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INTERNATIONAL STUDENTS' COGNITIVE LOAD IN LEARNING THROUGH A FOREIGN LANGUAGE OF INSTRUCTION: A CASE OF LEARNING USING BAHASA - INDONESIA

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Abstract

Previous studies on cognitive load model have been entirely theoretical and there are no empirical studies currently that have been carried out to test the hypotheses in these theoretical models. Therefore, this study is aimed at proving Choi's cognitive load model using empirical data. The empirical data was collected in a foreign language-learning environment. The research questionnaire was extracted from the work design questionnaire, learning process questionnaire, mental effort, intrinsic load, extraneous load and germane load scales and was administered to foreign students in Indonesia (N=191). Descriptive statistics showed the foreign students' Indonesian language proficiency (mean = 4.76 and standard deviation = 2.594) and English proficiency (mean =7.72 and standard deviation =1.732). Foreign students have good *fluency in English language as compared to Bahasa Indonesia. Structural Equation Modeling (SEM) using SmartPLS was carried out and the researcher found out that there is a significant relationship between physical environment and learner characteristics, physical environment and lecture characteristics, lecture characteristics and learner characteristics and finally lecture characteristics and cognitive load. The researcher also carried out bivariate correlation analysis using SPSS to determine the relationships between cognitive load factors, physical environment, lecture characteristics, and learner characteristics. The researcher found out that learning in Bahasa Indonesia demotivates students, whilst learning in English (which the foreign students are fluent in) encourages investment of germane load, which is good for learning. Also, the ergonomic condition of the classroom influences the extent at which students invest in mental effort and germane load in learning. In conclusion, our results support the cognitive load theory and we recommend more empirical studies be carried out to enhance our understanding of the cognitive load theory.*

Keywords

Cognitive Load, Foreign Language, Learner Characteristics, Lecture Characteristics, Physical Environment and Structural Equation Modeling

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1. Introduction

The ability of nations to embrace globalization has contributed to the mobility of students around the world in pursuit for good education. Every country has its own national language and medium of instruction in schools. The shift in global education has posed a challenge to academicians to first learn a foreign language of a country they want to take their studies from. Most countries to include Indonesia, China, Japan, South Korea, France, Germany, and USA etc. give a timeline of about one year for students to take the language course and then later get enrolled in their study programs. These students still face challenges in reading, listening, writing and speaking.

Civan & Coskun, 2016, studied 'The Effect of the Medium of Instruction Language on the Academic Success of University Students', and the analysis of the results indicated that instruction in the non-native language affects negatively the academic success (i.e., semester point average) of students.

There are many other studies conducted on influence of language of instruction on students' performance for example (Mekonnen, 2005; 2009) found that primary students educated in their mother tongue obtained higher scores in mathematics and sciences than those educated in a non-native language. Maleki & Zangani, 2007, discovered that Students whose language proficiency levels are not adequate have difficulty in grasping the subject matters. Many researchers also found that students who are more proficient in the instruction language are on average more successful (Arsad et al., 2014; Fakeye, 2009; Kumar, 2014). But less research has been conducted on the cognitive load developed by students during lectures conducted in foreign language of instruction.

The original model of the construct of cognitive load proposed by (Paas and Merrienboer, 1994a) shows the relationship between causal factors and measurement factors of cognitive load. In this model, physical environment is part of the lecture environment and is not considered as an independent casual factor of cognitive load. Choi, Merrienboer & Paas, 2014, revised the cognitive load theory model by considering physical environment as an independent casual factor. A distinction is made between causal factors and assessment factors of cognitive load, corresponding to factors that affect cognitive load and factors that can be measured to assess cognitive load (Paas and Merrienboer, 1994a). With regard to its measurement, cognitive load can be conceptualized in the dimensions of mental load, mental effort, and performance (Paas and Merrienboer, 1994a).

According to (Paas and Merrienboer, 1994a), a cognitive load assessment based on mental load is a task-centered, subject independent dimension, which is solely based on the characteristics of the task (e.g., number of interacting information elements). Mental effort is considered a human-centered dimension, which refers to the amount of capacity or resources that is actually allocated by the learner to accommodate the task demands. A cognitive load assessment based on mental effort is believed to reflect the amount of controlled processing the learner is engaged in (Paas and Merrienboer, 1994a). Consequently, it is assumed to reflect the interaction between learner and learning-task characteristics (Paas and Merrienboer, 1994a). The level of performance can also be used to assess the cognitive load (Paas and Merrienboer, 1994a). For similar learners, faster task performance with less effort can be considered to indicate a lower cognitive load than slower task performance with more errors (Choi et al., 2014). Choi, Merrienboer & Paas, 2014, recommended that an empirical study be conducted to test the new model of cognitive load, and to determine the impact of the physical learning environment on cognitive load, learning processes, and performance. See Fig 1 and 2 below.

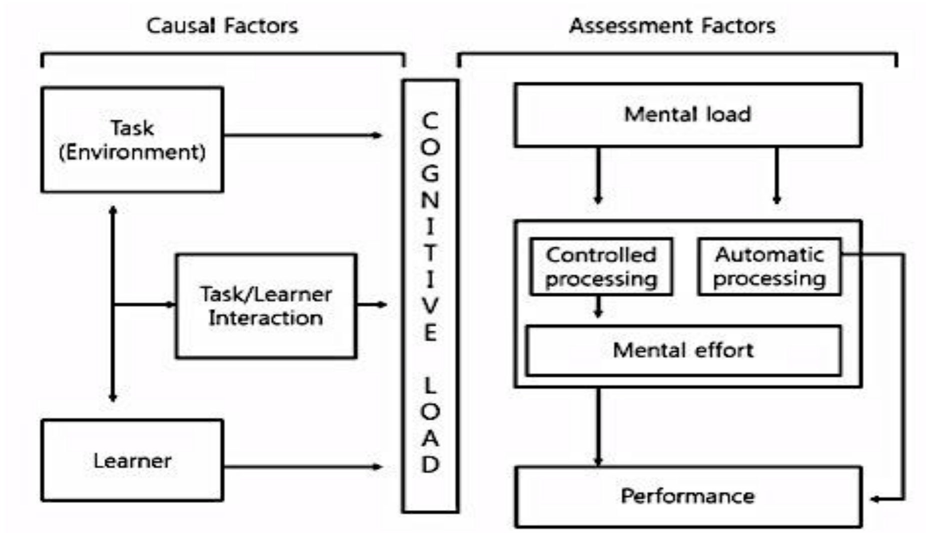

Figure 1: *The original model Adapted from Paas and Merrienboer, 1994a.*

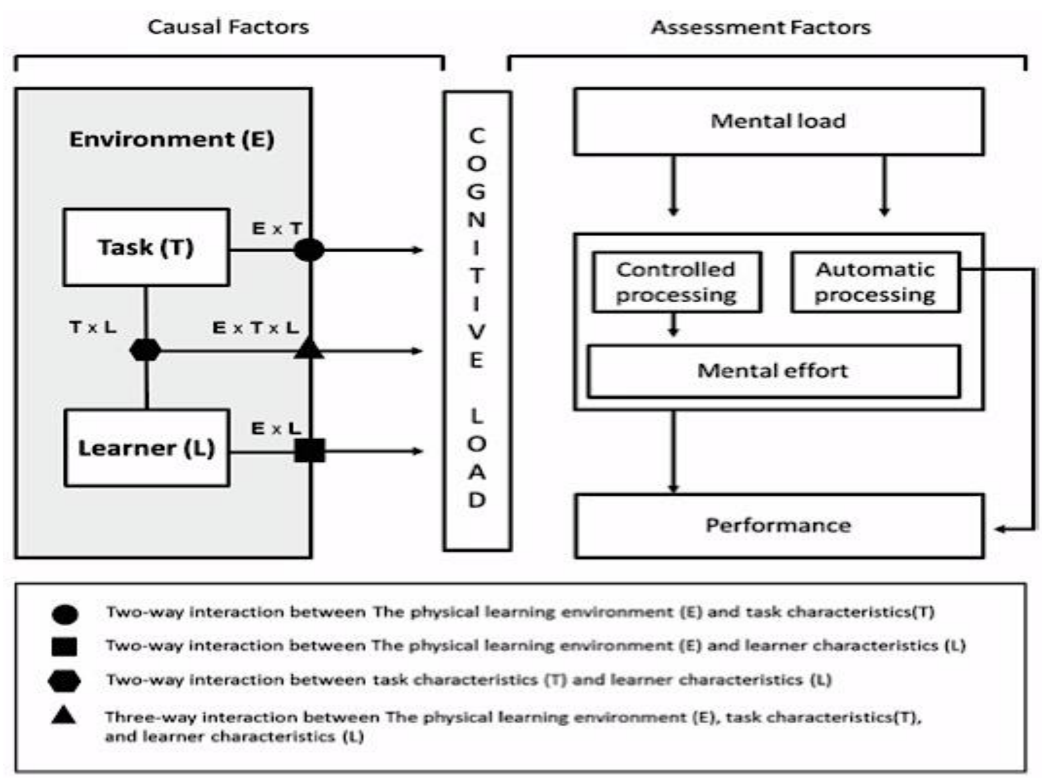

Figure 2: *The new model adapted from Choi et al., 2014.*

There is an increasingly growing need to make use of cognitive load theory to understand how individuals learn and seek ways to maximize varying learning styles. Cognitive load theory

(CLT) is concerned with techniques for managing working memory load to facilitate the changes in long term memory associated with schema construction and automation (Paas et al., 2004). CLT is based on the concepts of a long-term memory with a virtually unlimited capacity for storing information, and the working memory, which has a limited capacity in processing information (Paas et al., 2003a & Paas et al., 2004).

Cognitive load of a task may end up from two main causes: intrinsic cognitive load (ICL) is innate to a task and depends on how hard and complex it is, extraneous cognitive load (ECL), that does not contribute to learning itself, refers to working memory capacity required to deal with the structure of a task and with the associated activities (Paas et al., 2004). A third component, germane cognitive load (GCL) depends on ICL. GCL results from intentional learning processes and refers to the mental effort invested to deal with ICL requirements. Guidelines for the instructional design of demanding tasks aim at achieving adequate levels of intrinsic, reduction of extraneous, and encouragement of germane cognitive load (Sweller, 2010 & Sweller et al., 1998).

Intrinsic cognitive load through element interactivity depends on the interaction between the nature of the material being learned and also the experience of the learners. Instructional designers cannot directly influence it. Extraneous cognitive load is the extra load beyond the intrinsic cognitive load resulting from mainly poorly designed instructional materials, whereas germane cognitive load is the load related to processes that play a significant role in the construction and automation of schemas. Both extraneous and germane load are under the direct management of tutorial designers. The basic assumption is that a tutorial style that ends up in unused working memory due to low extraneous cognitive load because of appropriate tutorial procedures may also be improved by encouraging learners to interact in intensely conscious cognitive process that is directly relevant to the development and automation of schemas. Because intrinsic load, extraneous load, and germane load are additive, from a cognitive load perspective, it is important to realize that the total cognitive load associated with an instructional design, or the total sum of intrinsic cognitive load, extraneous cognitive load, and germane cognitive load, ought to be kept within working memory limits.

1.1 Research Gap

Paas and Merrienboer, 1994a, developed the first theoretical cognitive load architecture describing the interrelationships between causal factors, cognitive load and measurement factors.

In 2014 Choi et al reviewed this model, but it is still theoretical. Choi, Merrienboer & Paas, 2014 recommended that an empirical study to be carried out in order to prove the cognitive theory. Therefore the researcher opted to do this research in a foreign language environment, 191 questionnaires were sent to foreign students in Indonesia. This was chosen so as to evaluate the influence of foreign language learning on students cognitive load, motivation and interest in learning through a foreign language of instruction.

1.2 Objectives

The Purpose of this study is to determine the cognitive load developed by foreign students when taught in Bahasa Indonesia. From Maleki & Zangani's argument, students whose language proficiency levels are not adequate have difficulty in understanding lectures, this implies that the students will try to develop an understanding of the lecture material on their own, hence are most likely to have a higher cognitive load than the senior students. The researcher opts to;

- Determine the relationship between causal factors and cognitive load factors
- Determine the relationship between causal factors of cognitive load
- Determine the amount of cognitive load imposed on foreign students studying in a foreign language.

1.3 Hypotheses

With regard to the theoretical implications of the new model of cognitive load, including the physical learning environment as a distinct causal factor of cognitive load extends CLT. However, the significance of this extension can only be shown by empirical studies revealing interactions between the physical learning environment and the characteristics of the learner and/or the learning task (Choi et al., 2014). The hypotheses derived from the literature review that were tested in the model are listed below;

- H1: There is a significant relationship between physical environment and learner characteristics.
- H2: There is a significant relationship between learner characteristics and cognitive load.
- H3: There is a significant relationship between physical environment and lecture characteristics.
- H4: There is a significant relationship between lecture characteristics and cognitive load.

- H5: There is a significant relationship between lecture characteristics and learner characteristics.

The conceptual model in Fig 3 below was developed in line with the new model of cognitive load theory.

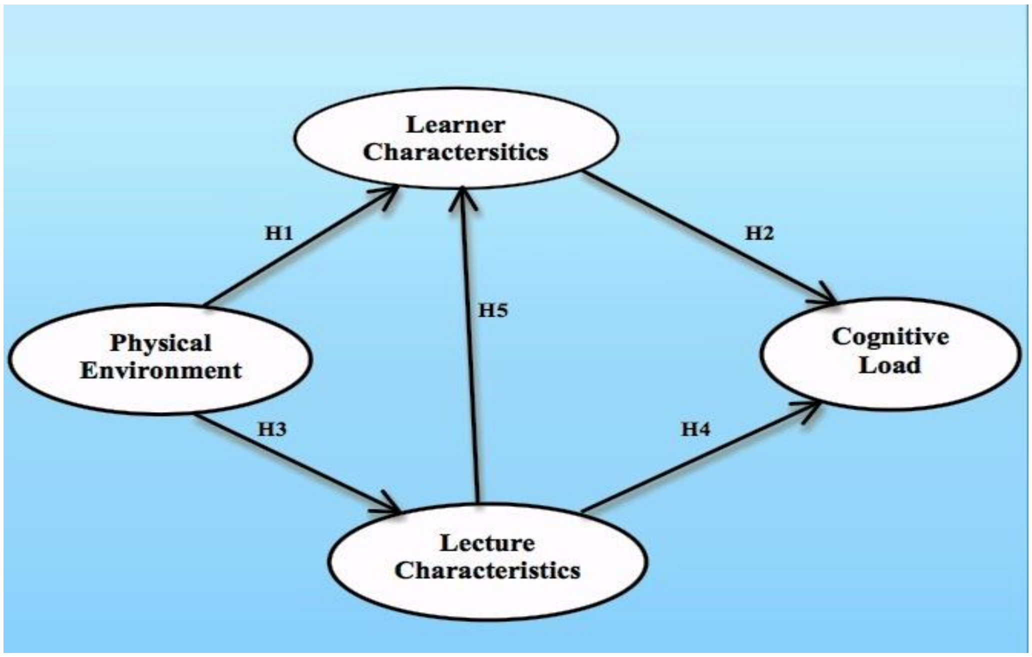

Figure 3: *Conceptual Model as extracted from (Choi et al., 2014) theoretical model*

2. Methodology

This chapter is concerned with how data was collected. It consists of the methods that were used by the researcher in the process of obtaining/collecting, analyzing and presenting the data. It therefore provides a description of the research design, population of the study, sampling size, sampling methods, tools for data collection and sources of data, variables of the study, procedure for data collection, data processing, analysis and presentation.

2.1 Data sources

Primary data was obtained directly from the respondents and secondary data was obtained through review of previous studies, this gave the researcher an insight on how to carry out the study, method of data collection, which was used, method of data analysis and presentation, which was used. This made it easy for the researcher to carry out the survey with minimal supervision.

2.2 Population of the Study

The population surveyed consisted of foreign students whose languages of instruction at previous universities were different from the languages of instruction at current universities. The students surveyed were enrolled in Indonesian universities, this gave the researcher a clear understanding on how a foreign language of instruction influences students' cognitive load.

2.3 Sample population and size

The sample was drawn from a pool of international students in Indonesia, from both undergraduate level and graduate level. Our samples were from, Jakarta, Bogor, Bandung, Yogyakarta, Surakarta, Semarang, Malang and Surabaya. This helped the researcher get a clear picture of factors influencing foreign students' cognitive load in Indonesia.

A total of 191 responses were received, 130 boys and 61 girls, 106 were aged, 25 – 34, 73 were aged, 18 – 24 and 12 were older 35 years. 106 master students, 75 bachelor students and 10 doctorate students filled our online survey form.

The respondents were from many countries around the world for example; Tanzania, Madagascar, Cambodia, Rwanda, Malaysia, Uganda, Zimbabwe, Myanmar, Yemen, Ethiopia, Nigeria, Laos, Vietnam, Timor-Leste, Sudan, South Korea, Japan, Gambia, Afghanistan, Egypt, Burundi, Lithuania, Namibia, Brunei, Pakistan, Bangladesh, Benin, Morocco, Kenya, Malawi, Germany, Sierra Leone, China, Italy, United States of America, Nepal, India, Libya, Russia, Colombia, Hong Kong, Philippines, France, Czech Republic, Slovak Republic.

The respondents were from the following Universities; Bandung Institute of Technology, Telkom University, Universitas Gadjah Mada, Universitas Pendidikan Indonesia, Institut Teknologi Sepuluh Nopember, Universitas Airlangga, Bogor Agricultural University, Sebelas Maret University, Universitas Muhammadiyah Surakarta, Universitas Negeri Yogyakarta (UNY), Universitas Padjadjaran, Universitas Atma Jaya Yogyakarta, Universitas Diponegoro, Semarang, Universitas Brawijaya, etc.

2.4 Tools for data Collection and Analysis

According to the researcher, the main tool for data collection was an online questionnaire derived from Work Design Questionnaire (Morgeson & Humphrey, 2006), R-SPQ-2F (Biggs et al., 2001), Mental effort scale (Paas, 1992), Intrinsic load scale (Ayres, 2006), Extraneous load scale (Cierniak et al., 2009), Germane load scale (Salomon, 1984). This was because of its robustness, ease in administering and its low cost implication.

Data analysis was done using Microsoft Excel, SPSS and SmartPLS 3.0 software (Ringle et al., 2015) and the main application is on SEM so as to test for construct validity of the model. This was done in accordance to the research objectives.

2.5 Procedure for data collection

This study began with the review of the literature entailing factors that influence cognitive load. Following (Paas & Merrienboer, 1994a) and (Choi et al., 2014) models of cognitive load architecture. The researcher attempted to develop a model of factors that influence foreign students' cognitive load.

After sketching the measurement model the researcher then developed an online questionnaire for physical environment, task and learner's factors that influence foreign students' cognitive load in class. The researcher also applied cognitive load scales for measuring the three types of cognitive load, i.e. Intrinsic, Extrinsic and Germane cognitive load, which the students experienced while attending classes facilitated in a foreign language of instruction.

After developing the questionnaire, a Google form survey was then generated, together with a letter of consent. The link to this Google form was sent to prospective respondents and their responses awaited.

After getting responses from 191 respondents, the researcher then carried out bivariate data analysis and structural equation modeling to determine the relationship between latent constructs and also between measured variables.

The measurement model was sketched as in the Fig 4 below;

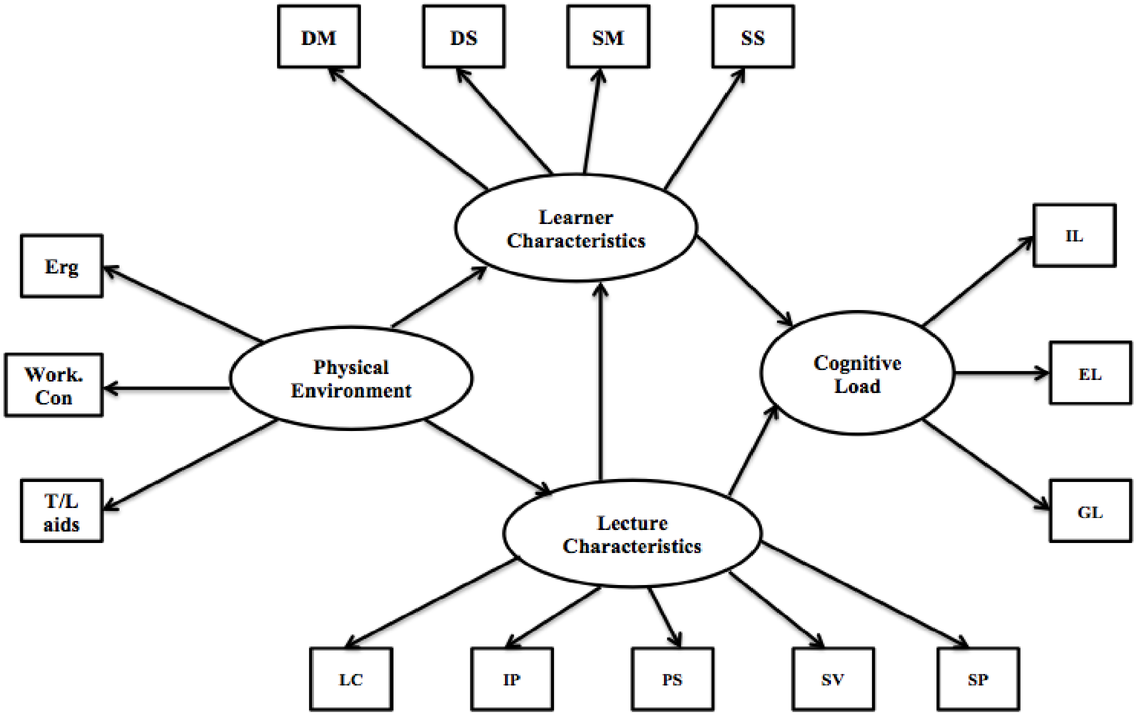

Figure 4: *Measurement model adapted from Choi et al., 2014. Erg (ergonomics), Work.Con (lecture conditions), T/L aids (teaching or learning aids), LC (lecture complexity), IP (information processing), PS (problem solving), SV (skill variety), SP (specialization), IL (intrinsic load), EL (extraneous load), GL (germane load), DM (deep motive), DS (deep strategy), SM (surface motive) and SS (surface motive).*

3. Results and Discussion

3.1 Results

3.1.1 Descriptive Statistics

From the descriptive statistics in table 1 below, the mean for Bahasa Indonesia is 4.76 and standard deviation is 2.594 and for English language the mean is 7.72 and standard deviation is 1.732. The statistics show that most of the foreign students have good English fluency and poor Indonesian language fluency. The mean for English is above the mid point of the 10-point scale, whilst for Bahasa Indonesia it is below the midpoint of the 10-point scale.

Table 1: *Descriptive Statistics*

	Mean	Std. Deviation	N
Bahasa Indonesia (B.Indo)	4,76	2,594	191
English (Eng)	7,72	1,732	191
Mental Effort (ME)	6,50	1,638	191
Intrinsic Load (IL)	5,94	1,674	191
Extraneous Load (EL)	5,60	1,944	191
Germane Load (GL)	6,84	1,883	191
Ergonomics (Ergon)	10,64	1,606	191
Lecture Conditions (Work.Con)	20,53	3,491	191
Teaching/Learning aids (T/L.aids)	10,57	2,281	191
Lecture Complexity (LC)	11,83	3,188	191
Information Processing (IP)	15,04	3,184	191
Problem Solving (PS)	14,51	3,055	191
Skill Variety (SV)	15,06	3,107	191
Specialization (SP)	15,17	2,965	191
Deep Motive (DM)	12,40	3,050	191
Deep Strategy (DS)	13,15	3,056	191
Surface Motive (SM)	13,82	3,357	191
Surface Strategy (SS)	14,47	3,751	191

3.1.2 Data Analysis using Structural Equation Modeling (SEM)

In this study the researcher adopted the application of Structural Equation Modeling (SEM) for data analysis. SEM has the ability to statistically test the prior theoretical assumptions against empirical data. SEM assesses the properties of the scales employed to measure the theoretical constructs and estimates the hypothesized relationships among the said constructs (Barclay et al., 1995, Chin, 2003 & Westland, 2007). Thus, SEM is able to answer a set of interrelated research questions simultaneously through measurement and structural model. While other SEM tools exist, the researcher’s choice to use PLS was driven by several factors.

First, PLS was developed to handle each formative and reflective indicators whereas alternative SEM techniques don't allow this. The existence of this ability permits the designation of the sort of relationship that the researcher believes to exist between the manifest variables and also the latent constructs.

Second, (Wold, 1981) specifically advises that PLS isn't appropriate for validating testing, rather should be used for prediction and the exploration of plausible causality. Other techniques are primarily concerned with parameter accuracy.

Thirdly, PLS does not make the assumption of multivariate normality that the SEM techniques LISREL and AMOS do, and being a nonparametric procedure, the problem of multicollinearity is not an issue (Lowry & Gaskin, 2014).

Finally, PLS's requirement on sample size is lower than the other SEM techniques (Chin, 1998, Chin 1999 & Westland, 2007). Sample size necessities are capable of the larger of ten times the quantity of indicators on the foremost complicated formative construct or ten times the biggest number of independent constructs leading to an endogenous construct (Chin, 2003 & Westland, 2007).

3.1.3 Partial Least Squares Analysis (PLS)

A PLS model is normally analyzed and interpreted in two stages consecutively. First is that the assessment and refinement of adequacy of the mensuration model and followed by the assessment and analysis of the structural model. This is to ensure the reliability and validity of the measures prior to the attempt in crafting and outlining the conclusion on the structural model.

3.1.4 Assessment of Measurement Model

The assessment of measurement models is crucial and completely necessary as it provides detailed testing for the reliability and validity of the scales employed to measure the latent constructs and their manifest variables (Loehlin, 1998). The researcher carried out assessment of convergent and discriminant validity, and evaluation of the measurements' reliability.

3.1.5 Convergent Validity

Convergent validity specifies that items that are indicators of a construct should share a bigger proportion of variance (Hair, 2006). The convergent validity of the scale items was evaluated using three conditions. First, the factor loadings should be greater than 0.50 as proposed by (Hair, 2007). See table 2 below.

Table 2: *Factor Loadings*

	Cognitive Load	Learner	Lecture	Physical Environment
Deep Motive		0,788		
Deep Strategy		0,826		
Extraneous Load	0,618			
Ergonomics				0,578
Germane Load	0,648			
Intrinsic Load	0,863			
Information Processing			0,783	
Problem Solving			0,773	
Surface Motive		0,791		
Specialization			0,876	
Surface Strategy		0,763		
Skill Variety			0,922	
Teaching/Learning Aids				0,845
Lecture Conditions				0,739

In this study, the factor loadings revealed support for convergent validity for the four constructs, except for lecture complexity that was less than 0.1, therefore the researcher excluded it from structural analysis with support from (Ashby, 1958) definition of complexity as the quantity of information required to describe something. Some problems are in principle unsolvable because of complexity, this clearly gives us the impression that from the lecture characteristics scale, information processing, problem-solving, skill variety and specialization, measure complexity. Therefore after eliminating lecture complexity, all loadings were greater than 0.50, with most loadings exceeding 0.60. The factor loadings ranged from 0.578 to 0.922.

Secondly, the composite reliability for each construct should exceed 0.70 and lastly, the Average variance extracted (AVE) for each construct should be above the recommended cut-off 0.50 (Fornell & Larcker, 1981). See table 3 below.

Table 2: *PLS Quality (AVE, R^2, Composite Reliability and Cronbach's Alpha)*

	Cronbach's Alpha	R^2	Composite Reliability	AVE
Cognitive Load	0,538	0,087	0,757	0,515
Learner	0,807	0,255	0,871	0,628
Lecture	0,862	0,203	0,906	0,707
Physical Environment	0,619		0,769	0,531

From table 3 above, it is clear that all the variables used in this research were reliable since it attained the Composite Reliability values of more than 0.7 and Average Variance Extracted values of greater than 0.5.

3.1.6 Discriminant Validity

The following step in the construct validation process is the assessment of discriminant validity. Discriminant validity shows the extent to which the measure is distinctive and not merely a reflection of other variables (Peter & Churchill, 1986). Each dimension of a construct should be inimitable and dissimilar from the other even though each reflects a portion of that construct. There are numerous ways to assess discriminant validity. Average Variance Extracted (AVE) is a common method of testing discriminant validity (Anderson & Gerbing, 1988). Discriminate validity was gauged by examining the cross-loadings of each item in the constructs and the square root of AVE calculated for respective constructs. All the items ought to have a higher loading on their corresponding constructs than the cross-loadings on the other constructs in the model. The square root of AVE for all factors should be larger than all the correlations between that construct and other constructs. See table 4 below.

Table 3: *Correlations and measures of validity among variables*

	AVE	**Cognitive Load**	**Learner**	**Lecture**	**Physical Environment**
Cognitive Load	0,515	**0,718**			
Learner	0,628	-0,123	**0,792**		
Lecture	0,707	0,294	-0,453	**0,841**	
Physical Environment	0,531	0,104	-0,403	0,450	**0,729**

Table 4, shows the AVE and cross factor loadings extracted for all latent variables. All the items are having higher loadings on their corresponding constructs than the cross loadings on the other constructs in the model. The AVE for each latent factor exceeded the respective squared correlation between factors, thus providing evidence of discriminant validity (Fornell & Larcker, 1981).

3.1.7 Reliability of Measures

The last step in investigating construct validity is to determine the reliability of the construct items. Reliability is the degree to which a set of indicators is internally consistent, the extent to which the instrument yields the same results on repeated trials. Reliability is necessary but not sufficient for validity of the measures; even measures with high reliability may not be valid in measuring the construct of importance (Hair, 2006). Reliable indicators should measure the same construct. To measure internal consistency, composite reliability or a composite alpha value was considered. This value was used to assess the reliability of the four constructs. Construct reliability coefficients should all surpass the 0.70 lower limits (Hair et al., 1998, & Rossiter, 2002). However, some researchers prefer to use Composite Reliability (CR) rather than Cronbach Alpha because Cronbach Alpha is being criticized for its lower bound value, which underestimates the true reliability (Peterson & Kim, 2013). Since Cronbach's Alpha tends to provide a serious underestimation of the internal consistency reliability of latent variables in PLS path models, it is more suitable to apply a dissimilar measure, the composite reliability (Werts et al., 1974). The composite reliability takes into account that indicators have distinct loadings, and can be interpreted in a similar manner as Cronbach's Alpha. No matter which certain reliability coefficient is used, an internal consistency reliability value exceeding 0.7 in early stages of research and values larger than 0.8 or 0.9 in more advanced stages of research are deemed satisfactory (Nunnally & Bernstein, 1994), whereas a value below 0.6 indicates a lack of reliability. Hence this model has good reliability since all the composite reliability measures are greater than 0.7. The composite reliability and Cronbach's alpha values for the studied constructs were computed by SmartPLS and ranged from 0.757 to 0.906 and 0.538 to 0.862, respectively. Please refer to table 3.

3.1.8 Assessment of the Structural Model

As noted by (Hair et al., 1998), a structural model is applied to capture the linear regression effects of the endogenous constructs on each other. The structural model has the ability to specify the pattern of the relationships among the constructs (Loehlin, 1998). Thus, this model is an evolving area and one of great interest to researchers because of its ability to perform direct testing of the theory of interest (Cheng, 2001).

The model was evaluated using three items: 1) path coefficients (β); 2) path significant (p-value); and 3) variance explained (R2). The validation of the structural model was achieved using SmartPLS 3. The model was developed in PLS, with reference to the guidelines given in the SmartPLS Guide (Ringle et al., 2005). Following (Chin, 1998), bootstrap re-sampling method was employed to test the statistical significance of each path coefficient. Five thousand (5000) iterations using randomly selected sub-samples were performed to estimate the theoretical model and hypothesized relationships.

See fig.5 below;

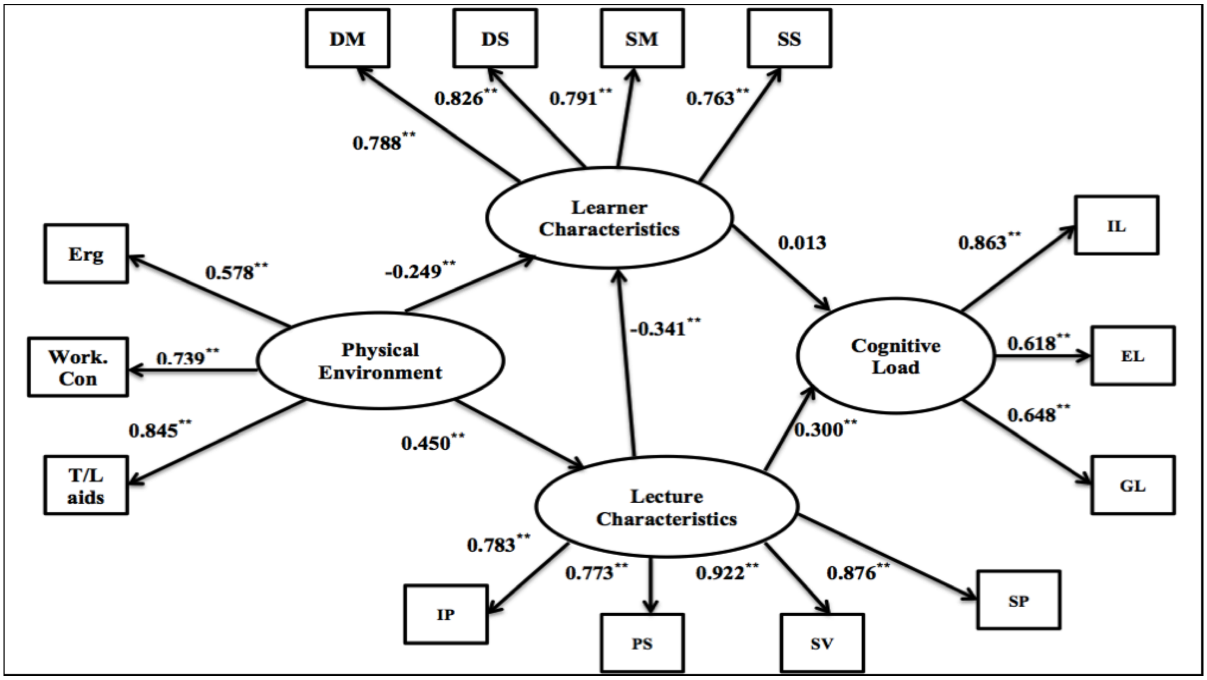

Figure 5: *Structural Model*

The criterion put forth by (Rossiter, 2002) states that for the structural model, all paths should result in a t-statistic value greater than 2 and latent variable R-Squared (R^2) greater than 50%. Hair, Ringle & Sarstedt, 2011, stated that R^2 value ranges from 0 to 1, with higher levels indicating higher levels of predictive accuracy. It is challenging to specify rules of thumb for acceptable R^2 values as this depends on the model complexity and the research discipline. Whereas R^2 values of 0.20 are considered high in disciplines such as consumer behavior (psychology), in success driver studies (e.g., in studies that aim at explaining customer satisfaction or loyalty), researchers expect much higher values, such as 0.75 and above. In scholarly research that focuses on marketing issues, R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rule of thumb, be respectively described as substantial, moderate, or weak (Hair et al., 2011 & Henseler et al., 2009).

Cohen's Conventions for Small, Medium, and Large Effects should be used with caution. What is a minor or even insignificant effect in one context may be a large effect in another context. For example, (Rosnow & Rosenthal, 1989) discussed a 1988-biomedical-research study on the effects of taking a small, daily dose of aspirin and concluded that for researches performed on human subjects, even the lowest R^2 can have a serious impact. Cohen's definitions for small, medium and large effect sizes are tabulated in table 5 below.

Table 4: *Multiple R^2*

Size of effect	f^2	% of variance
Small	.02	2
Medium	.25	13
Large	.4	26

Source: *Cohen, 1980*

Also R^2 values of 0.67, 0.33, or 0.19 for endogenous latent variables in the inner path model are described as substantial, moderate, or weak by (Chin, 1998).

Cross-validated redundancy should be greater than zero (Q^2>0), while cross-validated communality should be 0.02, 0.15, and 0.35: small, medium, and large, respectively (Hair et al. 2013).

From our results we determine that there is no significant relationship between the learner characteristics and cognitive load, hence proving (Paas & Merrienboer, 1994a), statement that "a cognitive load assessment based on mental load is a task-centered, subject independent dimension, which is solely based on the characteristics of the task (e.g., number of interacting information elements)." While on the other hand we can deduce that there is a significant relationship between lecture characteristics and cognitive load, lecture characteristics and learner characteristics, physical environment and learner characteristics and finally physical environment and lecture characteristics. These results prove the interrelationships between causal factors of cognitive load, cognitive load and measurement factors of cognitive load as explained according to (Choi et al., 2014) and (Paas & Merrienboer, 1994a). See table 6 below.

Table 5: *Summary of bootstrap results and f^2*

	f^2	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values
Learner -> Cognitive Load (H2)	0.000	0,013	0,013	0,098	0,129	0,898
Lecture -> Cognitive Load (H4)	0,078	0,300	0,313	0,072	4,186	0,000
Lecture -> Learner (H5)	0,124	-0,341	-0,344	0,069	4,929	0,000
Physical Environment -> Learner (H1)	0,067	-0,249	-0,254	0,069	3,593	0,000
Physical Environment -> Lecture (H3)	0,254	0,450	0,459	0,060	7,504	0,000

According to (Hair et al., 2013), CV-Red values must be greater than zero and CV-Com values must be within 0.02, 0.15, and 0.35: small, medium, and large, respectively. Our structural model meets these conditions. With reference to Cohen's criteria, our R^2 values also lie within the acceptable range of between 2, 13 and 26%. This implies that this model has good predictive power. Hair, Ringle & Sarstedt, 2011, further gives assurance that our model has a high predictive power because our research deals with human subjects. See table 7 below;

Table 6: *Indices of the structural model for latent variables*

Latent variable	R^2 (%)	CV-Red	CV-Com
Cognitive Load	8.7	0,035	0,111
Learner	25.5	0,139	0,370
Lecture	20.3	0,125	0,486
Physical Environment			0,136

CV-Red is cross-validated redundancy, CV-Com is cross-validated communality.

From the table above learner characteristics and lecture characteristics explain 8.7% of the variance in cognitive load and it is classified as small in explaining the variance in the cognitive load, while physical environment and lecture characteristics explain 25.5% of the variance in the learner characteristics and 20.3% of the variance in the lecture characteristics is explained by the physical environment. Therefore, the predictive power of the model is good, with reference to Cohen's criteria.

3.1.9 Correlation Results

The correlation results will help us determine the relationship between measured variables. We shall also find the correlation between the language of instruction and cognitive load, students' approaches to learning and physical environment. The researcher also determined the relationship between lecture complexity and other measured variables, though it wasn't considered in our model evaluation, we can also identify how lecture complexity influences other variables. See table 8 below;

Table 7: *Pearson Correlations*

	B.Indon	Eng	ME	IL	EL	GL	Ergon	Work.Con	T/L.aids	LC	IP	PS	SV	SP	DM	DS	SM	SS
B.Indon	1	,329**	.116	-.033	-.139	.085	-.026	-.002	.073	-.053	-.036	.039	-.036	-.035	-,153*	-.035	-.047	-.012
Eng		1	,168*	-.069	-.021	,143*	,166*	,157*	-.068	.094	.129	.022	.088	.096	-.016	.038	,148*	.134
ME			1	,423**	,225**	,362**	,149*	,241**	,164*	,165*	,192**	.099	,207**	,206**	-.120	-.132	.029	.060
IL				1	,552**	,237**	-.067	-.006	.119	,218**	,217**	,205**	,258**	,213**	-.099	-.130	-.121	-.103
EL					1	.048	-.065	-.048	-.047	,208**	,144*	.116	.067	.078	.043	-.074	-.048	-.043
GL						1	,172*	.110	.129	-.030	,263**	,156*	.125	,193**	-.080	-,166*	.082	.066
Ergon							1	,543**	,200**	-.062	,147*	.109	,163*	,234**	-,181*	-.139	.077	.093
Work.Con								1	,311**	-,240**	,236**	,156*	,301**	,383**	-,173*	-,212**	-.067	-.072
T/L.aids									1	-.124	,172*	,212**	,381**	,492**	-,370**	-,397**	-,363**	-,333**
LC										1	.056	.023	.093	-.006	.129	.134	,173*	,248**
IP											1	,554**	,642**	,538**	-,263**	-,326**	-,153*	-.135
PS												1	,641**	,507**	-,299**	-,313**	-,327**	-,218**
SV													1	,780**	-,341**	-,311**	-,353**	-,247**
SP														1	-,332**	-,444**	-,312**	-,270**
DM															1	,522**	,459**	,461**
DS																1	,498**	,471**
SM																	1	,655**
SS																		1

***. Correlation is significant at the 0.01 level (2-tailed), and *. Correlation is significant at the 0.05 level (2-tailed)*

- As proposed by (Choi et al., 2014) & (Paas & Merrienboer, 1994a). Physical environment, lecture characteristics and learner characteristics interact and influence student's cognitive load. From literature review a number of factors affect students' cognitive load, they lie under physical environment, lecture characteristics and learner characteristics.
- From the table above we can deduce that, there is a positive correlation between English Language and Bahasa Indonesia and a negative correlation between Bahasa Indonesia and deep motive.
- There is a positive correlation between English Language and mental effort, germane load, ergonomics, lecture and surface motive.

- Mental effort has a significant positive correlation with intrinsic load, extraneous load, germane load, ergonomics, lecture conditions, teaching aids, lecture complexity, information processing, skill variety and specialization.
- Intrinsic load has a positive correlation with extraneous load, germane load, lecture complexity, information processing, problem solving, skill variety and specialization.
- Lecture complexity is positively correlated with surface motive and surface strategy.
- Extraneous load has a significant positive correlation with lecture complexity and information processing.
- Germane load has a positive correlation with information processing, problem solving and specialization, while negatively correlated with deep strategy.
- Ergonomics is positively correlated with lecture conditions, teaching aids, information processing, skill variety, specialization, while negatively correlated with lecture complexity and deep motive.
- Lecture conditions have a positive correlation with teaching aids, information processing, problem solving, skill variety and specialization, while negatively correlated with lecture complexity, deep motive and deep strategy.
- Teaching aids have a positive correlation with information processing, problem solving, skill variety and specialization, while negatively correlated with deep motive, deep strategy, surface motive and surface strategy.
- Information processing has a positive correlation with problem solving, skill variety and specialization, while a negative correlation with deep motive, deep strategy and surface motive.
- Problem solving has significant positive correlation with skill variety and specialization, while negatively correlated with deep motive, deep strategy, surface motive and surface strategy.
- Skill variety is positively correlated with specialization, while negatively correlated with deep motive, deep strategy, surface motive and surface strategy.
- Specialization is negatively correlated with deep motive, deep strategy, surface motive and surface strategy.
- Deep motive is positively correlated with deep strategy, surface motive and surface strategy.

- Deep strategy has a positive correlation with surface motive and surface strategy.
- Surface motive is positively correlated with surface strategy.

3.2 Discussion

With four out of five hypotheses supported (H1, H3, H4 & H5), the empirical results of the structural model with all hypothesized paths revealed a model with adequate fit. SmartPLS calculated the R-Square and t-Statistic for the full structural model and four paths t-Statistic met the required cut off, while one didn't meet the t-statistic. The learner – cognitive load (H2) didn't meet the t-statistic test. According to (Paas & Merrienboer, 1994a), a cognitive load assessment based on mental load is a task-centered, subject independent dimension, which is solely based on the characteristics of the task (e.g., number of interacting information elements). With reference to that statement, our results clearly show that there is a significant relationship between cognitive load and lecture characteristics, while there is no significant relationship between learner's characteristics and cognitive load. This is because cognitive load of a task can result from two main causes: (a) intrinsic cognitive load (ICL) which is inborn to a task and depends on its difficulty and complexity; (b) extraneous cognitive load (ECL), which does not contribute to learning itself, refers to working memory capacity required to deal with the structure of a task and with the associated activities. These results prove (Choi et al., 2014) & (Paas & Merrienboer, 1994a) findings of the interrelationships between causal factors, cognitive load factors and assessment factors.

From the researcher's findings, cognitive load is directly imposed by the lecture characteristics and indirectly influenced by the environment characteristics and learner characteristics. This is because the physical environment influences both the lecture characteristics and the learner characteristics, while the lecture characteristics influence only the learner characteristics. It is the interaction between these three causal factors that influences cognitive load. Hence providing proof for (Choi et al., 2014) new cognitive model, where physical learning environment is considered a distinct causal factor that can interacts with learner characteristics (H1), lecture characteristics (H2), or a combination of both.

From the correlation results we can deduce that the use of English language in teaching foreign students directly influences germane cognitive load that is important in learning. This implies that the students are willing to learn when taught in English and therefore lecturers should try to use English while delivering lectures. Merrienboer, Kester & Paas, 2006, suggested that learning tasks should always be combined with methods that induce *germane* cognitive load, such as high variability and limited guidance or feedback. In our results, using the language students are fluent in for delivering lectures is one of the methods of inducing germane cognitive load. There is also a negative correlation between Bahasa Indonesia and deep motive. This shows that the use of Bahasa Indonesia as a medium of instruction demotivates students, it agrees with (Moe, 2018), finding that students lack motivation to study a second language. The reason behind the lack of motivation is that, the students are made to listen, understand, translate and communicate with lecturers who are native speakers of Bahasa Indonesia (Chua et al., 2018). This is another support that language of instruction plays a big role in instructional design. Instructional designers should develop instructional materials in the language students are fluent in, so as to enhance the learning process.

Also ergonomics aspect of the lecture room is negatively correlated with deep motive, hence demotivates students if not looked upon and improved. Choi, Merrienboer & Paas, 2014, reviewed extensive literature on effects of the physical learning environment on learning. They assumed that a good quality of the physical learning environment (e.g., seat design, spatial distance, seating arrangement, fresh air and well-managed temperature in a classroom) may have a positive effect on learners' affect, their motivation to invest mental effort, and consequently on learning. This viewpoint assumes that emotional state, mood, or motivation act as a mediator of the relationship between the physical learning environment and learning performance. This can be shown in our correlation results in the positive correlation between mental effort, germane load and ergonomics, lecture conditions and learning aids. A poor quality of physical environment demotivates students and a good quality physical environment motivates them.

Lecture complexity is positively correlated with surface motive and surface strategy; this implies that if the lectures are complex, students tend to use surface approach in learning. The fact that foreign students tend to use a surface approach in studying signals that the students are engaged in applying strategies to pass, than to learn. The student's intention to learn is to only carry out the task because of external positive or negative consequences; if he fails life will be hostile but if he performs well in the subject he will win his instructor's favor. A typical surface strategy is rote learning, and surface-motivated students focus on what appears to be the most important items and memorize them. Because of this focus, they do not see interconnections between the meanings and implications of what is learned (Biggs et al., 2001).

While information processing is negatively correlated with deep strategy, deep motive and surface motive. Problem solving, skill variety and specialization are negatively correlated with deep motive, deep strategy, surface motive and surface strategy, hence lecture characteristics influence students' motives and strategies of learning.

There is a positive correlation between ergonomics and English language, mental effort and germane load. This implies that, the lecture environment has an influence on mental effort and germane load. This agrees with (Choi et al., 2014) research findings on influence of physical environment on students willingness in investing mental effort.

Lecture conditions are positively correlated with English language and mental effort. This also agrees with (Choi et al., 2014) and other researchers (Erez & Isen, 2002 & Uline & Tschannen, 2008) findings that the physical environment influences the learner's interest in investing mental effort to study.

4. Conclusions, Contributions, Limitations and Future Research

4.1 Conclusions

This study aimed at testing (Choi et al., 2014) & (Paas & Merrienboer, 1994a) cognitive load theory through structural equation modeling and bivariate analysis. The conclusions from this research can be summarized as follows;

Physical environment significantly influences lecture characteristics and learner characteristics. While lecture characteristics significantly influence learner characteristics and cognitive load.

Hypotheses H1, H3, H4 & H5 passed, while H2 failed. This proves the cognitive load theory by (Choi et al., 2014) & (Paas & Merrienboer, 1994a).

Instructors should endeavor to develop instruction materials in the language students are fluent in and also use the same language during instruction. This will motivate students to invest in germane load, necessary for learning.

Since ergonomic condition of the classroom influences students' interest in investing in mental effort and germane load during learning, the lecture rooms must be of good ergonomic design.

Foreign students in Indonesia also apply a surface approach in learning complex topics, this is because their intention is to pass and not to understand and may be because of fear of failing (Biggs, 1987).

4.2 Contributions

This research examined the interaction between causal factors, cognitive load factors and measurement factors. This study used quantitative method (empirical data) to test (Choi et al., 2014) & (Paas & Merrienboer, 1994a) cognitive load theory. The results of this study are a confirmation of the cognitive load theory.

The results of this study can be considered by the universities worldwide to set regulations and polices that encourage instructors/lecturers to develop instructional materials and deliver lectures in languages that students are fluent in. This is because as per this research, when students are taught in a language they are fluent in, they easily invest in germane load that is good for learning.

4.3 Future Research

Given that there are many foreign students studying in many countries worldwide, this research can be conducted in other countries as well but with a larger sample size, different languages of instruction and another SEM method.

Since the researcher adapted the questionnaire applied in this research from many different scales. The researcher recommends that a study to develop scales for measuring causal factors of cognitive load be conducted.

Also this being among the first studies to use empirical data to test cognitive load theory, the researcher suggests more studies of this kind be conducted so as to ensure a proper understanding of cognitive load from empirical data.

From our results we realize foreign students in Indonesia use surface approach in learning. The researcher recommends that, a comparative study be carried out to identify the study approaches used by foreign students in different countries.

4.4 Limitations

Foreign students we used in the study had different languages of instruction in their home countries, for example Korean, Japanese, English, Arabic, French, Germany, etc. The effect of this variation has not been tested yet because our main concern was studies conducted in Bahasa

Indonesia. Universities in Indonesia encourage making teaching materials in English language and Bahasa Indonesia only. Therefore those students, whose English language proficiency is low, will face some challenges even if the lecturer's decided to teach in English.

The questionnaire was administered at the end of the semester not at the end of each lecture. Therefore, it did not measure the exact feelings immediately after lectures, but general feeling during the entire semester.

Since the questionnaires were administered online, we relied on subjective measurement scales to determine the language proficiencies of the respondents. We would have loved to base on standardized tests as well. However, since time and costs involved in doing standardized tests were unaffordable, we opted for subjective measurement.

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