e-ISSN: 2289-8042

Terima	Wasit	Muat Naik e-Jurnal
12 OGOS 2021	10 NOV 2021	15 NOV 2021

Correlation between Cognitive Engagement and Performance of AFL Undergraduate Students in Virtual Learning Environment

Korelasi antara Penglibatan Kognitif dan Prestasi Pelajar Prasiswazah dalam Persekitaran Pembelajaran Maya

Noorafini Kassim[1], Muhammad Sabri Sahrir[2], Tunku Badariah Tunku Ahmad[3]

ABSTRACT

The virtual learning environment (VLEs) is becoming an essential instructional technology in this new era due to its effects and impacts on the learning process. It has been implemented by many Malaysian higher educational institutions. The design of this study is correlational which is a type of non-experimental research. This study aims to examine the correlation between cognitive engagement and performance among undergraduate students in an online learning environment. Apart from investigating the relationships, this study seeks to predict an outcome or effect of the measures. A quantitative approach is utilized in this study, through the implementation of a cross-sectional survey. The using survey items were adapted from Greene (2015) and data were collected from 216 Arabic Foreign Language (AFL) students. In evaluating the correlation and factors of cognitive engagement that affect student performance, this study employed the Partial Least Square Structural Equation Modelling (PLS-SEM) and a conceptual model was designed. The findings demonstrated a positive correlation between cognitive engagement and student performance. The study indicated that the strongest predictor among the three factors of cognitive engagement is Self-Regulatory Strategy Use (SR), followed by Shallow Strategy Use (SSU) and Deep Strategy Use (DSU). As a result, cognitive engagement was demonstrated to be a critical predictor that can moderately affect students' performance on the use of a virtual learning environment. The coefficient of determination R2 values predicting performance is 0.588 (R2 = 0.588), which means can explain 58.8% of the variance in students' performance. This proportion is considered as a moderate effect in affecting the performance of AFL undergraduate students. This study advances our understanding of how students utilize cognitive engagement and learning strategies in online learning environments that yield significant learning experiences and better-quality performance. This study also offers empirical and practical contributions to online Arabic Foreign Language (AFL) teaching and learning.

Keywords: *Cognitive Engagement, Learning Performance, Virtual Learning Environment (VLE), Arabic, Structural Equation Modeling (SEM).*

ABSTRAK

Persekitaran Pembelajaran Maya (VLE) menjadi teknologi pengajaran yang penting dalam era baharu ini kerana kesannya yang positif terhadap proses pembelajaran. Persekitaran pembelajaran secara maya ini telah dilaksanakan oleh banyak institusi pengajian tinggi di Malaysia. Kajian ini menggunakan kaedah penyelidikan korelasi yang bertujuan untuk

[1] Noorafini Kassim, PhD Candidate, Kulliyyah of Education, IIUM, noorafinikassim2@gmail.com
[2] Muhammad Sabri Sahrir, PhD, Kulliyyah of Education, IIUM, muhdsabri@iium.edu.my
[3] Tunku Badariah Tunku Ahmad, PhD, Kulliyyah of Education, IIUM, tbadariah@iium.edu.my

 e-ISSN: 2289-8042

mengkaji korelasi antara penglibatan kognitif dan prestasi pelajar prasiswazah dalam konteks persekitaran maya. Selain itu, kajian ini menggunakan pendekatan kuantitatif yang menggunakan soal selidik untuk mendapatkan data. Item soal selidik yang digunakan diadaptasi daripada Greene (2015) dan data dikumpul daripada 216 pelajar bahasa Arab. Data yang diperolehi akan dianalisis menggunakan Analisis Multivariate Pemodelan Persamaan Struktural (PLS-SEM). Dapatan kajian menunjukkan terdapat korelasi positif antara penglibatan kognitif dan prestasi pelajar. Kajian juga menunjukkan bahawa pembolehubah faktor peramal yang terbaik antara tiga faktor penglibatan kognitif ialah Strategi pengaturan diri (SR), diikuti oleh Strategi Pendekatan Cetek (SSU) dan Strategi pendekatan Mendalam (DSU). Secara keseluruhan, penglibatan kognitif merupakan peramal yang signifikan yang boleh mempengaruhi prestasi pelajar dalam penggunaan persekitaran pembelajaran maya. Pekali penentuan nilai R2 yang meramalkan prestasi ialah 0.588 (R2 = 0.588), yang menjelaskan sebanyak 58.8% varians dalam prestasi pelajar. Nilai pekali ini dianggap sebagai kesan sederhana dalam mempengaruhi prestasi pelajar prasiswazah. Kajian ini dapat memberikan kefahaman kepada kita tentang penglibatan kognitif dan strategi pembelajaran pelajar dalam persekitaran pembelajaran maya, selain ianya dapat menghasilkan pengalaman pembelajaran yang signifikan dan prestasi yang lebih berkualiti. Kajian ini juga diharap dapat memberi sumbangan empirikal dan praktikal kepada pengajaran dan pembelajaran Bahasa Arab sebagai bahasa asing.

Kata kunci*: Penglibatan Kognitif, Prestasi Pembelajaran, Persekitaran Pembelajaran Maya (VLE), Bahasa Arab, Pemodelan Persamaan Struktur (SEM).*

Introduction

Undoubtedly, the use of a virtual learning environment (VLEs) as a learning support aid is an essential instructional technology in this new era. Due to its enhancement and far-reaching effects on student learning, VLEs turn into progressively significant components adopted in many higher learning across the globe including Malaysia (Tahar et al., 2013). It is believed to contribute to the quality of the learning process (Simonova & Poulova, 2013) and proved to be effective in enhancing students' learning experience (Lochner et al, 2016). Although virtual learning is useful and effective in the process of learning, but then some significant issues are affecting this process. Factors that are particularly based on learners like attitude, autonomy, how learners remain connected during learning and their learning strategy are important for the effectiveness of online learning. As mentioned by Bayoumy & Alsayed (2021), learning experiences are considered effective when learners are actively engaged and certainly learn in the learning process.

Additionally, Rasouli et al. (2016) argued that VLEs have converted learning into student-centered learning, as they instigate active learners to construct their knowledge based on lessons that are conveyed synchronously or asynchronously (Reid-Martinez & Grooms, 2018). In other words, learners should be able to cognitively engage with the lesson to achieve learning objectives. Undoubtedly, a few learners were quite uncomfortable with this student-centered nature as a result reduced their engagement and led to a falloff in student performance (Lowell, 2001). In this regard, researchers have been prompted to emphasize more on in what way learners learn and engage in online environments in order to recognize learners' needs. This is because, online environment is absolutely dissimilar from an offline environment, where learners' behavior, mimic and response cannot be perceived easily (Rotgans & Schmidt, 2011).

 e-ISSN: 2289-8042

The virtual setting, in particular, can be tough for students to cognitively engage in their learning. Learners have a tendency to execute passive intellectual performance because they endured from overtime online learning undertakings in contrast to physical ones. Bao (2020) ascertain that learners encounter difficulties when performing self-isolation, like self-indiscipline, disruptive learning climate, plentiful learning tasks, and learning attitudes. When disengagement happens, it leads to educational struggles among learners, including boredom also unsatisfactory learning performance (Fredricks et al, 2016; McFarland et al, 2020). Learners who engage in cognitive activities are possibly to yield significant learning experience and better-quality performance (Greene et al., 2004, Zhu et al., 2009). In addition, cognitive engagement is frequently used as a learning performance marker since it is positively associated with learning performance (Henrie et al., 2015). Even though the aspect of cognitive engagement has been studied dates back several decades, nevertheless virtual environment is considered a contemporary area of research. Thus, this study aims to investigate the correlation of cognitive engagement with learner performance of AFL undergraduate learners in a virtual setting.

Related Literature Review

Cognitive Engagement

Cognitive engagement is very important in the learning process as it can help to produce creative problem solvers and independent thinkers among learners (Hudson, 2015). Besides that, cognitive engagement is significant in transforming students' approach to their studies because it played a role in students' connectedness to the content of the subject matter as explained by Wara et al (2018). In general, cognitive engagement describes as the degree of learners to which they are willing to disburse an effort and use different processing strategies in a work of learning (Frederick et al., 2004; Rotgans & Schmidt, 2010). It is also identified as the combination and employment of learners' motivations and approaches in learning (Richardson and Newbie, 2014). As for Reeve (2012), Greene (2015), and Kristine (2017) they defined cognitive engagement as learners' interest and capability to take on deep and tough mental encounters and the self-regulatory practices to observe the thought processes in learning. D'Mello et al (2017) identified cognitive engagement by focusing on students' psychological investment in the learning task, such as how they allocate effort toward learning and their understanding and mastery of the material. Li et al (2021) defined cognitive engagement as the extent to which individuals think strategically across the learning or problem-solving process in a specific task. Cognitive engagement, therefore, is asserted to be fundamental in predicting positive learning performance for learners since they can track their patterns' cognitive and employ various meaningful strategies of learning that can direct to diverging stages of learning (Hu & Li, 2017).

Pertaining to the definition of cognitive engagement by various scholars, the common explanation highlights the consumption of learning strategy use such as cognitive strategies and self-regulatory strategies (Green, 2015; Reeve, 2012). Susanti (2020) and Li et al (2021) explained that cognitive engagement can be shown in terms of being strategic or self-regulating. It accomplishes the students' comprehension, sharing ideas, and previewing knowledge. Greene et al. (2015) further categorize cognitive learning strategies into two which are deep and shallow strategies. Deep strategies involve high-order or meaningful processing strategies, whereas shallow strategies encompass more mechanical memorization strategies and other rote processing actions (Xie, Heddy, & Greene, 2019). Deep strategies require extra psychological effort to acquire information from the material comprising the strategy of summarizing, differentiating, and correlating new viewpoints. In contrast, shallow strategies

 e-ISSN: 2289-8042

grasp merely on typical or mechanical memory processing such as jotting down notes, underlining, and remembering terms.

In terms of self-regulatory strategies, it refers to the ability of learners to self-regulate and to use contemplative and strategic techniques to meet the complexity of the skills that are being taught (Fredricks & McColskey, 2012) and actively control, monitor, and adapt different aspects of learning toward the fulfillment of personal goals (Schunk & Greene, 2018 and Winne, 2018). Some researchers such as Cleary and Zimmerman (2012) and Li et al. (2021) defined it as the degree to which learners think strategically across the learning and exhibit control over their learning activities. The cognitive self-regulated learning strategy implies more orientation towards deeper processing (Wara et al, 2018) and emphasized the processes of controlling and monitoring to achieve learning goals (Winne, 2019). Hence, students will be broad-minded all the time, and so be better prepared for tasks ahead of them.

Student Performance

Without a doubt, students' performance is a critical aspect in the context of education (Rono, 2013), that determines educational bodies' success and failure (Narad and Abdullah, 2016). Performance is defined as a wrap-up of student-teacher hard work and it displays the students' learning interest in one particular course (Mensink and King, 2020). Zahir et al, (2018) further mentioned that learner performance is gauged as a learning after-effect of learners that should be observed to see how they perform in their learning. Zhai et al, (2017) further asserted the importance of learners' performance to be measured because it is considered as an essential feature in ascertaining the success of the implementation of an online learning environment. Besides, it is a very important component in order to identify the strength and weaknesses when assessing the effectiveness of online learning environments (Topal, 2016).

In general, student performance in a virtual learning environment was found to be positively associated with the students' understanding and learning during a lesson, called cognitive engagement. As mentioned in a study by Nagadeepa (2021), students' cognitive engagement is signified as a significant influence on the student's performance in an online environment. Another related study also has concerned on cognitive engagement as a high-quality sign of students' learning and performance. For instance, Vallee et al. (2016) underlined cognitive engagement in terms of learning goals such as competence control and the approach to coursework, and Greene (2015) highlighted the element of cognitive strategy use. DeVito (2016) exposed that students who are less actively engaged to be having poorer grades and stated that their learning is boring and useless. Correspondingly, Zohud (2015) proved that student engagement brings significant consequences on the achievement of students in language learning.

Research Questions

This study examined the following research questions:

1- Is there any positive correlation between Cognitive Engagement and Performance of AFL undergraduate students?

2- Which factor(s) of cognitive engagement highly predicts students' performance that can be used as best indicators for AFL undergraduate students' performance?

3- To what extent are the three of Cognitive Engagement statistically significant in explaining variations in Learning Performance of AFL undergraduate students?

 e-ISSN: 2289-8042

Methodology

This study is situated within the positivist paradigm. The positivist paradigm is associated with fact-based investigation, in which the researcher needs to concentrate on facts and presents them by empirical methods. Adopting the positivist paradigm enables the study to have a very objective view of cognitive engagement and students' performance in online learning environments. Therefore, a quantitative approach is utilized in this study, through the implementation of a cross-sectional survey. The design of this study is a correlational design which is a type of non-experimental research. The correlational design was used in this study because it examines the extent of the relationship between a range of factors of cognitive engagement and students' performance. Apart from investigating the relationships, this study seeks to predict an outcome or effect of cognitive engagement on students' performance. In this present study, a research model was established pertaining to the literature review to investigate the correlation between the three dimensions of cognitive engagement and performance of AFL undergraduate students on the use of virtual learning.

The sample for this study was drawn from the 216 undergraduate students who are taking the Arabic Foreign Language (AFL) course at University Malaysia Sabah (UMS). These 216 students have come forward to fill the survey instrument using the systematic random sampling method. All the participants also have completed one Arabic language online course. The variable cognitive engagement was measured using survey items adapted from Greene (2015), which is comprised of three (3) dimensions; self-regulatory strategy use (SR), deep strategy use (DSU) and shallow strategy use (SSU). Learning performance as the dependent variable in this present study was evaluated by the 10 survey items from Alanzi et al. (2020) and Hitz (1994) in which covers the dimension of perceived learning and performance effectiveness. All participants were requested to select the response which best expressed their level of agreement to a statement typically with 5 points Likert Scale ranging from 'strongly disagree' (1) to 'strongly agree' (5).

In evaluating the correlation and factors of cognitive engagement that affect student performance, this study employed the Partial Least Square Structural Equation Modeling (PLS-SEM) and a conceptual model was designed. As described by Hair et al., (2012), PLS-SEM is a common multivariate analysis technique that aims to evaluate variance-based structural equation models, mainly in the discipline of social sciences. Besides that, PLS-SEM poses a chance to determine the multidimensional procedure of correlations and causal relationships in which is quite difficult to disclose. PLS-SEM conducts data to calculate the path coefficient. Furthermore, PLS-SEM permits such association and differences by combining measurement invariance testing (Henseler et al, 2016). It is considered the most frequently used application in this present era since it is appropriate for quantitative data analysis.

This study aims to utilize PLS-SEM to apprehend the cognitive engagement influencing the performance of online learners. The model designed elucidated the association between the variables. Thus, by utilizing the SEM method, this study designed a model, and a total of 16 cognitive engagement factors were formed into three constructs in line with the literature. The three constructs which are (1) Self-Regulatory Strategy Use (SR), (2) Deep Strategy Use (DSU) and (3) Shallow Strategy Use (SSU) were named as exogenous latent constructs. While the endogenous latent variable called performance consisted of ten (10) observed variables. This model displaying the relationship between the constructs can be seen in Figure 1.

 e-ISSN: 2289-8042

Results and Findings

Reliability and Validity

The reliability, as well as internal consistency, can be calculated from the outer measurement model. In terms of evaluation of internal consistency, Cronbach's alpha and Composite Reliability (CR) were applied. As for convergent validity, Average Variance Extracted (AVE) was calculated. Bagozzi and Yi (1998) proposed assessment standards for the composite reliability (CR) should be exceeded 0.7. According to hair et al, (2011) and Barclay et al. (1995) in Hussain et al (2018), the variance should be at least 50%. Therefore, AVE for all constructs must exceed 0.5. As shown in Table 1, good internal consistency and convergent validity were achieved as Cronbach's alpha and Composite Reliability (CR) standards are exceeding 0.7, signifying internal consistency and all average variance extracted (AVE) also are surpassing 0.5, signifying convergent validity.

Table 1: Construct reliability and validity

Main Constructs	Cronbach's Alpha	CR	AVE
Self-Regulatory Strategy Use	0.790	0.867	0.624
Deep Strategy Use	0.717	0.824	0.544
Shallow Strategy Use	0.900	0.919	0.587
Performance	0.935	0.945	0.635

Model Goodness of Fit

PLS-SEM results in this study proposed a good fit by observing the value of SRMR, as it is a measure of estimated model fit. Chen (2007) asserted that SRMR is the value of the standard of standardized residuals between the observed and the hypothesized covariance matrices. According to Hu & Bentler (1998) in Hussain et al. (2018), the model indicated a good fit if the value of SRMR is = <0.08. The following table 2 shows that SRMR = 0.070, Chi-Square was equal to 948.013 and NFI = 0.766 in which showed that the model had a good fit.

Table 2: Model fit summary

Estimated Model	
SRMR	0.070
d_ULS	1.735
d_G	0.833
Chi-Square	948.013
NFI	0.766

Is there any positive correlation between Cognitive Engagement and the Performance of AFL undergraduate students?

Following RQ1, the study investigated the correlation between cognitive engagement and student performance. The outcome is displayed in the following table 3. Fortunately, the outcome indicated that cognitive engagement significantly correlated with student performance as all correlation factor loadings showed 0.59 and above. This is a very good indicator as the variables should be correlated to the same degree as the previous literature.

Table 3: Latent Variable Correlations

	SR	DSU	SSU	PER
Self-Regulatory Strategy Use	1.000			
Deep Strategy Use	0.730	1.000		
Shallow Strategy Use	0.643	0.727	1.000	
Performance	0.704	0.653	0.680	1.000

Which factor(s) of cognitive engagement highly predicts students' AFL undergraduate students' performance and can be used as best indicators?

This study explores the dominant item and construct or factor of cognitive engagement that can be deliberated as the best indicator for the AFL undergraduate students' performance on the use of online learning. Referring to the calculation conducted, all loading factors indicated that all indicators were exceeded 0.6. In other words, all indicators were valid and good measures of their corresponding factors (Hair et al., 2010). As presented in table 4, it shows that 'self-regulatory strategy use students' for item 2 "*I tried to learn new material by mentally associating new ideas with similar ideas that I already knew*" has the highest standardized factor loading squared (R^2 = 0.878). In addition, item 2 under 'deep strategy use' in which "*While learning new concepts, I tried to think of practical applications*" indicated as the best indicator with higher factor loading (R^2 = 0.830). For the 'shallow strategy use', item 5 "*I wrote out lists of new terms and definitions*" has the highest standardized factor loading (R^2 = 0.824). On the other hand, the lowest factor loading in the entire model is item 4 under self-regulatory strategy use "*I copied down main ideas from my reading*" (R^2 = 0.610).

Table 4: Loadings of the Items

Main Constructs	Items	Loadings
Self-Regulatory Strategy Use	SR_1	0.764
	SR_2	0.878
	SR_3	0.876
	SR_4	0.610
Deep Strategy Use	DSU_1	0.811
	DSU_2	0.830
	DSU_3	0.666
	DSU_4	0.620
Shallow Strategy Use	SSU_1	0.733
	SSU_2	0.807
	SSU_3	0.740
	SSU_4	0.716
	SSU_5	0.824
	SSU_6	0.740
	SSU_7	0.784
	SSU_8	0.781

When speaking about high factor prediction, the result of the study presented in table 5 depicted that the factor or predictor that can be seen by examining the result of β path coefficient. All constructs are significant at p< .05 in which the strongest predictor is Self-Regulatory Strategy

Use (SR) with β = 0.404, followed by Shallow Strategy Use (SSU) with β = 0.339 and Deep Strategy Use (DSU) with β = 0.111.

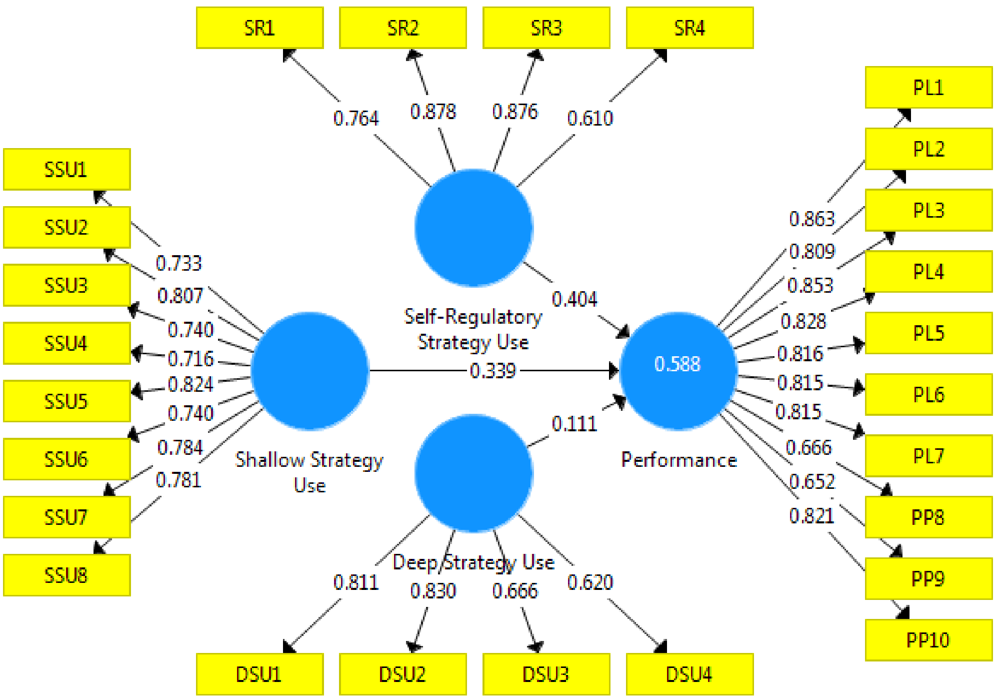
Table 5: Significant predictor

No.	Construct	β Path Coefficient
01	Self-Regulatory Strategy Use (SR)	β = 0.404
02	Shallow Strategy Use (SSU)	β = 0.339
03	Deep Strategy Use (DSU)	β = 0.111

To what extent are the three of Cognitive Engagement statistically significant in explaining variations in Learning Performance of AFL undergraduate students?

Figure 1 shows outer or factor loadings, β path coefficients, and R2 values. All the item loadings on their respective constructs were measured above 0.50 and all were significant at p<.001. In a nutshell, the three factors (SR, DSU and SSU) were significant in predicting student performance in an online learning environment. However, the overall model quality and variance explained can be measured based on the ability of its exogenous constructs to predict the endogenous constructs. Thus, the coefficient of determination (R2) measures the model's predictive accuracy. As shown in figure 1, the coefficient of determination R2 values of all the three factors in independently predicting performance are 0.588 (R2 = 0.588), which means the exogenous construct can explain 58.8% of the variance in students' performance. According to Hair et al., (2013), R2 value of 0.75 is regarded as substantial, 0.50 is considered as moderate, and 0.26 is viewed as weak. Hence, the result of R2 value in this present study has achieved moderate prediction accuracy.

Figure 1: Dimension of Cognitive Engagement Predicting Performance



Discussions of Findings

Correlation of Cognitive Engagement and Performance

This study explores the correlation between cognitive engagement and the performance of AFL Undergraduate Students. It is explored the leeway of three factors which are (1) Self-

 e-ISSN: 2289-8042

Regulatory Strategy Use (SR), (2) Deep Strategy Use (DSU) and (3) Shallow Strategy Use (SSU) as imperative elements of the cognitive engagement. From the result of the analysis of the data, it is found that all three factors are crucial that positively correlated to student performance in the context of online learning. This finding is in line with previous studies done by other researchers such as Al-Alwan (2014); Kamla-Raj and Ugur (2015); Alhoot (2016), Vallee et al., (2016), Wara et al. (2018) and Bayoumy & Alsayed (2021) in that similarly uncovered positive relationship between cognitive engagement and students' academic performance. Cognitively engaged in learning is very important as it tends learners to utilize several learning strategies (Fredericks et al., 2004), better task accomplishment and reflect better academic performance (Vallee et al., 2016). Additionally, being cognitively engaged in the learning process is imperative in order to achieve meaningful learning since it plays an eminent role to foster skills of critical thinking, problem-solving as well as more cognitive aptitudes. On the contrary, the study of Abid and Akhtar (2020) unexpectedly indicated a weak relationship between students' intellectual engagement and learning performance. However, this study was done among secondary school students. Researchers further explained that the reason behind this negative correlation is perhaps due to teacher factors in terms of behavior or instructional strategies. Hence, to possess better engagement among students and reach effective learning activities, it is critical to equip instructors with Technological and Pedagogical Content Knowledge (TPACK) and provide all the instructors with ICT-related set-ups and facilities (Peng & Daud, 2015).

Dominant Factor of Cognitive Engagement

This study also identified the dominant factor that highly predicts students' performance and can be used as best indicators for AFL undergraduate students' performance. The ranking of the three dimensions of cognitive engagement (SR, DSU and SSU) can be identified through the result or value of β path coefficient. The finding indicated that the strongest predictor among these three is Self-Regulatory Strategy Use (SR). The study found AFL students use a self-regulatory strategy by psychologically connecting new concepts with comparable concepts they already recognized whilst acquiring new material. Besides, they are also able to evaluate the ideas presented in course materials practically and effectively. As mentioned by Fredricks & McColskey (2012), learners with self-regulation skills can self-regulate and use thoughtful and strategic ways to meet the complexity of the skills in learning. Those self-regulated learners were normally able to manage time and invest their effort in learning. Besides, they frequently used metacognitive and cognitive strategies to succeed and to achieve learning objectives to make them perform better (You & Kang, 2014). Existing literature has noticeably declared that for students to learn effectively and successfully in online learning, students need to equip themselves with self-regulated learning strategies (Greene et al, 2018; Kizilcec et al, 2017; Phillips et al, 2015). Self-regulated learning strategies are pertinent to students learning performance in an online context due to their capability to assist students to become aware of their thought processes and actively participate in their learning process in all study contexts.

The second strongest predictor of cognitive engagement that predicts students' performance is Shallow Strategy Use (SSU). Among the shallow strategies that students use are jotting down the new terms and definitions, reading the course resources provided to acquire desirable information, and underlining details and main ideas. According to Trevors et al. (2014), shallow strategies enable students to achieve learning outcomes, particularly when the assessments are coherent with shallow processing. For instance, when the task of learning needed learners to memorize definitions or terms, rather than to elaborate the concept they have acquired. Therefore, the role of shallow strategies may vary depending heavily on learning

 e-ISSN: 2289-8042

contexts, such as subjects or learning tasks (Greene, 2015). Students should be able to select the different strategies they need to enact for the specific learning conditions (Rovers et al. 2018).

Finally, Deep Strategy Use (DSU) is considered as the lowest predictor of cognitive engagement in this current study. Among the deep strategies that students use is putting the thoughts and concepts collectively thenceforth illustrating their assumptions and trying to think of practical applications while learning. Even though the deep strategy is the lowest predictor in influencing AFL students' performance, this type of cognitive strategy in point of fact is the most essential strategy students should apply in learning as it is connected with higher achievement or performance (Green & Miller, 2004). In addition, students who use deep processing strategies in online learning have been associated with other positive regulatory and cognitive strategies (Shalaby & Kamal, 2021). Besides, they are predicted to demonstrate higher learning performance compare to those who use shallow approaches (Everaert et al. 2017; Heikkilä; Sakurai et al. 2014 Sedaghat et al., 2011).

The Effect of Cognitive Engagement on Performance

After all, this study furthermore examines the effect of the three dimensions of cognitive engagement (SR, DSU and SSU) on students' learning performance. The finding showed that all three dimensions were positively found as a significant predictor of learners' performance in language learning using virtual settings. The coefficient of determination R2 values of all the three factors in independently predicting performance are 0.588 (R2 = 0.588), which means can explain 58.8% of variances in students' performance. This proportion is considered as a moderate effect in affecting the performance of AFL undergraduate students. As a result, cognitive engagement is demonstrated to be a critical predictor that can give an impact on students' performance on the use of VLEs. The finding of this study is in accordance with the study done by Zohud (2015), Wara et al. (2018), Bayoumy & Alsayed (2021) and Nagadeepa et al. (2021).

All three factors of cognitive engagement in this present study were found to be significant in explaining variations in learning Performance among AFL undergraduate students. As described, among the three cognitive strategies used in learning, self-regulatory strategy use (SR) is contributing more effect on student performance compared to deep strategy use (DSU) and shallow strategy use (SSU) in this study. This finding showed that learners typically use SR while online learning to make sure they can control over and keep pace with learning. Throughout utilizing self-regulated skills, learners are capable to draw resolutions on their own when they are facing difficulties in learning. They further ascertain that learners should know "learn to learn" and practice appropriate strategies in accomplishing tasks. As described by Anthonysamy & Choo (2021), self-regulated learning strategies are used by students to self-observe their progress and to identify the strengths of the used learning strategies as well as gain awareness of any weaknesses throughout their learning process.

This finding is concurrence with the previous research that has found that self-regulated learning to be a significant predictor in learning and did contribute positively to digital learning success in blended learning environments in Malaysia (Anthonysamy & Choo, 2021; Lilian, 2021; Haron et al, 2015). The literature has shown that SR plays a role in distinguishing high scorers from low scorers, based on academic tasks which are focused on understanding instead of acquisition (Greene et al., 2018). Likewise, previous research has revealed that students performed better with the use of self-regulated learning strategies as opposed to students who

e-ISSN: 2289-8042

did not (Haron et al., 2015). Thus, it is clear that self-regulated learning strategies are necessary for the higher education sector to improve students' learning and performance.

On the other hand, this study indicated deep strategy use (DSU) is contributing the lowest amount to student performance. This finding thenceforth suggests that learners should be always encouraged to use deep strategies to enhance their learning experience. Moreover, the virtual learning environment requires the student to be more active and self-sufficient, thus deep strategy use is an essential cognitive strategy in learning seeing that it allows students to acquire more understanding and to gain knowledge effectively from the material. Kollerup (2015) mentioned that deep learning helps where learners actively engage in the learning process that includes critical analysis, understanding and application of knowledge. Moreover, online deep learning is more effective in developing students' meta-cognitive and analytic skills and stimulating their enthusiasm and motivation (Shalaby & Kamal, 2021). In an online learning setting, it is not merely important to count on how many efforts students give in accessing learning materials, posting in the learning discussions, or submitting tasks. But, it is also important to observe deeper learners' engagement, particularly cognitive engagement while learning in order to facilitate them in reaching desired learning outcomes.

This study concludes that cognitive engagement was found to be significant in affecting online learners' performance. This finding was supported by Nagadeepa (2021) in which students understanding and learning in an online classroom are affected the most by their cognitive engagement. Cognitive engagement is very important as it helps students to keep actively engaged in their learning and to enhance knowledge acquisition. Hence, all students needed to utilize cognitive engagement strategies and anticipate their success by reflecting on what has been learned and how to learn better.

Conclusion

This study attempted to shed light on the critical facet of the correlation of cognitive engagement and student performance, particularly in the Malaysian higher institution context. The analysis of this study helps in providing such information of cognitive learning strategies used by students in an online setting that can help them to achieve deep and significant learning. Besides, cognitive engagement and its relationship to student performance is one of the up-to-date increasing catches of educational investigation that strive for enhancing the learning quality of the students. In an online learning environment, the participation alone by the students is not sufficient. The instructor should put substantial effort to enhance student engagement, not just behaviourally and emotionally engaged but also cognitively engaged. It will result in an effective and meaningful learning environment. This study offers empirical and practical contributions to online Arabic Foreign Language (AFL) teaching and learning. Empirically, the current study extends the investigative attempts of correlation between cognitive engagement and performance and dimensions of cognitive engagement that highly predict students' performance emphasizing Arabic language teaching practices in a virtual learning environment. This study allows us to better understand how undergraduates Malaysian students adapt to virtual learning environments through their cognitive engagement and learning strategies across different academic disciplines at the university level. Moreover, this study also outlines how students' cognitive engagement contributes to the success of online learning by identifying the strengths of the used variety of cognitive learning strategies as well as gaining awareness of any weaknesses throughout their learning process.

 e-ISSN: 2289-8042

References

Abid, N., & Akhtar, M. (2020). Relationship between academic engagement and academic achievement: an empirical evidence of secondary school students. *Journal of Educational Research, 23*(1), 48.

Alanazi, A. A., Frey, B. B., Niileksela, C., Lee, S. W., Nong, A., & Alharbi, F. (2020). The role of task value and technology satisfaction in student performance in graduate-level online courses. *TechTrends, 64*(6), 922-930.

Anthonysamy, L., & Choo, A. (2021). Investigating Self-Regulated Learning Strategies for Digital Learning Relevancy. *Malaysian Journal of Learning and Instruction*, *18*(1), 29-64.

Bayoumy, H. M. M., & Alsayed, S. (2021). Investigating Relationship of Perceived Learning Engagement, Motivation, and Academic Performance Among Nursing Students: A Multisite Study. *Advances in Medical Education and Practice, 12*, 351.

Bao, W. (2020). COVID-19 and online teaching in higher education: A case study of Peking University. *Human Behavior and Emerging Technologies*, *2*(2), 113-115.

Barlow, A. J. (2019). An Investigation of Student Cognitive Engagement in the STEM Classroom—A Compilation of Faculty and Student Perspectives.

Casimiro, L. T. (2016). Cognitive engagement in online intercultural interactions: Beyond analytics. *International journal of information and education technology, 6*(6), 441.

Cendaña, D. I., Ocay, A. B., Bustillo, N. V., & Cruz, J. D. (2019). The empirical study on the impact of student-centered learning application to cognition and social learning. In *IOP Conference Series: Materials Science and Engineering* (Vol. 482, No. 1, p. 012006). IOP Publishing.

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural equation modeling: a multidisciplinary journal*, *14*(3), 464-504.

Chen, S. B. A. (2020). *Examining the Effect of Self-Regulated Learning on Cognitive Engagement in Mastery-Based Online Courses: A Learning Analytics Perspective*. The Ohio State University.

Exeter, D. J., Ameratunga, S., Ratima, M., Morton, S., Dickson, M., Hsu, D., & Jackson, R. (2010). Student engagement in very large classes: The teachers' perspective. *Studies in higher education*, *35*(7), 761-775.

DeVito, M. (2016). Factors Influencing Student Engagement (Unpublished master's thesis). Sacred Heart University, Fairfield, CT

Fredricks, J. A., Filsecker, M., & Lawson, M. A. (2016). Student engagement, context, and adjustment: Addressing definitional, measurement, and methodological issues.

Fredricks, J. A., & McColskey, W. (2012). The measurement of student engagement: A comparative analysis of various methods and student self-report instruments. In *Handbook of research on student engagement* (pp. 763-782). Springer, Boston, MA.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research*, *74*(1), 59-109.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

García-Pérez, D., Fraile, J., & Panadero, E. (2021). Learning strategies and self-regulation in context: How higher education students approach different courses, assessments, and challenges. *European Journal of Psychology of Education*, *36*(2), 533-550.

Greene, B. A. (2015). Measuring cognitive engagement with self-report scales: Reflections from over 20 years of research. *Educational Psychologist*, *50*(1), 14-30.

Greene, B. A., Miller, R. B., Crowson, H. M., Duke, B. L., & Akey, K. L. (2004). Predicting high school students' cognitive engagement and achievement: Contributions of classroom perceptions and motivation. *Contemporary educational psychology*, *29*(4), 462-482.

Greene, J. A., Copeland, D. Z., Deekens, V. M., & Seung, B. Y. (2018). Beyond knowledge: Examining digital literacy's role in the acquisition of understanding in science. *Computers & Education*, *117*, 141-159.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long range planning*, *46*(1-2), 1-12.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The use of partial least squares structural equation modeling in strategic management research: a review of past practices and recommendations for future applications. *Long range planning*, *45*(5-6), 320-340.

Haron, H. N., Harun, H., Ali, R., Salim, K. R., & Hussain, N. H. (2015). Self-regulated learning strategies between the performing and non-performing students in statics. Proceedings of 2014 International Conference on Interactive Collaborative Learning, ICL 2014, (December), 802–805.

Hayati, H., Idrissi, M. K., & Bennani, S. (2020, July). Automatic classification for cognitive engagement in online discussion forums: text mining and machine learning approach. In *International Conference on Artificial Intelligence in Education* (pp. 114-118). Springer, Cham.

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education*, *90*, 36-53.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial management & data systems*.

Hu, M., & Li, H. (2017). Student engagement in online learning: A review. In *2017 International Symposium on Educational Technology (ISET)* (pp. 39-43). IEEE.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological methods*, *3*(4), 424.

Hudson KF. Nursing student engagement: student, classroom, and clinical engagement. *Int J Nurs*. 2015;4(1):44–52.

Humber, J. F. (2018). Student engagement in online courses: A grounded theory case study. The University of Alabama.

Hussain, S., Fangwei, Z., Siddiqi, A. F., Ali, Z., & Shabbir, M. S. (2018). Structural equation model for evaluating factors affecting quality of social infrastructure projects. *Sustainability*, *10*(5), 1415.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & education*, *104*, 18-33.

Li, Y., & Lerner, R. M. (2013). Interrelations of behavioral, emotional, and cognitive school engagement in high school students. *Journal of Youth and Adolescence*, *42*(1), 20-32.

Li, S., Zheng, J., & Lajoie, S. P. (2020). The relationship between cognitive engagement and students' performance in a simulation-based training environment: an information-processing perspective. *Interactive Learning Environments*, 1-14.

Lilian, A. (2021). Self-Regulated Learning Strategies for Smart Learning: A Case of a Malaysian University. *Asian Journal of Research in Education and Social Sciences*, *3*(1), 72-83.

Lochner, L., Wieser, H., Waldboth, S., & Mischo-Kelling, M. (2016). Combining traditional anatomy lectures with e-learning activities: how do students perceive their learning experience?. *International journal of medical education*, *7*, 69.

 e-ISSN: 2289-8042

McFarland, J., Cui, J., Holmes, J., & Wang, X. (2020). Trends in High School Dropout and Completion Rates in the United States: 2019. Compendium Report. NCES 2020-117. *National Center for Education Statistics*.

Mensink, P. J., & King, K. (2020). Student access of online feedback is modified by the availability of assessment marks, gender and academic performance. *British Journal of Educational Technology*, *51*(1), 10-22.

Miller, P. A., Eisenberg, N., Fabes, R. A., & Shell, R. (1996). Relations of moral reasoning and vicarious emotion to young children's prosocial behavior toward peers and adults. *Developmental psychology*, *32*(2), 210.

Nagadeepa, C. (2021). Students' Understanding and Learning: Mediation Effects of Cognitive Engagement in Online Classes. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(6), 2932-2939.

Narad, A., & Abdullah, B. (2016). Academic performance of senior secondary school students: Influence of parental encouragement and school environment. *Rupkatha Journal on Interdisciplinary Studies in Humanities*, *8*(2), 12-19.

Phillips, B. N., Turnbull, B. J., & He, F. X. (2015). Assessing readiness for self-directed learning within a non-traditional nursing cohort. *Nurse education today*, *35*(3), e1-e7.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology*, *82*(1), 33.

Peng, C., & Daud, S. (2015). Exploring elementary special education (hearing impairment) teachers' technological pedagogical content knowledge (TPACK). In *1st International Conference on Special Education, Bangkok, Thailand*.

Rasouli, A., Rahbania, Z., & Attaran, M. (2016). Students' Readiness for E-Learning Application in Higher Education. *Malaysian Online Journal of Educational Technology*, *4*(3), 51-64.

Rono, R. (2013). *Factors Affecting Pupils' Performance in Public Primary Schools at Kenya Certificate of Primary Education Examination (Kcpe) in Emgwen Division, Nandi District, KENYA* (Doctoral dissertation, University of Nairobi).

Reid-Martinez, K., & Grooms, L. D. (2018). Online learning propelled by constructivism. In *Encyclopedia of Information Science and Technology, Fourth Edition* (pp. 2588-2598). IGI Global.

Reeve, J. (2012). A self-determination theory perspective on student engagement. In *Handbook of research on student engagement* (pp. 149-172). Springer, Boston, MA.

Richardson, J. C., & Newby, T. (2006). The role of students' cognitive engagement in online learning. *American Journal of Distance Education*, *20*(1), 23-37.

Rotgans, J. I., & Schmidt, H. G. (2011). Cognitive engagement in the problem-based learning classroom. *Advances in health sciences education*, *16*(4), 465-479.

Sedaghat, M., Abedin, A., Hejazi, E., & Hassanabadi, H. (2011). Motivation, cognitive engagement, and academic achievement. *Procedia-Social and Behavioral Sciences*, *15*, 2406-2410.

Shalaby, D., & Kamal, N. M. (2021). The Use of an Online Deep Learning Approach for Improving Self-Regulation. *مجلة القراءة والمعرفة*, *21*(238), 1-41.

Li, S., & Lajoie, S. P. (2021). Cognitive engagement in self-regulated learning: an integrative model. *European Journal of Psychology of Education*, 1-20.

Simonova, I., & Poulova, P. (2013). Respondentsfeedback on online learning reflecting individual learning preferences. In *proceedings of the international scientific conference*. [LLU].

Susanti, Yunik. (2020). The Students' Engagement in EFL Online Class. *Lingual: Journal of Language and Culture*, [S.l.], v. 10, n. 2, p. 8,. ISSN 2716-3091

 e-ISSN: 2289-8042

Trevors, G., Duffy, M., & Azevedo, R. (2014). Note-taking within MetaTutor: Interactions between an intelligent tutoring system and prior knowledge on note-taking and learning. *Educational Technology Research and Development*, *62*(5), 507-528.

Topal, A. D. (2016). Examination of University Students' Level of Satisfaction and Readiness for E-Courses and the Relationship between Them. *European Journal of Contemporary Education*, *15*(1), 7-23.

Valle, A., Regueiro, B., Núñez, J. C., Rodríguez, S., Piñeiro, I., & Rosário, P. (2016). Academic goals, student homework engagement, and academic achievement in elementary school. *Frontiers in Psychology*, *7*, 463.

Wara, E., Aloka, P. J., & Odongo, B. C. (2018). Relationship between cognitive engagement and academic achievement among Kenyan Secondary School Students. *Mediterranean Journal of Social Sciences*, *9*(2), 61-61.

Xie, K., Heddy, B. C., & Greene, B. A. (2019). Affordances of using mobile technology to support experience-sampling method in examining college students' engagement. Computers & Education, 128, 183–198.

You, J. W., & Kang, M. (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers & Education*, *77*, 125-133.

Yundayani, A., Abdullah, F., Tandiana, S. T., & Sutrisno, B. (2021). Students' cognitive engagement during emergency remote teaching: Evidence from the Indonesian EFL milieu. *Journal of Language and Linguistic Studies*, *17*(1).

Zhai, X., Gu, J., Liu, H., Liang, J. C., & Tsai, C. C. (2017). An Experiential Learning Perspective on Students' Satisfaction Model in a Flipped Classroom Context. *J. Educ. Technol. Soc.*, *20*(1), 198-210.

Zhu, X., Chen, A., Ennis, C., Sun, H., Hopple, C., Bonello, M., ... & Kim, S. (2009). Situational interest, cognitive engagement, and achievement in physical education. *Contemporary educational psychology*, *34*(3), 221-229.

Zohud, N. W. I. (2015). *Teaching Strategies and their Role on Students' Engagement in Learning English* (Doctoral dissertation).