Analysis of Knowledge and Ability of Building Construction Workers on Attitudes on Work Accident Risk

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ABSTRACT

Construction work, especially building construction, has a high risk of work accidents, because it involves many elements. Now in building construction projects, the importance of knowledge about K3 and the ability of workers has become a basic need. Attitudes towards occupational safety also have an important role, because they can reflect the level of attention a person has to work safety aspects. The purpose of this study is to determine and analyze whether the knowledge and ability of building construction workers affect attitudes on accident risk. The approach applied is an associative approach. The population in this study is individuals involved in building construction, with the total population obtained is 44 respondents. Data is collected through the use of online questionnaires through the Google Form platform. After that, the data was analyzed using SEM-PLS 4.0 software. The results showed that there was a positive and significant influence between workers' knowledge of attitudes with a path coefficient value of 0.348. There is a positive and significant influence between the ability of workers to attitudes with a path coefficient value of 0.484. There is a moderate influence between workers' knowledge and ability on attitudes, as evidenced by the R^2 value obtained 0.598.

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1. INTRODUCTION

Construction work has a fairly high level of risk of work accidents, which are caused by various factors. This risk is not only related to the heavy physical workload for workers, but also relates to various other supporting elements. From the use of heavy equipment to the use of large amounts of materials, which together play a role in increasing the risk of work accidents [1]. In construction work, especially building construction, there is a significant level of risk of work accidents. This risk is caused by a number of factors, namely the work environment in building construction work that is quite complex, the use of heavy equipment that is quite dangerous, and the involvement of many workers in building construction projects that have different roles and responsibilities [2].

The level of knowledge, understanding and practice of occupational safety prevention by related parties in the implementation of construction K3 is far from adequate. This causes problems in the implementation of construction projects, because there are still many people who think that safety efforts (safety) is something that drains the budget and causes discomfort when using safety clothing [3]. It can also increase the risk of workplace accidents in construction projects. In today's construction projects, knowledge of K3 in doing its duties is very important, considering the potential risk of work accidents in the work environment [4] [5] [6]. In addition, knowledge of how workers apply K3 in the work environment is also very important [7]. Workers with good knowledge are better able to identify risks associated with their work, and vice versa [8]. In addition to having knowledge of K3 and the dangers of work accidents, workers must also have the ability to carry out the work they have. If workers have the knowledge and ability to carry out their work, then the risk of workplace accidents can be reduced.

The possibility of work accidents can be caused by unsafe actions and unsafe conditions [9] [10]. In general, these risky actions often occur due to lack of knowledge of K3, capabilities and dangerous actions. In addition, it is also important to pay attention to individual attitudes towards occupational safety, as this can affect the extent to which a person values safety in the workplace. This attitude can also be influenced by the work environment and the actions of those around him. With knowledge of the risk of work accidents and having the ability to carry out work, it is expected that workers have a positive attitude in carrying out their work.

Based on this, the author intends to conduct research that focuses on analyzing the knowledge and ability of building construction workers on attitudes on work accident risk. Based on this, what can be done is to analyze the knowledge of building construction workers on attitudes on the risk of work accidents, analyze the ability of building construction workers on attitudes on the risk of work accidents and analyze the knowledge and ability of building construction workers on attitudes on the risk of work accidents.

2. METHODS

2.1 Data Collection Methods

This research is quantitative research where questionnaires are used as a tool to collect data. A questionnaire is an instrument used to obtain responses or answers from respondents by providing written statements to respondents [11]. This questionnaire will contain questions or statements to find information about respondents' perceptions of the influence of knowledge and ability of building construction workers on attitudes on work accident risk. Data collection through filling out questionnaires carried out online using the Google Form application.

2.2 Research Instruments

Research instruments are data collection tools needed in the analysis process, thus enabling more accurate data analysis and ultimately achieving predetermined goals [12]. The instrument used a questionnaire that was distributed with the aim of determining the effect of knowledge and ability of building construction workers on attitudes on work accident risk. The research instrument used was a Likert scale-based questionnaire. The use of Likert scale in this questionnaire aims to measure the views, perceptions, and attitudes of individuals or groups towards certain social phenomena [11]. The choice of the number of scales is because the Likert scale with 5 scales will result in increasing answer differences and this shows that respondents tend to choose variables rather than obtain balanced results. Here's the likert scale to use:

Table 1. Likert scale

Scale	Information
1	Strongly disagree
2	Disagree

3	Neutral
4	Agree
5	Totally agree

From the questionnaires that have been distributed and collected, measurement results will be obtained from each variable based on respondents' perceptions. The results of filling out this questionnaire will later be processed using the Structural Equation Modeling (SEM) approach. The following is a table of research instruments with their variables and indicators:

Table 2. Research variables and indicators

No.	Variable	Indicators
1.	Knowledge	Education Understanding about K3 Insight into the work Use of PPE at work Outlining how to prevent accidents Work experience Identify the causative factors of work accidents
2.	Ability	Ability to work together Knowledge Work responsibilities Work experience Skills (expertise) Workability Upbringing and training Timeliness of work
3.	Attitude	Working environment conditions Teamwork Beliefs about K3 Responding to work procedures Responding to efforts to prevent work accidents Use of PPE at work Beliefs about the dangers of work accidents

2.3 Data Analysis Methods

The method applied in this study is the Structural Equation Modeling (SEM) method, which is a statistical technique that is useful for testing and giving validity to theories that include various phenomena through hypothesis tests [13]. In the context of this research, SEM is used to conduct field studies aimed at testing or verifying theories. Thus, it is expected that within the framework of the structural equation model concept, this research will help in developing a solid theoretical foundation for designing research models [13].

In this study, SEM software known as PLS was used. Partial Least Square (PLS) is an SEM analysis method that relies on components with formative construct characteristics [14]. One of the advantages of PLS is its non-reliance on many assumptions, thus making it a very effective analytical tool. The PLS approach requires several independent variables specifically designed to predict the dependent variable. Usually, PLS is useful for performing Confirmatory Factor Analysis (CFA), but it can also be used in situations where the theoretical basis or model is still not strong, such as Exploratory Factor Analysis (EFA). In addition, PLS can be used to analyze data that does not follow a specific distribution pattern, such as nominal, categorical, ordinal, interval or ratio data [14] [15].

In this study, PLS analysis was carried out in two steps, namely:

a. The first step involves testing the measurement model, whereby the validity and construct reliability of each indicator are tested [16].
b. In the second step, structural model testing is carried out. The aim is to evaluate whether there is an influence between variables or correlations, as well as test the relationships between the constructs measured using the t test provided by the PLS itself [16].

The following are the stages of analysis with PLS:

a. Model estimation in PLS-SEM
   In this step, the analysis involves a series of repeated procedures to generate the value of the latent variable and once the value of the latent variable is obtained, the next step of the analysis is executed [14].
b. Model evaluation in PLS-SEM
   1) Evaluation of outer model (measurement model)
      In this study, researchers used questionnaires as a tool to collect research data. To test the level of validity and reliability of the questionnaire, researchers used the Smart PLS device. The validity test step that is carried out is convergent validity, where a correlation of the item score (component score) with the construct score is carried out which will ultimately provide a value of loading factor. A loading factor value is considered high if the indicator has a correlation of ≥ 0.7 with the variable you want to measure. However, for early stage research in research development, it is still acceptable if the loading factor value ≥ 0.5. In fact, some experts consider the figure 0.4 also acceptable. Thus, the requirement for the value of the loading factor is ≥ 0.4 [14].
      Reliability refers to the degree to which confidence in measurement results and the extent to which those results remain consistent when we take measurements repeatedly. In measuring the extent to which research variables have reliability, cronbach's alpha and composite reliability coefficients are used. The measurement is considered to have good reliability if the resulting coefficient value ≥ 0.6 [14].
   2) Evaluation of the inner model (structural model)
      The goal is to evaluate the relationship between the measured constructs tested using the t-test in the PLS itself. To measure the inner workings of the model, you can check the R-Square value of the model which indicates the extent to which the variables in the model influence each other. Next, estimate the path coefficient by performing a bootstrapping procedure, where the values are considered to have a significant effect if the static t value ≥ 1.96 (significant level 5%) and P value < 0.05 (significance 5%) [17].

The following table illustrates the assessment criteria of model evaluation in PLS-SEM:

Table 3. PLS-SEM model assessment criteria

No.	Criterion	Explanation	Condition
Evaluation of the measurement model (outer model)			
1.	Loading Factor (LF)	Shows the extent of the correlation between each measurement element (indicator) and the construct it measures	≥ 0.4
2.	Composite reliability	Serves to measure the consistency or stability of indicators	≥ 0.6
3.	Average Variance Extracted (AVE)	Specifies the high variation or variety of manifest variables that a latent construct can have	≥ 0.5
4.	Validity of discriminants	Indicates that a construct is unique. The √AVE value must be > the correlation value between latent variables	√AVE ≥ correlation between variables

5.	Cross loading	Relates the correlation between an indicator with its construct and the construct of other blocks	Blocks reviewed ≥ blocks not reviewed
		Structural model evaluation	
1.	Estimation of path coefficients	The estimated value for path relationships in the structural model should be significant, resulting from the path coefficients during the bootstrapping process	Tsat > 1.96 P value < 0.005 and Koef line > 0
2.	R^2 for endogenous latent variables	To assess how well exogenous variables can explain endogenous variables	> 0.19 weak > 0.33 medium > 0.67 substantial
3.	Q^2	To validate the model so that we can know the exogenous variable can predict the endogenous variables (relevance of prediction)	> 0

3. RESULTS AND DISCUSSION

3.1 Characteristics of Respondents

By applying a survey using questionnaires to respondents, information on respondents' characteristics is classified into several parts, namely age, recent education, and work experience. The results are in the table below:

Table 4. Age of respondents

Age (Years)	Frequency	Percentage
20 - 30	6	13,6%
31 - 40	13	29,5%
41 - 50	10	22,7%
> 51	15	34,1%
Sum	**44**	**100%**

Table 5. Respondents last education

Recent Education	Frequency	Percentage
SMA	2	4,5%
SMK	2	4,5%
D1 - D3	2	4,5%
S1	31	70,5%
S2	7	15,9%
Sum	**44**	**100%**

Table 6. Respondents work experience

Work Experience (Years)	Frequency	Percentage
1 - 5	4	9,1%
6 - 10	8	18,2%
11 - 15	7	15,9%
16 - 20	6	13,6%
21 - 25	4	9,1%

> 26	15	34,1%
Sum	**44**	**100%**

3.2 Data Analysis

3.2.1 Evaluation of the outer model (measurement model)

Model evaluation at this stage involves checking various aspects, such as checking the value of individual item reliability by looking at the value of standardized loading factor, construct reliability using Cronbach's Alpha and Composite Reliability methods, checking the value of Average Variance Extracted (AVE) and assess the Discriminant Validity value by checking the cross loading value.
The following are the results of the outer model evaluation in this study:

a. Loading Factor

Indicators that have a strong correlation with their construct can be recognized by a high loading factor value [14]. Generally, the loading factor value that is considered optimal is ≥ 0.7, which describes the level of validity of the indicator against the construct being measured. Even so, the study still considers the value of loading factor ≥ 0.5 as an acceptable value. In fact, some experts also argue that a value of 0.4 is still acceptable. Therefore, if there is an indicator with a loading factor value of ≤ 0.4, you should consider excluding it from the analysis. After removing indicators that do not meet the criteria, recalculate [14]. The following is the loading factor result data obtained:

Table 7. Value of loading factor (outer loading)

	X1 (Knowledge)	X2 (Capability)	Y (Attitude)
A1	0.172		
A2	0.569		
A3	0.308		
A4	0.571		
A5	0.791		
A6	0.721		
A7	0.598		
B1		0.627	
B2		0.778	
B3		0.827	
B4		0.717	
B5		0.725	
B6		0.730	
B7		0.604	
B8		0.866	
C1			0.810
C2			0.849
C3			0.690
C4			0.826
C5			0.697
C6			0.695
C7			0.686

Refer to table 7. It is known that from 8 ability variable indicators, a loading factor value of ≥ 0.4 was obtained with a range of 0.604 – 0.866. From 7 attitude variable indicators, a loading factor value of ≥ 0.4 was obtained with a range of 0.686 – 0.849. This means that all variable indicators of ability and attitude, are valid in measuring the constructs they form. However, of the 7 knowledge variable indicators, only 5 indicators obtained a loading factor value of ≥ 0.4 with a range of 0.569 – 0.791 which means that these five indicators are valid in measuring the constructs they form. While the other 2 indicators obtained a loading factor value of ≤ 0.4 with values obtained of 0.172 and 0.308 which means these two indicators are less valid in measuring the construct they form. According to Siswoyo Haryono (2016) if a loading factor value of less than 0.4 is found on an indicator, it is recommended to remove the indicator from observation and repeat the calculation step again.

Table 8. Loading factor (outer loading) value after invalid indicator is removed

	X1 (Knowledge)	X2 (Capability)	Y (Attitude)
A2	0.541		
A4	0.583		
A5	0.791		
A6	0.755		
A7	0.629		
B1		0.627	
B2		0.778	
B3		0.827	
B4		0.716	
B5		0.725	
B6		0.730	
B7		0.604	
B8		0.866	
C1			0.809
C2			0.850
C3			0.694
C4			0.823
C5			0.694
C6			0.693
C7			0.687

b. Composite Reliability (CR)

The Composite Reliability (CR) value reflects the level of internal consistency. In this context, the higher the CR value, the stronger the consistency between indicators in measuring a construct [16]. CR testing is carried out to measure the stability of an indicator in the variables of a questionnaire, so that it can be said to be reliable. A CR value of ≥ 0.7 is acceptable, while a CR value of ≥ 0.8 is considered very satisfactory. The following is the data from the composite reliability measurement obtained:

Table 9. Composite Reliability (CR) value

	Composite reliability	Result
X1 (Knowledge)	0.797	Acceptable
X2 (Capability)	0.905	Very satisfying
Y (Attitude)	0.901	Very satisfying

Refer to table 9. It is known that the knowledge variable has a CR value of ≥ 0.7 which means that the indicator can be said to be reliable or reliable with acceptable properties. While the ability variable and attitude variable have a CR value of ≥ 0.8 which means that the indicator can be said to be reliable with very satisfactory properties.

c. Average Variance Extracted (AVE)
The desired AVE value must be at least equal to 0.5 or more. If the AVE value is at least 0.5 it indicates that a good degree of convergent validity has been reached, indicating that the latent variable may account for at least half or more than half of the variance of the indicator [14]. Here are the AVE values obtained:

Table 10. Average Variance Extracted (AVE) Value

	Average variance extracted (AVE)
X1 (Knowledge)	0.445
X2 (Capability)	0.546
Y (Attitude)	0.568

Refer to table 10. It is known that the ability variable and the attitude variable have an AVE value of ≥ 0.5 which indicates that the variable has a good measure of convergent validity. While the knowledge variable has an AVE value of ≤ 0.5 which indicates that the variable lacks a good measure of convergent validity. This can happen because of different responses of respondents to these indicators.

d. Discriminant Validity
Discriminant validity is useful for determining whether a particular reflective indicator accurately reflects or is a good gauge for its construct [17]. If the value of the AVE square root of each construct exceeds the relationship between constructs with other constructs in the model, then it can be said that the discriminant validity of the model is good. The following is the value of the validity of the discriminant obtained:

Table 11. Discriminant validity value

	X1 (Knowledge)	X2 (Capability)	Y (Attitude)
X1 (Knowledge)	0.667		
X2 (Capability)	0.720	0.739	
Y (Attitude)	0.697	0.735	0.753

Refer to table 11. It is known that the knowledge variable has a discriminant validity value smaller than other construct correlation values, this indicates that the knowledge variable has a discriminant validity value that is not good. While the ability variable and attitude variable have a higher discriminant validity value than the relationship with other constructs, which indicates that both variables have a good discriminant validity value.

e. Cross Loading
The way to measure cross loading is to examine the degree to which indicators correlate with the constructs they represent compared to the correlations with the constructs of different blocks. If indicators have a higher correlation with the construct they represent than with the construct of different blocks, this indicates that they are better at predicting the size of their block than other blocks [14]. Here are the cross loading values obtained:

Table 12. Cross loading value

	X1 (Knowledge)	X2 (Capability)	Y (Attitude)

A2	**0.541**	0.285	0.355
A4	**0.583**	0.558	0.311
A5	**0.791**	0.645	0.507
A6	**0.755**	0.552	0.519
A7	**0.629**	0.366	0.553
B1	0.552	**0.627**	0.554
B2	0.529	**0.778**	0.629
B3	0.557	**0.827**	0.622
B4	0.640	**0.716**	0.619
B5	0.397	**0.725**	0.372
B6	0.337	**0.730**	0.434
B7	0.598	**0.604**	0.454
B8	0.559	**0.866**	0.535
C1	0.479	0.437	**0.809**
C2	0.575	0.672	**0.850**
C3	0.507	0.657	**0.694**
C4	0.612	0.558	**0.823**
C5	0.563	0.446	**0.694**
C6	0.529	0.506	**0.693**
C7	0.372	0.538	**0.687**

Refer to table 12. It can be concluded that on the variables of knowledge, ability and attitude, indicators tend to have a higher correlation with their own constructs than with constructs in other blocks. This shows that these constructs are better at predicting the values in their block compared to other blocks.

3.2.2 Evaluation of the inner model (structural model)

There are several stages that become criteria for the assessment of the inner model (structural model), namely the value of R 2, Q^2, and path coefficient. The assessment of the structural model is obtained through bootstrapping procedure.

The following are the results of the inner model evaluation in this study:

a. Path coefficient

The path coefficients reflect the extent to which the relationships between various constructs are related. The direction and sign in this path should correspond to the assumptions proposed in the theory and to evaluate its significance value, it is necessary to refer to the T-stat and P-values obtained through bootstrapping techniques.

Table 13. The value of the path coefficient

	Path Coefficient	**T statistics (|O/STDEV|)**	**P values**
X1 (Knowledge) -> Y (Attitude)	0.348	2.414	0.018
X2 (Ability) -> Y (Attitude)	0.484	3.557	0.001

Refer to table 13. It is known that the results of the path coefficient test between knowledge variables and attitude variables have a path coefficient value of 0.348 and T-stat 2.414 > 1.96 and a p-value of 0.018 < 0.05. These results explain that knowledge variables have a positive and significant influence on attitude variables. It is also known that the results of the path coefficient test between the ability variable to the attitude variable have a path coefficient value of 0.484 and T-stat 3.557 > 1.96 and a p-value of 0.001 < 0.05. These results show that the ability variable has a positive and significant influence on the attitude variable.

b. R^2

R^2 is used to assess the extent to which exogenous (free) latent variables have a significant influence on endogenous (bound) latent variables [14]. According to Chin (1998) quoted in Yamin and Kurniawan (2011: 21) classifies the values of R^2 into the following three categories: if $R^2 \geq 0.67$ then the effect is said to be good (substantial); if $R^2 \geq 0.33$ then the effect is said to be moderate; and if $R^2 \geq 0.19$ then the effect is said to be weak. Here is the value of R^2 obtained:

Table 14. R^2 value

	R-square	R-square adjusted
Y (Attitude)	0.598	0.579

Referring to table 14, it is known that the value of R^2 obtained by 0.598 means that the knowledge variable and the ability variable can explain the attitude variable by 59.8%, and the knowledge variable and ability variable have a moderate influence on the attitude variable.

c. Q^2

The Q^2 predictive relevance value is used as a tool to test and validate the model. If the value of $Q^2 > 0$, reflects the ability of the model to provide good predictive relevance and shows that the independent variable is good as an explanatory variable that plays a major role in predicting the dependent variable (bound). Conversely, if the value of $Q^2 < 0$, reflects that the model is not good enough in doing predictive relevance [14]. Here is the calculation of the value of Q^2:

$$Q^2 = 1 - (1 - R^2Y)$$
$$= 1 - (1 - 0.598)$$
$$= 0.598 > 0$$

From the calculation above, it can be said that this model has a good ability to predict relevance, with a Q^2 value obtained 0.598. This shows that the knowledge variable and the ability variable are both explanatory variables that play a major role in predicting attitude variables.

The following are the results of the analysis output with SMART-PLS:

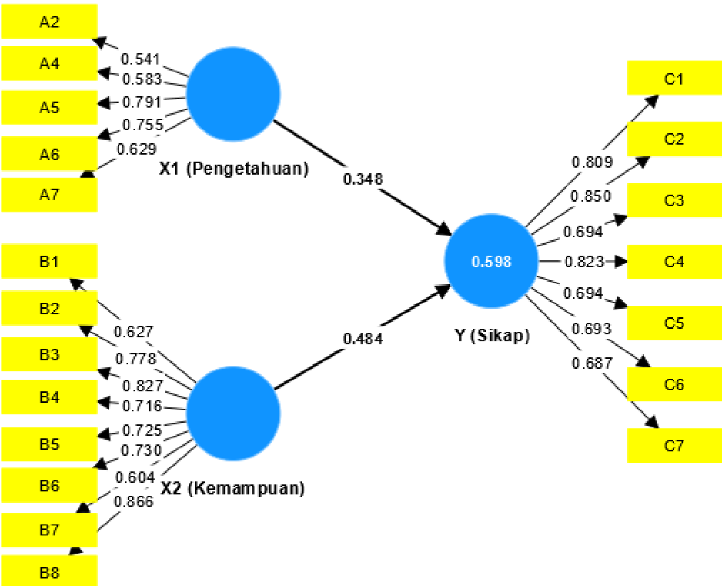

Figure 1. Analysis output results with SMART-PLS

4. CONCLUSION

The conclusion of this study shows that the results of the analysis between the knowledge variable (X1) and the attitude variable (Y) obtained a path coefficient value of 0.348 and T-sat 2.414 and a p-value of 0.018. This shows that the knowledge variable (X1) has a positive and significant influence on the attitude variable (Y) because the T-sat value > 1.96 (2.414 > 1.96) and the p-value < 0.005 (0.018 < 0.05) with an influence value of 34.8%. The results of the analysis between the ability variable (X2) and the attitude variable (Y) obtained a path coefficient value of 0.484 and T-sat 3.557 and a p-value of 0.001. This shows that the ability variable (X2) has a positive and significant influence on the attitude variable (Y) because the T-sat value > 1.96 (3.557 > 1.96) and p-value < 0.005 (0.001 < 0.05) with an influence value of 48.4%. The results of the analysis between the knowledge variable (X1) and the ability variable (X2) on the attitude variable (Y) obtained an R Square value of 0.598. This shows that the knowledge variable (X1) and the ability variable (X2) have an influence of 59.8% on the attitude variable (Y) and are included in the moderate influence (moderate). This result is in line with an interview conducted with a QHSE Officer on one of the building construction projects who said that the knowledge and ability of workers influence workers' attitudes on the risk of work accidents.

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