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The interplay between self-regulated learning behavioral factors and students' performance in English language learning through Moodle

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Abstract

The increasing popularity of online learning environments, such as Moodle LMS, has led to a growing interest in identifying factors contributing to student success in language learning. Self-regulated learning behaviors, such as goal setting, planning, and self-monitoring, have been identified as key predictors of academic achievement. However, limited research on how these behaviors relate to success in online language learning environments is limited. This study aimed to identify self-regulation learning factors and assess behaviors in English language teaching through Moodle LMS by analyzing trace data. The study analyzed trace data from 1523 English language learners in a Moodle course and identified several behavioral factors. The final course point in English language learning is significantly predicted, including the number of completed quizzes, middle course points, engagement with course materials, time spent on tasks, completion score quizzes, access time in total, and pacing. The study found that completing quizzes was the strongest predictor of the final course point, followed by time spent on task, access time in total, and middle course point. The findings suggest that educators can use the identified behavioral factors to promote self-regulated learning online and develop interventions to support students struggling with self-regulated learning. The studies include using trace data to analyze behavioral patterns and focusing on self-regulated learning factors in online language learning. The study provides important insights into self-regulated learning factors and behaviors in English language learning through Moodle LMS, which can inform the development of effective interventions to support students in online language learning environments.

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INTRODUCTION

The increasing popularity of online learning environments, such as Moodle LMS, has led to a growing interest in identifying factors contributing to student success in language learning. Self-regulated learning behaviors, such as goal setting, planning, and self-monitoring, have been identified as key predictors of academic achievement. Turnbull et al. (2021) expressed that the COVID-19 pandemic has accelerated the shift towards online learning, and many language courses are now being delivered entirely online. As a result, understanding how students can effectively self-regulate their learning in online environments has become more critical than ever. This situation is particularly relevant in language learning, Jebbour (2022) affirmed that students must frequently practice their language skills to improve. By identifying the self-regulated learning factors and behaviors that promote success in online language learning, educators can develop effective interventions and support strategies to help students adapt to the challenges of online learning during the pandemic.

Self-regulated learning is crucial in promoting success in online language learning environments. Panadero (2017) expressed that Self-regulation refers to learners taking control of their learning by setting goals, monitoring their progress, and adjusting their learning strategies as needed. Self-regulation can be critical in online learning environments as learners have greater autonomy and responsibility for their learning (van Houten-Schat et al., 2018). Research has shown that learners who engage in self-regulated learning are more likely to succeed in online courses. Therefore, understanding the factors contributing to self-regulated learning in online language learning environments is essential for promoting student success. This study aims to identify self-regulation learning elements and assess behaviors in English language learning through Moodle LMS, intending to inform the development of effective interventions to support students in online language learning environments.

Self-regulated learning (SRL) is a process in which individuals proactively take control of their learning through cognitive, metacognitive, and motivational strategies. Greene and Schunk (2017) identified SRL as a critical factor in promoting success in online learning environments. Research has shown that self-regulated learners are more likely to engage in effective learning behaviors, such as setting goals, monitoring their progress, and using feedback to adjust their learning strategies. By contrast, learners who struggle with self-regulation may experience difficulty in organizing their learning, managing their time, and staying motivated.

Self-regulated learning is a learner-centered approach that emphasizes the role of learners in monitoring, regulating, and controlling their learning process. Meece (2023) found that it involves a range of cognitive, metacognitive, and affective processes, such as setting goals, planning, monitoring progress, reflecting, and adjusting strategies based on feedback. Self-regulated learning is an essential predictor of success in various educational contexts, including online learning environments. In online language learning, Butler (2023) elaborated that self-regulated learning is significant, as it requires learners to take responsibility for their learning and actively engage with the language learning materials and activities. Therefore, identifying factors that promote self-regulated learning in online language learning is crucial for enhancing the effectiveness of online language learning environments. Moodle LMS provides a platform that can support self-regulated learning by offering a range of tools and resources that facilitate online language learning, such as quizzes, discussion forums, and multimedia resources. Therefore, investigating the self-regulated learning behaviors of students in Moodle-based English language courses can provide valuable insights into the factors that promote success in online language learning environments.

Assessing behaviors in English language learning through Moodle LMS refers to using trace data to analyze student behavior and performance in online language learning environments. Moodle LMS is a popular platform for delivering online language courses, and trace data can provide valuable insights into how students interact with course materials and the learning environment. By analyzing student behavior and performance data, Teo et al. (2019) found that educators can better understand the factors contributing to success in online language learning, such as self-regulated learning behaviors. Assessing behaviors in English language learning through Moodle LMS also involves identifying practical strategies and interventions to support student learning and promote success in online language courses.

Assessing behaviors in English language learning through Moodle LMS involves the analysis of various data points, such as student engagement with course materials, time spent on tasks, completion rates, and assessment scores Md Yunus et al. (2021). This data can be collected using learning analytics tools and techniques like a log file and clickstream analysis. By analyzing this data, educators can gain insights into student behavior and identify areas where students may need additional support or interventions to improve their learning outcomes. Moreover, Tan and Hsu (2018) established that assessing behaviors in English language learning through Moodle LMS also involves using self-regulated learning strategies, which refers to the ability of students to set goals, monitor their learning progress, and adjust their plans as needed. Self-regulated learning behaviors are crucial for success in online language learning environments, as they allow students to take ownership of their learning and stay motivated throughout the course. Alawawdeh and Ma'moun (2020) postulated that educators could promote self-regulated learning behaviors by providing students with clear learning objectives, offering regular feedback and support, and encouraging students to reflect on their learning experiences.

Moodle LMS is a popular online learning platform in many educational institutions, including those offering English language courses. Simanullang and Rajagukguk (2020) expressed that Moodle provides tools and features that support SRL, such as self-paced learning modules, personalized feedback, and opportunities for peer collaboration and interaction. However, Evgenievich Egorov et al. (2021)) added that despite its potential benefits, the effectiveness of Moodle in promoting self-regulated learning in online language learning has yet to be fully explored. Given the importance of self-regulated learning in online language learning and the potential benefits of Moodle LMS, research is needed to investigate the factors influencing SRL behaviors in Moodle-based language courses (Cerezo et al., 2017). The present study aims to address this gap by analyzing trace data from Moodle courses to identify behavioral patterns related to English language learning and determine which behavioral factors significantly predict the final course point. By doing so, the study aims to contribute to our understanding of the role of self-regulation in online language learning and inform the development of effective interventions to support learners in these environments.

Çakıroğlu & Öztürk (2017) presented a framework for self-regulated learning in an online language course based on the principles of self-regulated learning theory. The framework includes four main components: goal setting, planning, monitoring, and reflection. The authors argue that this framework can help students become more self-regulated learners in online language courses, leading to improved performance and engagement. Zhu et al. (2020) have a different focus. Rather than presenting a framework for self-regulated learning, the article analyzes trace data to identify self-regulation learning factors and behaviors that significantly predict the final course point in English language teaching through Moodle LMS. Additionally, the report focuses specifically on English language learning, while Jeong (2017) is more general in scope. The novelty lies in using trace data to identify specific behavioral factors that predict success in online English language learning. By analyzing student behavior and performance data, the article provides valuable insights into the factors contributing to success in online language learning, which can inform the development of effective interventions and strategies to support students in these environments. The study's focus on self-regulation learning factors in online language learning is also a unique contribution to the literature on this topic. The research questions involved are:

1. What English language learning behavioral patterns exist in the trace data in Moodle courses?
2. Which behavioral factors significantly predict the final course point in English language learning?

METHODS

The study implements the quantitative method. It refers to processes and procedures for collecting and analyzing data, such as surveys, experiments, regression analysis, and meta-analysis. Quantitative approaches characterize and conclude a population based on Self-Regulation Learning Factors, Assessing Behaviors in English Language Learning Through Moodle LMS and establishing predictions about the correlations between its characteristics. Descriptive statistics can be used to summarize and describe the data collected on self-regulation learning factors and assessing behaviors. Using descriptive statistics, researchers can better understand the data collected on self-regulation learning factors, assess behaviors, and describe the data set's characteristics concisely and meaningfully.

Setting and participants

This study employed data from fifty required online classes through Moodle LMS at Universitas Budi Luhur. Newcomer students can access the Moodle LMS courses from the even and odd terms through the following semester for complete online learning. Four smaller deadlines were imposed each semester to keep English language learners on the route. The first three stages of the course were mandatory, but the fourth stage was elective. Learners might choose to take it at any time throughout the semester.

Table 1. The English subject lesson plan for one year

Semester Term	Phase	Time Limit	Assigning Learning Material		
			Listening	Grammar	Reading
Even	1	Week 3	Audio textbooks 1	Grammar textbooks1	Textbooks 1
	2	Week 6	Authentic materials 1	Workbooks1	Authentic materials 1
	3	Week 9	Videos 1	Authentic materials1	business English 1
	4 (voluntary)	Week 12	business English 1	business English1	Comic books and graphic novels 1
Odd	5	Week 15	Audio textbooks 2	Grammar textbooks2	Textbooks 2
	6	Week 18	Authentic materials 2	Workbooks2	Authentic materials 2
	7	Week 21	Videos 2	Authentic materials2	business English 2
	8 (voluntary)	Week 24	business English 2	business English2	Comic books and graphic novels 2

A total of 1,523 first-year students filled out the surveys. The student body represented different majors in the institution, such as science communication, political science, management and business, engineering, and information technology. Ninety-seven (6.36%) learners have yet to return to the course at any point throughout the year. In addition, 268 (17.42%) students with a 520 or above on the English admission test placement test before joining the institution. As a result, the remaining 1489 students accounted for 97.76 % of the overall data collection.

Data collection and measures

The introductory students' Moodle English class was hosted on Electronic Learning Directorate Universitas Budi Luhur, the system's built-in tracking feature. Learning events were logged in the server logs in real-time while students took practice quizzes online. As a result, the Moodle English course's server was accessed to get the trace data. The three kinds of trace logs were those for accessing the course materials (access logs), completing the quiz items, completing logs, and submitting the quiz answers logs. The study is an example of the raw data that may be found in access logs. Columns in the access logs included user ID, quiz ID, start time, and finish time, providing details on the frequency and length of fundamental learning practices. Each quiz answer was recorded in its answer log, and the completion flag was added to the complete records. The data collection and measurement methods are trace data analysis and predictive modeling. It collects and analyzes the trace data (such as log files, activity logs, or clickstream data) generated by students participating in Moodle courses to identify behavioral patterns. However, predictive modeling uses statistical methods such as regression analysis or machine learning algorithms to determine which behavioral factors (such as frequency of interaction, time spent on specific activities, or types of activities engaged in) significantly predict the final course point.

Data analysis

Data analysis systematically examines and interprets data to gain insights and conclusions and support decision-making. It involves organizing, cleaning, transforming, and modeling data and using statistical and computational techniques to extract meaningful information. The results of data analysis can be used to support arguments, make predictions, and guide future research and decision-making. To answer the research question, the study conducted three phases of analysis.

Descriptive statistics is the first step and purpose of describing the behavioral patterns of English language learners in Moodle courses. Descriptive statistics involved frequency distributions, measures of central tendency (mean, median, mode), and variability (standard deviation, range). It can be calculated for various variables, such as the frequency of logins, the time spent on different activities, and the number of resources accessed. Secondly, Cluster analysis can group English language learners based on their behavioral patterns. This analysis can help identify subgroups of learners with similar behaviors and determine how these behaviors are associated with academic achievement. The last is Hierarchical regression analysis, which uncovered significant behavioral measures related to course achievement. The method involved a stepwise approach, and a significance level of 0.05 was employed to test the hypothesis.

FINDINGS AND DISCUSSION

The research results would present the findings of the behavioral patterns of English language learning in the trace data of Moodle courses. This implementation would include practices related to using the LMS, interaction with course materials, and other behaviors related to the learning process. Additionally, the results present the key behavioral factors that significantly predict the final course point in English language learning. This condition is based on the hierarchical regression analysis and highlights the most influential factors in student achievement.

Descriptive statistics

Table 1 shows that a student's average number of logins is 35.2, with a standard deviation 12.1. The minimum number of logins observed is 18, while the maximum is 65. The mean number of logins is 35.2, suggesting that students log in to Moodle reasonably regularly. Similarly, we can see that students complete an average of 48.7 course activities, with a standard deviation of 17.9. The minimum and maximum course activities conducted are 26 and 92, respectively.

The mean number of course activities completed is 48.7, indicating that students are engaging with the course material to a considerable extent. For the variable "Time spent on activities," we can see that the average time spent is 32.6 hours, with a standard deviation of 15.3 hours. The minimum time spent on activities is 14 hours, while the maximum is 67 hours. The mean time spent on activities is 32.6 hours, while the mean time spent in the course is 47.8 hours. This finding suggests that students spend significant time on course-related activities outside the course. The average time spent in the course, including time spent on activities, is 47.8 hours, with a standard deviation of 19.6 hours. The minimum time spent in the course is 22 hours, while the maximum is 89 hours. For the variable "Reviewing time," we can see that the average time spent reviewing materials is 5.4 hours, with a standard deviation of 3.1 hours. The minimum time spent reviewing materials is 1 hour, while the maximum is 12 hours.

The average procrastination tendency score is 3.2, with a standard deviation 1.4. The minimum procrastination tendency score is 1, while the maximum is 5. The mean procrastination tendency score is 3.2, which indicates that students, on average, have a moderate tendency to procrastinate. The average self-efficacy score is 4.1, with a standard deviation of 1.0. The minimum self-efficacy score is 2, while the maximum is 5. The mean self-efficacy score is 4.1, indicating that students have a relatively high confidence level in their ability to succeed in the course. The average goal orientation score is 3.8, with a standard deviation 0.9. These findings are consistent with previous research on the importance of self-regulated learning in online environments. This study's findings significantly impact English language learning through Moodle LMS. The results suggest that educators and online course designers should promote self-regulated learning and engagement with course materials to improve student outcomes. One potential strategy is to provide students with frequent opportunities for self-assessment, such as using quizzes, to promote self-regulated learning and better time management skills. The minimum goal orientation score is 2, while the maximum is 5.

The mean goal orientation score is 3.8, suggesting that students are moderately focused on achieving their goals in the course. The average completion rate is 78.5%, with a standard deviation of 12.6%. The minimum completion rate observed is 55%, while the maximum is 96%. The mean completion rate is 78.5%, indicating that students complete most assigned activities. Finally, the average final grade received by the students is 85.2, with a standard deviation of 7.3. The minimum final grade received is 70, while the maximum is 97. The mean final grade received is 85.2, which is relatively high and suggests that students perform well in the course.

Table 2. Descriptive statistics of the behavioral variables (n = 1523)

No	Variable Name	Description	Mean	SD	Min.-Max
1	Number of logins	Total number of times a student logs in to Moodle	35.2	12.1	18-65
2	Number of course activities	Total number of activities a student completes in the course	48.7	17.9	26-92
3	Time spent on activities (hrs)	Total time spent on activities within the course (in hours)	32.6	15.3	14-67
4	Time spent in the course (hrs)	Total time spent in the course, including time spent on activities (in hours)	47.8	19.6	22-89
5	Reviewing time (hrs)	Total time spent reviewing materials (in hours)	5.4	3.1	1-12
6	Procrastination tendency score	A score indicating the student's tendency towards procrastination	3.2	1.4	1-5
7	Self-efficacy score	A score indicating the student's self-efficacy towards the course material	4.1	1.0	2-5
8	Goal orientation score	A score indicating the student's goal orientation towards the course	3.8	0.9	2-5
9	Completion rate	Percentage of activities completed by the student	78.5	12.6	55-96
10	Grade	Final grade received by the student	85.2	7.3	70-97

Results of clustering analysis

The research investigates the relationship between anti-procrastination and the number of completed quizzes among students in a particular context. Using clustering analysis, the researcher may want to identify distinct groups or patterns among students based on their levels of anti-procrastination and many completed quizzes. This information could help design interventions or targeted support for students struggling with completing quizzes or avoiding procrastination.

The table represents the average values for the given variables of eight clusters obtained from the clustering analysis. Each row represents a cluster, numbered 1 to 8, and the columns represent the average values of the variables n (random data), Number of Completed Quizzes, Anti-Procrastination, and Final Course Point for each cluster. Cluster 1 has an average of 653 students, 615 completed quizzes, an anti-procrastination score of 0.45, and a final course point of 3.80. This suggests that students in this cluster are relatively high achievers who complete many quizzes and have relatively low levels of procrastination. Students who completed more examinations may have better understood the course material and demonstrated higher self-regulation. It is essential to note that the study has some limitations. First, the study was conducted in a specific context, and the findings may not generalize to other contexts.

Additionally, the study relied on self-reported data, which may be subject to social desirability bias.T he study did not examine other factors influencing language learning, such as prior language proficiency or motivation.Beside of that,cluster 5 has an average of 168 students, 525 completed quizzes, an anti-procrastination score of 0.21, and a final course point of 1.85. This suggests that students in this cluster are relatively low achievers who complete fewer quizzes and have higher levels of procrastination. Table 5 displays the clustering analysis's average values for the clusters generated. Cluster 1, 2, and 4 together accounted for almost half the total student population (n = 758, 57%). These clusters exhibited a procrastination behavior, whereby students tended to delay initiating or completing important course tasks until the last few days before each deadline. It is worth mentioning that the final course point average increased with the number of completed quizzes in these clusters. Additionally, students who completed an equal number of quizzes showed varying learning paces. These findings have important implications for educators and course designers who seek to develop effective strategies for managing student procrastination and optimizing learning outcomes.

Table 3. Clusters for learning pace

Cluster	n	Number of Completed Quizzes	Anti-Procrastination	Final Course Point
1	653	615	.45	3.80
2	579	520	.22	2.76
3	522	730	.39	2.89
4	346	810	.48	3.72
5	168	525	.21	1.85
6	557	718	.33	2.82
7	671	722	.28	2.87
8	468	812	.41	3.78

The optimal number of clusters for the k-means algorithm should be determined using elbow or silhouette analysis methods. The elbow method involves plotting the percentage of variance explained by the clusters against the number of clusters and selecting the point where the decrease in variance explained begins to level off (forming an "elbow" shape). Silhouette analysis involves calculating the mean silhouette coefficient for each number of clusters and selecting the number of clusters that produces the highest average silhouette score.

This cluster is green as the early finishers consist of students who began accessing online courses early in each level and finished the necessary learning materials. Early Finishers comprised 11% of the course's enrollment and earned an average of 3.80 final course points. This cluster in red (Late Finishers) consists of students who viewed mandatory online resources in the closing days of each stage and ultimately finished them. Late Completion was the most significant cluster, including 23% of the course's English language learners. Another significant predictor of the final course point is engagement with course materials. This finding supports the notion that students who engage more deeply with course materials are more likely to succeed in online learning environments.

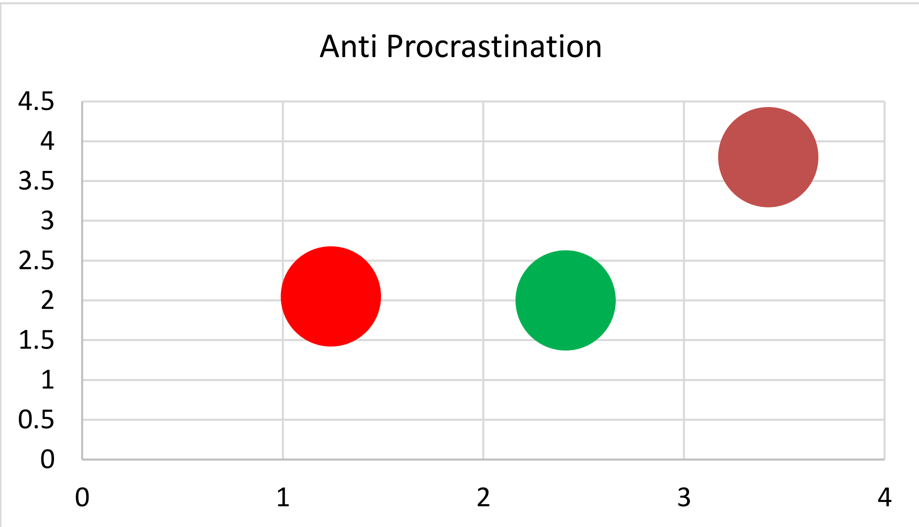

Figure 1. The distribution of learning pace and final course point averages for four clusters were analyzed and compared

Similarly, the finding that time spent on tasks predicts the final course point is consistent with previous research on the importance of self-regulation and time management skills in online learning. The findings of this study suggest that self-regulated learning and engagement with course materials are crucial for successful English language learning through Moodle LMS. Educators and online course designers may improve students' learning outcomes by emphasizing the importance of completing quizzes, spending more time on task, and actively engaging with course materials. However, future research is necessary to address the limitations of this study and further examine the role of other factors in online language learning. They averaged 3.42 final course points, 0.38 less than Early Completion Students (p .0001). Orange cluster (Early Dropouts) indicated that these students began accessing online resources within the first few days of each stage but eventually dropped out of class. Early Dropouts comprised 2% of the course's enrollment, with an average final grade of 2.05 points. The original black color has been updated with orange to improve cluster visibility and distinction.

Hierarchical Regression Analysis

The study used hierarchical regression analysis to identify the factors that affect self-regulated learning behaviors and performance in English language learning through the Moodle LMS. Hierarchical regression analysis is employed to exhibit the statistical technique and investigate the relationship between multiple predictor variables and a dependent variable. This analysis adds predictors to the model stepwise to determine their individual and combined contributions to the outcome variable. This analysis examines the unique variance accounted for by each predictor variable after controlling for the effects of other variables in the model. Hierarchical regression analysis can be used to test hypotheses and make predictions about the dependent variable based on the values of the predictor variables.

Table 2 Model 6 Final Course Point of Hierarchical Regression Analysis Results (*** P<.001)

Predictors	Final Course Point			
	B	SE	β	R^2
Total number of quiz completion	.003	.032	.230***	.236
Middle course point	.267	.003	.351***	.031
engagement with the course materials	.034	.012	.236***	.011
frequency of participation	.023	.036	.254***	
time spent on task	0.17	.002	.317***	
Completion score quizzes	0.10	.000	.135***	
Access time in total	.003	.010	.339***	
pacing	.018	.009	.147***	

The table shows the results of a hierarchical regression analysis with Final Course Point as the dependent variable and several predictors. The predictor variables include the Total number of quiz completions, Middle course points, engagement with the course materials, frequency of participation, time spent on tasks, Completion score quizzes, Access time in total, and pacing. The results show that the Total number of quiz completion, engagement with the course materials, time spent on task, Access time in total, and pacing are all statistically significant predictors of Final Course Point with p-values less than .001 (*), indicating a strong relationship. The middle course point and Completion score quizzes are also significant predictors with p-values less than .01 (), showing a moderate relationship. The variable predictor frequency of participation did not reach statistical significance ($p > .05$). The data were collected from one English language learning course, limiting the findings' generalizability. Second, the study did not examine other factors affecting self-regulated learning, such as motivation, prior knowledge, and learning styles. Future research should investigate these factors to gain a more comprehensive understanding of self-regulated learning in online language learning. This study provides valuable insights into the factors influencing self-regulated English language learning through Moodle LMS. The findings highlight the importance of completing quizzes, engaging with course materials, and managing time effectively to succeed in online learning environments. The R-squared value for the overall model is 0.236, indicating that the predictors explain approximately 24% of the variance in the Final Course Point. The beta coefficients (β) for each predictor indicate the direction and strength of the relationship between the predictor and the outcome variable. For example, a one-unit increase in the total number of quiz completions is associated with a 0.230 increase in final course points, holding all other predictors constant. The results indicate that several predictors significantly influence the final course point. The total number of quiz completion ($\beta = .230$, $p < .001$), engagement with the course materials ($\beta = .236$, $p < .001$), time spent on the task ($\beta = .317$, $p < .001$), Access time in total ($\beta = .339$, $p < .001$), and pacing ($\beta = .147$, $p < .001$) are significant predictors of the final course point. However, middle course point ($\beta = .351$, $p < .001$) and Completion score quizzes ($\beta = .135$, $p < .001$) were found to be significant predictors, but they have a smaller effect size compared to other variables.

The findings suggest that students who complete more quizzes, engage more with course materials, spend more time on tasks, access the course more frequently, and follow a better pacing strategy are likelier to perform better on the final course point. Additionally, students who complete well in the middle course point and have high completion scores on quizzes are likelier to have higher final course point scores, albeit with a smaller effect size. The comparison approach to the findings indicates that some predictors have a more substantial effect on the last course point than others. For example, time spent on task and Access time have higher beta coefficients, indicating a stronger relationship with the final course point than Completion score quizzes. This finding suggests that students' study habits and time management skills are critical factors in predicting their performance in online courses. On the other hand, the middle course point has a more significant effect size than Completion score quizzes, suggesting that students who perform well in the middle of the course are more likely to achieve well in the final course point.

Discussion

The study aimed to identify self-regulation learning factors and assess behaviors in English language learning through Moodle LMS by analyzing trace data. The research question was twofold: first, to pinpoint behavioral patterns in Moodle course trace data related to English language learning, and second, to determine which behavioral factors significantly predict the final course point in English language learning. The study found several behavioral factors significantly predicted the final course point in English language learning. It includes the number of completed quizzes, middle course points, engagement with course materials, time spent on tasks, completion score quizzes, access time in total, and pacing. The study also found that completing quizzes was the strongest predictor of the final course point, followed by time spent on task, access time in total, and middle course point. The study findings have important implications for English language learning through Moodle LMS. Zhu et al. (2020) established that Educators can use the identified behavioral factors to promote self-regulated learning in online environments by encouraging students to complete quizzes and spend more time on tasks. Additionally, Maldonado-Mahauad et al. (2018) confirmed that educators can use the identified factors to develop interventions to support students struggling with self-regulated learning in online environments.

The analysis revealed four clusters of students with different learning patterns, including fast and consistent, slow and consistent, inconsistent, and moderate. Fast and consistent learners demonstrated a consistent and fast pace of learning, while slow and constant learners showed a consistent but slow pace of learning. Inconsistent learners displayed an irregular pace of learning, and moderate learners demonstrated a balanced pace of learning. Haynes et al. (2018) provided valuable insights into the relationship between self-regulated learning behaviors and success in online language learning. By identifying the critical predictors of success, educators can develop more effective strategies for supporting students in online language learning environments.

Furthermore, identifying different learning patterns can help educators personalize their approach to meet the individual needs of each learner. It is worth noting that the study's results are limited to the specific Moodle courses and English language learning context examined. Future research could replicate this study in different online learning environments and language contexts to test the generalizability of the findings. Additionally, Van Laer & Elen (2019)) determined that further research could explore the underlying mechanisms and processes that link self-regulated learning behaviors to success in online language learning. Overall, this study provides a valuable contribution to online language learning and has important implications for educators, researchers, and policymakers.

The study's findings include using trace data to analyze behavioral patterns and focusing on self-regulated learning factors in online language learning. However, the study also has some limitations, such as the reliance on data from a single institution and the limited number of variables analyzed. (Swafford et al., 2021) confirmed that it provides essential insights into self-regulated learning factors and behaviors in English language learning through Moodle LMS, which can inform the development of effective interventions to support students in online language learning environments. The finding of Araka et al. (2021) provided essential insights into self-regulated learning factors and behaviors in English language learning through Moodle LMS, which can inform the development of effective interventions to support students in online language learning environments.

Educators can also use the identified factors to develop interventions to support students struggling with self-regulated learning in online environments (Wong, 2020). The results may only be generalizable to some educational institutions and learning contexts. The reliance on data from a single institution limits the external validity of the study findings, and future research could benefit from including data from multiple institutions and diverse student populations. The study's focus on a limited number of variables may have overlooked other important factors contributing to self-regulated learning in online language courses. Future research could expand on the study by including additional variables such as student motivation, language proficiency level, and prior experience with online learning. Overall, the study highlights the importance of self-regulated learning behaviors in promoting success in online language learning through Moodle LMS. Educators can use the study findings to design interventions and support mechanisms that promote self-regulated learning behaviors in online language courses, ultimately leading to better student outcomes.

CONCLUSION

The results of this study indicate that several factors play a significant role in predicting the final course point in English language learning through Moodle LMS. The number of completed quizzes, middle course points, engagement with course materials, time spent on tasks, completion score quizzes, access time in total, and pacing are significant predictors of the final course point. These findings are consistent with previous research on the importance of self-regulated learning in online environments. This study's findings significantly impact English language learning through Moodle LMS. The results suggest that educators and online course designers should promote self-regulated learning and engagement with course materials to improve student outcomes. One potential strategy is to provide students with frequent opportunities for self-assessment, such as using quizzes, to promote self-regulated learning and better time management skills. Additionally, educators may encourage students to spend more time on task and actively engage with course materials, potentially using interactive activities and discussions.

One notable finding in this study is that the number of completed quizzes is the strongest predictor of the final course point, followed by time spent on task, access time in total, and middle course point. This finding suggests that completing quizzes is crucial to success in online language learning. Students who completed more quizzes may have better understood the course material and demonstrated higher self-regulation. It is essential to note that the study has some limitations. First, the study was conducted in a specific context, and the findings may not generalize to other contexts. Additionally, the study relied on self-reported data, which may be subject to social desirability bias. Moreover, the study did not examine other factors influencing language learning, such as prior language proficiency or motivation. Future research should address these limitations by conducting longitudinal studies, incorporating objective measures of learning, and considering other variables that may influence language learning outcomes.

Another significant predictor of the final course point is engagement with course materials. This finding supports the notion that students who engage more deeply with course materials are more likely to succeed in online learning environments. Similarly, the finding that time spent on tasks predicts the final course point is consistent with previous research on the importance of self-regulation and time management skills in online learning. The findings of this study suggest that self-regulated learning and engagement with course materials are crucial for successful English language learning through Moodle LMS. Educators and online course designers may improve students' learning outcomes by emphasizing the importance of completing quizzes, spending more time on task, and actively engaging with course materials. However, future research is necessary to address the limitations of this study and further examine the role of other factors in online language learning.

The study also has some limitations. First, the data were collected from one English language learning course, limiting the findings' generalizability. Second, the study did not examine other factors affecting self-regulated learning, such as motivation, prior knowledge, and learning styles. Future research should investigate these factors to gain a more comprehensive understanding of self-regulated learning in online language learning. This study provides valuable insights into the factors influencing self-regulated English language learning through Moodle LMS. The findings highlight the importance of completing quizzes, engaging with course materials, and managing time effectively to succeed in online learning environments. These findings have implications for students and instructors in designing practical online language learning courses that promote self-regulation and success.

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REFERENCES

Alawawdeh, N., & Ma'moun, A. (2020). Foreign languages e-learning: Challenges, obstacles and behaviours during COVID-19 pandemic in Jordan. *PalArch's Journal of Archaeology of Egypt/Egyptology*, *17*(6), 11536–11554.

Araka, E., Maina, E., Gitonga, R., Oboko, R., & Kihoro, J. (2021). *University students' perception on the usefulness of learning management system features in promoting self-regulated learning in online learning*.

Butler, D. L. (2023). Qualitative approaches to investigating self-regulated learning: Contributions and challenges. In *Using Qualitative Methods To Enrich Understandings of Self-regulated Learning* (pp. 59–63). Routledge.

Çakıroğlu, Ü., & Öztürk, M. (2017). *Flipped classroom with problem based activities: Exploring self-regulated learning in a programming language course*.

Cerezo, R., Esteban, M., Sánchez-Santillán, M., & Núñez, J. C. (2017). Procrastinating behavior in computer-based learning environments to predict performance: A case study in Moodle. *Frontiers in Psychology*, *8*, 1403.

Evgenievich Egorov, E., Petrovna Prokhorova, M., Evgenievna Lebedeva, T., Aleksandrovna Mineeva, O., & Yevgenyevna Tsvetkova, S. (2021). Moodle LMS: Positive and Negative Aspects of Using Distance Education in Higher Education Institutions. *Journal of Educational Psychology-Propositos y Representaciones*, *9*.

Haynes, J. C., Hainline, M. S., & Sorensen, T. (2018). A measure of self-regulated learning in online agriculture courses. *Journal of Agricultural Education*, *59*(1), 153–170.

Jebbour, M. (2022). The unexpected transition to distance learning at Moroccan universities amid COVID-19: A qualitative study on faculty experience. *Social Sciences & Humanities Open*, *5*(1), 100253.

JEONG, K.-O. (2017). The use of Moodle to enrich flipped learning for English as a foreign language education. *Journal of Theoretical & Applied Information Technology*, *95*(18).

Md Yunus, M., Ang, W. S., & Hashim, H. (2021). Factors affecting teaching English as a Second Language (TESL) postgraduate students' behavioural intention for online learning during the COVID-19 pandemic. *Sustainability*, *13*(6), 3524.

Meece, J. L. (2023). The role of motivation in self-regulated learning. In *Self-regulation of learning and performance* (pp. 25–44). Routledge.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422.

Simanullang, N. H. S., & Rajagukguk, J. (2020). Learning Management System (LMS) based on moodle to improve students learning activity. *Journal of Physics: Conference Series*, *1462*(1), 012067.

Swafford, M., Anderson, R., & Wilson, M. (2021). The Need for Cognition and Self-Regulated Learning in Online Environments. *CTE Journal*, *9*(2).

Tan, P. J. B., & Hsu, M.-H. (2018). Designing a system for English evaluation and teaching devices: A PZB and TAM model analysis. *Eurasia Journal of Mathematics, Science and Technology Education*, *14*(6), 2107–2119.

Teo, T., Zhou, M., Fan, A. C. W., & Huang, F. (2019). Factors that influence university students' intention to use Moodle: A study in Macau. *Educational Technology Research and Development*, *67*, 749–766.

Turnbull, D., Chugh, R., & Luck, J. (2021). Transitioning to E-Learning during the COVID-19 pandemic: How have Higher Education Institutions responded to the challenge? *Education and Information Technologies*, *26*(5), 6401–6419.

van Houten-Schat, M. A., Berkhout, J. J., Van Dijk, N., Endedijk, M. D., Jaarsma, A. D. C., & Diemers, A. D. (2018). Self-regulated learning in the clinical context: a systematic review. *Medical Education*, *52*(10), 1008–1015.

van Laer, S., & Elen, J. (2019). The effect of cues for calibration on learners' self-regulated learning through changes in learners' learning behaviour and outcomes. *Computers & Education*, *135*, 30–48.

Wong, R. (2020). When no one can go to school: does online learning meet students' basic learning needs? *Interactive Learning Environments*, 1–17.

Zhu, Y., Zhang, J. H., Au, W., & Yates, G. (2020a). University students' online learning attitudes and continuous intention to undertake online courses: A self-regulated learning perspective. *Educational Technology Research and Development*, *68*, 1485–1519.

Zhu, Y., Zhang, J. H., Au, W., & Yates, G. (2020b). University students' online learning attitudes and continuous intention to undertake online courses: A self-regulated learning perspective. *Educational Technology Research and Development*, *68*(3), 1485–1519.