Inc.
IJBLE
Volume 6, Number 1, 2025
https://ijble.com/index.php/journal/index

Computer Ability Anxiety, Self-Efficacy Beliefs in Statistical Studies, Student Attitudes towards Course Statistics: An Empirical Study of Undergraduate Students in the Mathematics Study Program

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ABSTRACT
In the 21st century, the learning process continues to develop and undergo a paradigm shift. One of the characteristics of the 21st century is the presence of aspects of information, computing, automation, and communication that influence the learning paradigm. In learning statistics, it is not only cognitive skills that support student learning success but also non-cognitive skills. This study aims to determine the effect of student computer ability anxiety and self-efficacy beliefs on student attitudes toward statistical courses. The sample of this study was 203 students of the Mathematics Study Program of Pamulang University who were selected using a simple random sampling technique. Data collection techniques in this study used instruments with a Likert scale. The effect on the research variables was analyzed using structural equation modeling to determine the effect. From the results of the analysis, it is obtained that there is a direct influence of computer ability anxiety on self-efficacy beliefs in learning statistics, there is a direct influence of computer ability anxiety on attitudes towards statistics courses, there is a direct influence of self-efficacy beliefs in learning statistics on attitudes towards statistics courses, and there is an influence of computer ability anxiety in learning statistics on attitudes towards statistics courses through self-efficacy beliefs.

Keywords:
Computer Ability Anxiety.
Self-Efficacy Beliefs;
Student Attitudes toward Course Statistics.

INTRODUCTION

In the 21st century, the learning process continues to evolve and experience a paradigm shift. One of the characteristics of the 21st century is the presence of aspects of information, computing, automation, and communication which have an impact on changing the learning paradigm. In the information aspect, learning is directed at encouraging students to find out rather than being told. In addition, the presence of computing in 21st-century learning can develop students' abilities in formulating problems, not just solving or answering problems. When they are about to enter society, our students will face uncertainty and we are experiencing this now. The development of science and technology is in line with the growth and development of the industrial world which is very fast, learning through programming is also growing very rapidly. So in this era, the challenge of preparing human resources (HR) continues to be demanded to be able to compete in this competitive industrial era. The rapid development of technology requires that the Indonesian education system make more use of technology in the implementation of education so that it can prepare a creative, innovative, and competitive generation to face the era of the Industrial Revolution 4.0.

Indonesia has been evaluating students' mathematical abilities through the Program for International Student Assessment (PISA) since 2000. In PISA 2015, mathematics was assessed as a minor domain, providing an opportunity to make comparisons of student performance over time. This framework continues the description and illustration of the PISA mathematics assessment set out in the 2012 framework when mathematics was re-examined and updated for use as a key domain in that cycle (OECD, 2017). PISA evaluates the ability of students who are 15 years old (15 years 3 months to 16 years 2 months) at the time of the test and are currently in school equivalent to grade 7 in the Indonesian school system (Pusat Penilaian Pendidikan Balitbang & Kemendikbud, 2019). Each round of PISA measures students' abilities in reading, math, and science.

In the field of mathematics, the average score of Indonesian students on PISA tests fluctuated. The lowest average score was obtained in PISA 2003, amounting to 360. The highest average score was obtained in PISA 2006, 391 points. In PISA 2018, Indonesian students obtained an average score of 379. Indonesia's PISA results for mathematics learning outcomes for primary and secondary education show that 71% of students are below the minimum competency. In the mathematics category, Indonesia is ranked 7th from the bottom (73) with an average score of 379, down from 63rd place in 2015.

In this era of modern technology, information is one of the most important resources for understanding the world. Not infrequently, the information we obtain comes from mathematical calculations in the form of statistics. Interestingly, when used properly, statistics can tell us what happened in the past and are very useful for predicting conditions that will occur in the future. Therefore, awareness of the importance of statistics in everyday life must be raised so that we are not out of date. The importance of statistics in everyday life illustrates that one area of mathematics is very influential in many other fields.

Mathematical concepts and procedures are used as part of the solution of statistical problems. However, the need for the application of accurate calculations is rapidly being replaced by the need for the selective, judicious, accurate, and increasing use of technological tools. Many statistical problems do not have a single mathematical solution, but instead, start with questions and generate opinions that are supported by certain findings and assumptions. These answers need to be evaluated in terms of the quality of the reasoning, the adequacy of the methods used, and the nature of the data and evidence used. As statistics is distinguished from mathematics, statistical reasoning is also distinguished from mathematical reasoning (J. B. Garfield, 2003).

According to J. Garfield & Ben-Zvi at present, statistics education can still be seen as a new and developing discipline compared to other fields of study and inquiry. This new discipline has a research base that is often difficult to find and build upon. To many people interested in reading the field, statistics education research appears to be an invisible and fragmented discipline, as studies related to the topic of interest have appeared in publications from a variety of disciplines, and are more often thought of as studies within the field (J. Garfield et al., 2007)(J. Garfield & Ben-Zvi, 2009).

In studying statistics, it is not only cognitive skills that support student learning success, but non-cognitive skills as well. Several studies have shown that non-cognitive skill factors can support student academic achievement including showing that there is a strong relationship between achievement, self-efficacy, and self-concept in learning mathematics at the age of 15 where self-concept and self-efficacy are strong predictors as passing grades to enter higher education at the end of high school. Self-efficacy and self-concept in mathematics are significant predictors of university and postgraduate entry in science, technology, or mathematics. Students who have a high self-concept in the academic field have better academic abilities (Marjorie Seaton Philip Parker & Yeung, 2014). The taxonomy of non-cognitive constructs in general includes: 1) attitudes and beliefs, 2) social and emotional qualities, 3) habits and processes, 4) individual character (Lipnevich et al., 2013)(Li & Zheng, 2018).

Research conducted by Chiesi & Primi demonstrated that attitudes toward statistics changed during the learning of statistics, and the magnitude of this impact depended on background characteristics (i.e., non-cognitive factors that might change depending on experiences related to learning and individual differences) (Chiesi & Primi, 2010)(Hasabo et al., 2022)(Counsell & Cribbie, 2020). At the start of learning those with lower levels of mathematical competence lacked self-confidence, experienced more negative feelings, and considered statistics more valuable and more difficult than those with high competence (Cerbito, 2020). At the end of the lesson, the attitudes of the two groups improved. In particular, low-competence students did not change their feelings about the discipline and their perception of the difficulty of the discipline, but their self-confidence increased and they associated higher scores with statistics.

Referring to the results of this study, in the achievement of learning statistics, it is not only cognitive aspects that have an effect, but non-cognitive aspects also have an influence. Research conducted by Perepiczka et al, examines the extent of the relationship between self-efficacy learning statistics and statistical anxiety, attitudes toward statistics, and social support of postgraduate students in master's and doctoral programs in tertiary institutions (Perepiczka et al., 2011)(Hernández de la Hera et al., 2023). The results show that statistical anxiety and attitudes toward statistics are statistically significant predictors of self-efficacy for studying statistics, but social support is not a statistically significant predictor of self-efficacy.

Based on the background above, this study aims to determine the effect of anxiety on students' computer skills and self-efficacy beliefs on students' attitudes toward statistics courses. The research questions are as follows.

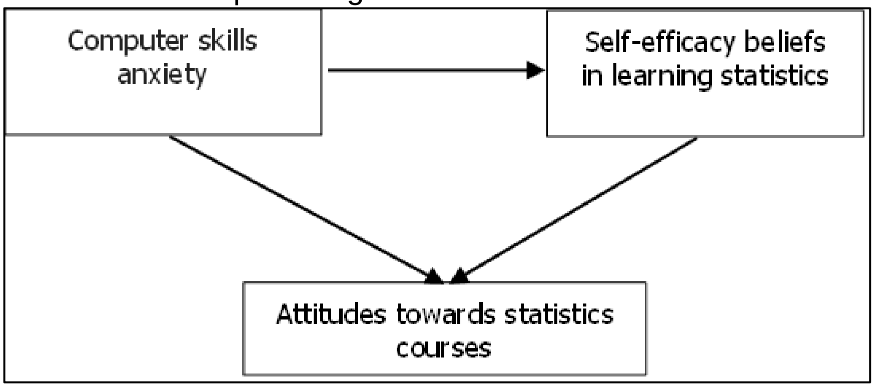
1. Does computer skills anxiety have a direct influence on Self-efficacy beliefs in learning statistics,
2. Does computer skills anxiety have a direct influence on Attitudes towards statistics courses,
3. Does Self-efficacy beliefs in learning statistics have a direct influence on Attitudes toward statistics courses,
4. Does Computer skills anxiety have an indirect effect on Attitudes towards statistics courses through Self-efficacy beliefs in learning statistics.

METHOD

This study used a type of quantitative research because the results were obtained through calculations from samples or students who were asked for their responses to the questions posed by researchers through the questionnaire provided. Quantitative research is formal, objective, rigorous, a deductive approach, and a systematic strategy for generating and perfecting knowledge for problem-solving (Mohajan, 2020). According to Best in Mohajan explain that quantitative research consists of the systematic observation and description of features or characteristics of events to find relationships between the independent (predictor) and dependent (outcome) variables in a population (Mohajan, 2020). Quantitative research is usually associated with the enumeration induction process. One of its main goals is to find out how many and what types of characteristics in the general population have certain characteristics that are found in the sample population (Brannen, 2016).

In this study to find the relationship between the variables used Structural Equation Modeling (Structural Equation Modeling). Structural Equation Modeling (SEM) is a second-generation statistical method that is widely used as an analytical tool in marketing research (Hair et al., 2021). Over the past three decades, research and analysis-based SEM has been increasingly applied in the social sciences, and in particular marketing, due to the availability of user-friendly software such as Lisrell, Amos, and others. SEM analysis involves the simultaneous evaluation of several variables and their relationships. Two SEM-based techniques are covariance-based SEM (CB-SEM) and partial least squares-based SEM (PLS-SEM). SEM facilitates the discovery and confirmation of relationships between several variables (Hair Jr. et al., 2014)(Collier, 2020). In this study, covariance-based SEM (CB-SEM) will be used.

There are three latent variables in this study which are presented in the following problem constellation path diagram.



Picture1. Problem Constellation Path Diagram

The target population in this study were all Pamulang University students who were active in the 2021/2022 academic year, totaling 18,000 students, while the reachable population in the study were all Pamulang University Mathematics Study Program students who were active in the 2021/2022 academic year, with a total of 303 students. The selected sample of 203 respondents was selected using a simple random sampling technique.

The instrument used in this study was a questionnaire given to students of the Mathematics Study Program at Pamulang University who were selected as samples. There are three instruments used in this study. The first is an instrument to measure the anxiety of students' computer skills from the Computer Anxiety Rating Scale (CARS) (Heinssen et al., 1987) which consists of 19 items that assess respondents' cognition and feelings about their abilities related to computer use. Each item in CARS is scored on a five-point Likert-type scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). The second is an instrument to measure students' self-efficacy beliefs in learning statistics adopted by Self-efficacy to Learn Statistics (SELS) (Finney & Schraw, 2003), where SELS measures confidence in one's ability to learn statistics needed in a statistics course to complete 14 specific tasks using a response scale of

1 (not confident at all) to 6 (complete confidence). The third is an instrument to measure student attitudes towards statistics courses adopted from the Attitude Toward Statistics (ATS) scale (Schau et al., 1995) consisting of 28 items, a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument grids used are as follows.

Table1. Research Instrument Grid

Variable	Indicator	Statement Item Number
Computer skills anxiety	A passion for computers	1, 2, 3, 4
	Confident in computer skills	5, 6, 7, 8, 9, 10
	Anxiety about the ability to use computers	11, 12, 13, 14, 15, 16, 17, 18, 19
Self-efficacy beliefs in learning statistics	Belief in one's ability to learn statistics	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18
Attitudes toward statistics courses	Affect	1,2,3,4,5,6
	Cognitive competence	7,8,9,10,11,12
	Value	13,14,15,16,17,18,19,20,21
	Difficulties	22,23,24,25,26,27,28

RESULTS AND DISCUSSION

This section describes the results of the analysis obtained using the Lisrell software-assisted Structural Equation Modeling (SEM).

Measurement Model Test

According to Yamin states that the convergent validity test is a test to test whether the indicator variables used are truly significant in terms of reflecting construct or latent variables (Yamin, 2014). Several measures in the convergent validity test, namely: standardized loading factor (SLF) measure, construct reliability (CR) measure, and average variance extracted (AVE) measure. An indicator or observed variable is said to have good convergent validity if the factor loading or standardized loading factor (SLF) value is significant. However, significant SLF values often have weak correlations. Therefore the rule of thumb is that SLF values ≥ 0.50 are acceptable and it is more expected that SLF values ≥ 0.7 ((Hair Jr. et al., 2014)(Imam, 2013)(Ghazali & Fuad, 2014).

In the following, the results of the analysis for testing convergent validity are presented based on the value of the standardized loading factor (SLF).

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IJBLE
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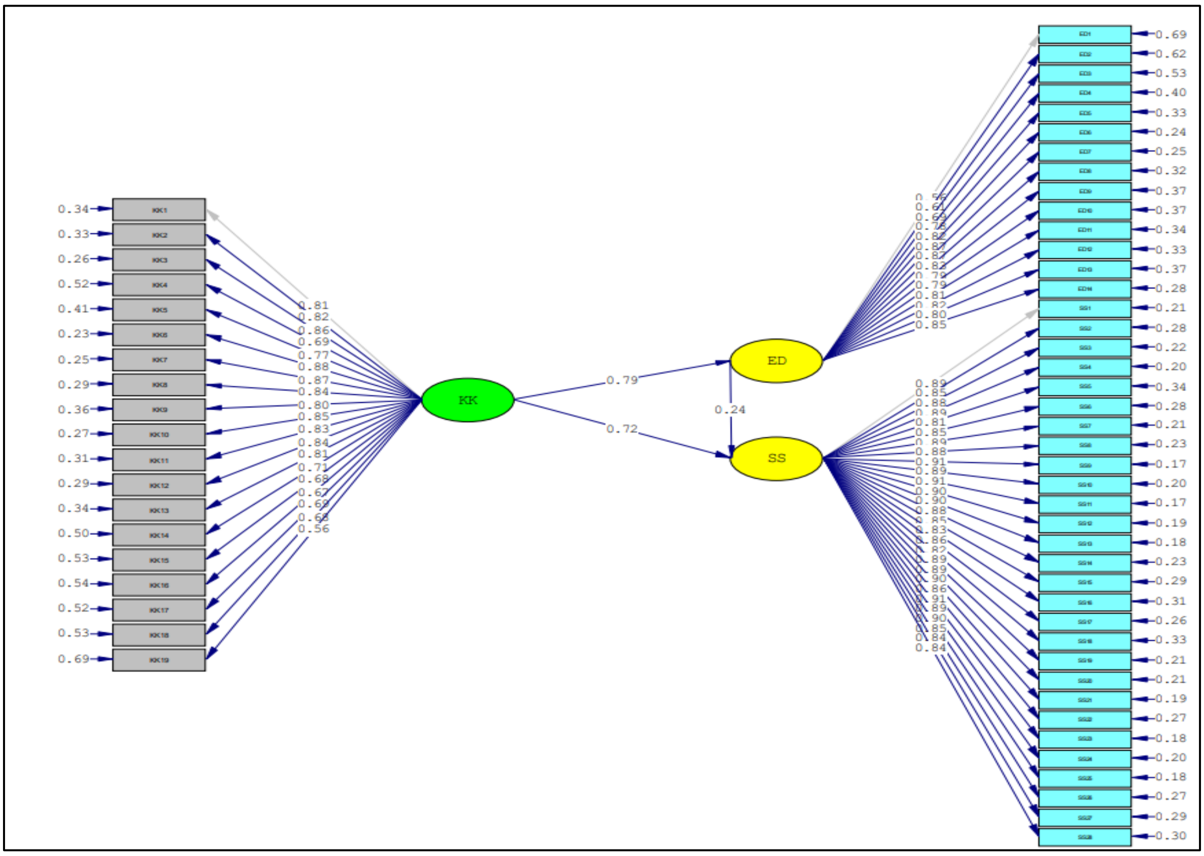
https://ijble.com/index.php/journal/index



Picture2. Convergent Validity Test Results

From the results of the analysis in the figure above, the value of the standardized loading factor (SLF) for all indicators is > 0.5, so it can be concluded that the indicators used have good Convergent Validity properties. This means that the indicators are valid for measuring the latent variables. States that reliability is also an indicator of convergent validity (I. Ghozali, 2014). Many also use Cronbach's alpha as a measure of reliability, even though in reality Cronbach's alpha provides lower reliability (estimate) compared to construct reliability (CR). Construct reliability (CR) 0.7 or more indicates good reliability, while reliability 0.6-0.7 is still acceptable on condition that the validity of the indicators in the model is good.

Table 2. Construct Reliability (CR) calculation results

Latent Variable	CR
KK	0.9388
ED	0.9462
SS	0.9891

The table above shows the CR values for the three latent variables > 0.7 so it can be concluded that the three latent variables have met the characteristics of good convergent validity based on the CR size.

Overall Model Fit Test

The results of the convergent validity and discriminant validity tests gave good results. Next, the overall model suitability test will be carried out. The following table presents several measures that can be used to test the model as a whole, along with the limit values.

International Journal of Business, Law, and Education
Publisher: IJBLE Scientific Publications Community Inc.
E-ISSN : 2747-1985
Volume 6, Number 1, 2025
https://ijble.com/index.php/journal/index

Table3. Overall Model Fit Test

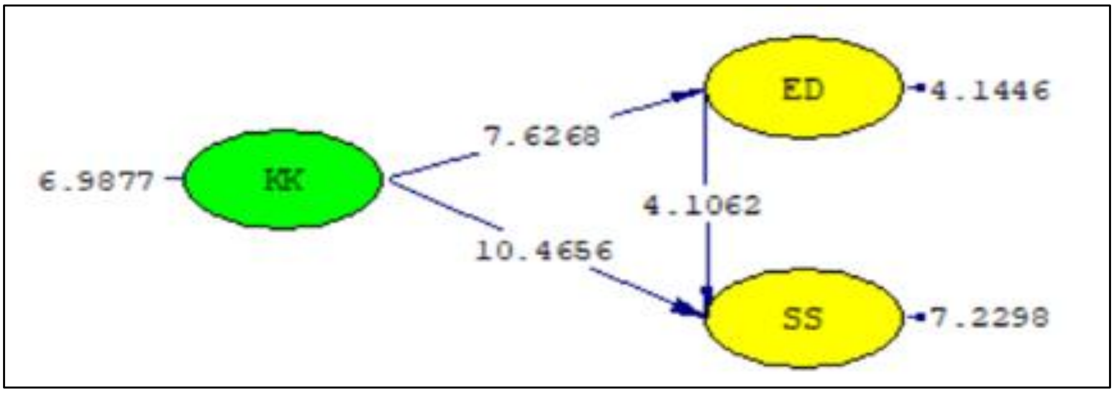
Model Fit Size	Mark	Model Fit Benchmark Value
RMSEA	0.0993	< 0.1
NFIs	0.9647	>0.9
PNFI	0.9310	>0.9
CFI	0.9766	>0.9

Structural Model Testing (Significance Test)

The hypotheses to be tested in this study are as follows,

a. Is there a direct effect of Computer skills anxiety on Self-efficacy beliefs in learning statistics,
b. Is there a direct effect of Computer skills anxiety on attitudes toward statistics courses,
c. Is there a direct effect of Self-efficacy beliefs in learning statistics on Attitudes toward statistics courses,
d. Is there any influence on Computer skills anxiety through Self-efficacy beliefs in learning statistics to Attitudes towards statistics courses.

Based on the results of the direct effect test (Direct Effects), the results are shown in the following table.



Picture 3. The t-values of the structural model

Table 4. Results of the Direct Effect Test

Direct Effects	Path Coefficient	Statistical Value t	P-Value	R-Square
KK → ED	0.5379	7.6268	0.0000	0.6308
KK → SS	1.0335	10.4656	0.0000	0.8283
***ED* → SS**	0.5171	4.1062	0.0000	0.8501

From the table above it can be seen that the t statistical value for the model is 7.6268, where the value is > 1.96, and the p-value obtained is also < 0.05. Therefore it can be concluded that computer ability anxiety has a direct influence on students' self-efficacy beliefs in learning statistics. For the KK → SS model, a t statistic value of 10.4656 is obtained where the value is > 1.96, and the p-value obtained is also <0.05 so it can also be concluded that anxiety about computer skills has a direct influence on sKK→ EDstudent attitudes toward statistics courses. Meanwhile, for the ED → SS model, a statistical value of t is obtained which is 4.1062the value is > 1.96 with a p-

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IJBLE
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https://ijble.com/index.php/journal/index

value obtained also < 0.05, meaning that Students' self-efficacy beliefs in learning statistics have a direct influence on student attitudes toward statistics courses.

From the results of the analysis as in the table above, the path coefficient is obtained for computer ability anxiety toward self-efficacy beliefs in statistical learning (KK → ED) of 0.5379, this value means that computer ability anxiety has a positive influence on self-efficacy beliefs in statistical learning. Likewise, the path coefficient of computer ability anxiety to attitudes toward statistics courses (KK→ SS) And self-efficacy beliefs in learning statistics toward attitudes toward statistics courses (ED → SS) are worth 1.0335 and 0.5171, respectively. These values indicate that computer ability anxiety has a positive effect on attitudes toward statistics courses and self-efficacy beliefs in learning statistics also have a positive effect on attitudes toward statistics courses. The R-Square values obtained for the three direct influence models were 63.08% each; 82.83%; and 85.01% which can be interpreted as variable anxiety the computer's ability to explain the variation of the variable self-efficacy beliefs in learning statistics for 63.08%. Variable anxiety computer ability can explain the variation of variables' attitudes toward statistics courses of 82.83%. Whereas self-efficacy beliefs in learning statistics can explain variations of variables attitudes toward statistics courses of 85.01%.

Then tested for indirect effects using the Sobel test approach. Where in the Sobel test, it is necessary to calculate the value of. The results of the indirect effect test are presented in the following table Z_sobel.

Table 5. Indirect Effect Testing

Direct Influence		Standard Error	Indirect Influence		Z Sobel
KK→ ED	0.5379	0.07053	KK → ED → SS	0.2781	3.616171
KK→ SS	10.335	0.09875			
ED→ SS	0.5171	0.1259			

From the calculation results, it is obtained that the value of |Z Sobel| > 1.96, so it can be concluded that computer skills anxiety indirectly influences to attitudes toward statistics courses through self-efficacy beliefs in learning statistics.

Discussion

The findings of the study suggest that self-efficacy views in learning statistics are positively and directly impacted by anxiety related to computer abilities. In other words, the more anxious a person is about computer skills, the more confident they are about their ability to master statistics. This research may suggest that people who are nervous about computer skills are attempting to overcome that fear by increasing their confidence in their ability to understand statistics. Put differently, the perceived fear may serve as a catalyst that inspires people to feel more comfortable taking on academic problems, particularly those related to statistics. However, additional analysis is required to comprehend the mechanisms underlying the association between self-efficacy in learning and anxiety related to computer abilities.

According to the study's findings, attitudes about the statistics course are positively and directly impacted by anxiety related to computer proficiency. This implies that a person's attitude toward the statistics course will be more positive the more anxious they are about their computer skills. This finding demonstrates that computer skills anxiety does not always have a bad effect; rather, it can motivate people to take the statistics course with greater positivity. People who are nervous about computer abilities may work harder to comprehend and become proficient in statistics, which makes them feel better about the course. Bandura (1997) explains that a person's belief in their ability to complete a certain task (self-efficacy) plays an important role in determining their success. In the context of research findings, anxiety toward computer skills that positively impact self-efficacy in learning Statistics can be explained by the compensation mechanism. Individuals who experience anxiety may be more motivated to overcome their limitations, thereby increasing their self-confidence in facing academic challenges.

Based on the research findings, it can be concluded that self-efficacy beliefs in learning Statistics have a direct and positive influence on attitudes toward the Statistics course. This means that the higher a person's confidence in their ability to learn Statistics, the more positive their attitude towards the course will be. This result is in line with the Self-Efficacy Theory (Bandura, 1977, 1997), which states that individuals with a high level of self-efficacy tend to be more confident in facing challenges, more persistent in completing tasks, and have a more positive attitude toward activities they believe they can master. In this context, students who have high self-efficacy in understanding Statistics are more likely to show a more open, enthusiastic, and motivated attitude in studying the subject. In addition, these findings also indicate that enhancing self-efficacy in learning Statistics can be an effective strategy in fostering a more positive attitude towards the subject. Therefore, educators need to implement teaching methods that can enhance students' self-efficacy, such as experiential-based approaches, technology-assisted learning, and providing constructive feedback.

Moreover, the research results also show that anxiety towards computer skills has an indirect influence on attitudes toward the Statistics course through self-efficacy beliefs in Statistics learning. In other words, anxiety about computer skills affects a person's self-efficacy in learning Statistics, which ultimately impacts their attitude toward the course. These findings indicate that self-efficacy acts as a mediator in the relationship between computer skills anxiety and attitudes toward the Statistics course. This means that individuals who experience anxiety towards computer skills can develop higher self-confidence in learning Statistics, which in turn shapes a more positive attitude towards the course. These results are in line with the Self-Efficacy Theory (Bandura, 1977, 1997), which emphasizes that individuals with high confidence in their abilities will be more capable of facing challenges and demonstrating a more positive attitude toward academic tasks. Moreover, these findings also support Attribution Theory (Weiner, 1985), which explains that how an individual interprets anxiety and challenges can affect their self-confidence and attitude towards a particular subject.

CONCLUSION

Based on the results of the analysis, some research conclusions concerning the objectives and research questions are:

1. There is a direct influence of Anxiety computer skills on Self-efficacy beliefs in learning statistics. The influence given from the variable Computer skills anxiety positive about Self-efficacy beliefs in learning statistics.
2. There is a direct influence of computer skills anxiety to Attitudes toward statistics courses. The influence exerted by computer skills anxiety to Attitudes toward statistics courses is positive.

3. There is a direct effect of Self-efficacy beliefs in learning statistics on Attitudes towards statistics courses. Self-efficacy beliefs in learning statistics also have a positive influence on Attitudes towards statistics courses.
4. There is an indirect effect of Computer skills anxiety to Attitudes toward statistics courses through Self-efficacy beliefs in learning statistics.

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