Comprehensive Analysis of Moodle Activity Recommendations considering Complex Thinking Theory for Enhancing Learning Outcomes

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Abstract. *In the rapidly evolving landscape of digital technologies, e-learning and blended learning face the challenge of delivering personalized teaching experiences. This paper investigates the effectiveness of Moodle activity recommendations, aligned with complex thinking theory, in enhancing teaching personalization. The study utilized a methodology that assessed student engagement, performance, and self-identification across seven crucial skills defined by the theory. Student profiles were evaluated in a course's initial module using activities embodying these characteristics, followed by personalized recommendations in subsequent modules. The analysis revealed a strong correlation between the proposed activities and improvements in academic performance, particularly in areas such as transdisciplinarity and metacognition. The findings highlight that students who engaged more actively with the recommended activities demonstrated significant improvements in their final grades.*

1. Introduction

Considering the emerging scenario of digital technologies, especially during and after the COVID-19 pandemic, traditional teaching methods struggle to meet personalized demands, including interactivity, non-linearity, and virtual reality, to engage learners effectively [Silva 2010]. Through Morin's theory of complex thinking, it is possible to obtain a theoretical basis for understanding the teaching-learning process, especially in distance education environments [Morin et al. 1994, Morin 2003]. The integration of technology-enhanced learning platforms has offered new avenues for pedagogical exploration and personalized learning experiences. Moodle, as a versatile learning management system, presents an opportunity to not only deliver course content but also to tailor activities based on pedagogical frameworks.

The theory of complex thinking acknowledges that phenomena in the world are interconnected and involve multiple layers of interactions and interdependencies,

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investigating how individuals deal with complex systems, problems, and situations, emphasizing cognitive skills [Morin et al. 1994]. In this scenario, the complex subject is defined as one constituted by characteristics that appear antagonistic but are actually complementary [Morin 2005]. Considering the theory of complex thinking and the formation of the individual by seemingly independent characteristics, Maissiat (2013) listed the necessary characteristics for the formation of the complex subject: metacognition, resilience, autonomy, subjectivity, creativity, transdisciplinarity, affectivity, cooperation, and flexibility [Maissiat 2013].

When considering the characteristics of the complex subject, although studies have explored the use of Moodle activities to develop higher-order cognitive skills (HOTS) in isolation, no recommendation system has yet integrated these activities holistically. Previous research, such as that by Bravo and Young (2011) and Rowe (2012), employed tools like WIKI to promote skills such as critical thinking and collaboration, while others, like Fernando (2020), linked specific activities, such as quizzes, to student autonomy [Bravo and Young 2011, Rowe 2012, Fernando 2020]. However, these approaches fail to capture the multifaceted nature of the complex subject, which necessitates an integrated set of skills, including metacognition, creativity, and critical thinking. The theory of complex thinking, as proposed by Morin, provides a strong foundation for developing a recommendation system that not only suggests activities but does so with the goal of fostering a holistic set of competencies. This study posits that leveraging Moodle activities labeled according to the characteristics of the complex subject can significantly enhance student engagement and performance, aligning instructional design with the interconnected and interdependent nature of learning, as emphasized by Maissiat (2013).

Therefore, the primary objective of this research is to bridge the gap between theoretical frameworks, such as the theory of complex thinking, and practical implementation within a digital learning environment. Moodle's versatility allows for categorizing and recommending activities aligned with specific cognitive aspects. The study aims to evaluate students' interactions with labeled activities and assess the subsequent impact on their learning outcomes.

This study highlights a correlation between student engagement in labeled Moodle activities and improved performance, demonstrating the efficacy of adaptive learning strategies within online learning environments. Furthermore, it offers insights into the pedagogical implications of aligning instructional design with complex subject attributes and proposes recommendations for the development of an effective Moodle recommender system grounded in complex thinking theory.

This paper focuses on the application and assessment of Moodle activities, specifically labeled in accordance with complex thinking theory, within online learning environments [Oliveira et al. 2023]. The remainder of this paper is organized as follows: Section 2 provides the related works. Section 3 delves into the methodology employed. Section 4 presents the results derived from the study, and finally, in Section 5, we conclude and outline directions for future research.

2. Related Works

Labeling Moodle activities based on complex thinking characteristics enables educators to align learning objectives with the development of complex thinking skills in students [Campos 2011]. This approach fosters a focused learning environment, allowing students to engage in activities that promote and enhance their complex thinking abilities.

Maissiat (2013) emphasized the necessity of multiple activities to cultivate the characteristics of a complex subject. Building on these insights, Maissiat introduced a series of pedagogical actions linked to the complex subject, which inspired Oliveira (2022) to propose an initial categorization of Moodle activities [Oliveira et al. 2022].

Oliveira (2022) further developed this work by creating a guide for the labeling process. This guide included definitions of Moodle activities and complex subject skills, and it established correlations between these skills and the pedagogical actions identified by Maissiat. Although the initial labeling process was qualitative and relied on subjective interpretation, transitioning to a quantitative approach is essential for automating this task and reducing the burden on specialists.

To address the subjectivity inherent in this process, Oliveira (2023) refined the labeling methodology, validating labels across seven distinct activities. This validation involved 30 educators with 2 to 15 years of experience in Distance Education, covering technical, higher, and postgraduate levels. The resulting dataset was converted into binary data, facilitating statistical analysis to identify the most and least cited labels for each activity, thus transforming the labeling process into a more quantitative and standardized approach.

Additionally, Oliveira (2023) analyzed the correlation between expert labeling and the initial labels defined by Oliveira (2022). Using the Hamming distance to measure dissimilarities, the study confirmed the accuracy of the labeled activities, validating the alignment between the initial and expert-generated labels.

As noted by Zheng (2022), labeling activities can effectively address diverse student needs and adapt instruction to various learning styles and individual interests [Zheng 2022]. The integration of artificial intelligence (AI) in online education supports personalized and adaptive learning experiences. By targeting different skills through various activities, aspects such as grading and assessment can be automated, freeing instructors to focus on more individualized and engaging teaching methods [Wei et al. 2021].

The aforementioned studies align with the objectives of this research, which aims to assess student engagement, performance, and self-identification through the recommendation and implementation of Moodle activities labeled according to the characteristics of the complex subject in an online learning context.

3. Methodology

The theoretical framework for this study is grounded in Morin's theory of complex thinking [Morin 2005], which explores the processes of thinking within complex systems. This theory emphasizes cognitive skills such as analysis, synthesis, evaluation, and creativity, which are interconnected with affective, social, and metacognitive factors. It underscores the importance of educational experiences that foster the development of these cognitive skills [Bransford et al. 2000], particularly through problem-based learning, inquiry-based learning, and constructivist teaching approaches that encourage students to engage with real-world complexities and devise solutions.

Complex thinking theory provides a basis for analyzing and developing cognitive abilities, problem-solving skills, critical thinking, creativity, metacognition, and other higher-order thinking skills (HOTS) essential for the formation of the complex subject [Morin 2005]. Maissiat [Maissiat 2013] identified these skills as necessary for the formation of a complex subject in e-learning environments, linking them to pedagogical actions informed by complex thinking theory.

This study is part of a broader project, the initial stage of which was conducted by Oliveira (2022) with the labeling of Moodle activities (table 1 - Initial Labeling), later validated by Oliveira (2023) (Table 1 - Final Labeling). This process allowed educators to align the learning objectives of the activities with the development of complex thinking skills in students [Campos 2011].

Table 1. Initial Labeling x Final Labeling - Source: [Oliveira et al. 2023]

Activities / Skills to Labeling	Glossary		Database		Chat		Choice		Forum		Workshop		Lesson		Wiki	
	Initial	Final	Initial	Final	Initial	Final	Initial	Final	Initial	Final	Initial	Final	Initial	Final	Initial	Final
Resilience													X	X		
Autonomy		X		X				X	X	X		X		X		X
Cooperation	X	X	X			X			X	X	X	X				X
Metacognition		X		X			X	X							X	
Transdisciplinary						X				X						X
Flexibility					X	X			X				X	X		
Criativity	X		X	X				X			X					
Match Rate	41,5%		41,5%		66,5%		66,5%		66,6%		50,0%		83,3%		0%	

To enhance the development of the aforementioned cognitive skills, instructional design must begin with an analysis of students' learning needs [Brown and Green 2019]. Accordingly, all activities listed in Table 1 were applied within Module I of the online Computer Science course in a Public Education Institution, aiming to carry out a diagnostic assessment.

To prioritize student-centered learning, activities such as Database and Glossary were employed to encourage students to actively explore, investigate, and construct their own knowledge, rather than passively receiving information. Additionally, activities like Chat, Forum, and Wiki, which provide both synchronous and asynchronous communication options, empower students by placing them at the center of the learning process. These activities encourage students to pose questions, explore problems, and seek solutions through active inquiry and discovery [Friesen and Scott 2013].

The Lesson and Choice activities were strategically included to promote active learning and knowledge construction through problem-based teaching. By utilizing case studies and challenging students to devise solutions to presented problems, these activities foster deep engagement and critical thinking [Hmelo-Silver 2004].

In this context, assessment strategies were designed not only to evaluate students' knowledge but also to assess their skills. Special attention was given to the final labeling (see Table 1) assigned to the aforementioned activities. The identification of student skills followed these criteria:

Table 2. Module I answer from students id 389 and 123 - source: The author

	Glossary	B.D.	Chat	Choice	Forum	Lesson		1	2	3	4	5	6	7
id_aluno	Ativ1	Ativ2	Ativ3	Ativ4	Ativ5	Ativ7	Ativ6	Resil	Auton	Coop	Metacog	Transdis	Flexib	Creativ
389	0.8	1	-	1	-	2	-	100%	76%	27%	93%	0%	50%	100%
123	1	1	-	1	2	2	-	100%	100%	67%	100%	50%	50%	100%

1. Score greater than or equal 60% of the assessment value.
2. A balanced distribution of grades across the skills labeled for each activity.
3. For skills labeled in multiple activities, a weighted average of the scores from all relevant activities was calculated and attributed to that skill.
4. The resulting skills profile was represented as a binary vector of seven positions, where zero indicates a skill that is not well-developed (Score $< 60\%$).

The methodology incorporated the labeled Moodle activities to the course's initial module to evaluate various characteristics of the complex subject. Subsequent modules were adapted based on individual student performance, with personalized recommendations provided to stimulate engagement and deepen understanding of these complex attributes.

The first round of solving labeled Moodle activities established an initial evaluation, defining a profile for each student as a binary vector representing the seven skills (see Table 2).For example, we might have two vectors representing the profiles of students 389 and 123 as follows: `student_profile[389] = [1, 1, 0, 1, 0, 0, 1]` and `student_profile[123] = [1, 1, 1, 1, 0, 0, 1]`. Here, zero values indicate skills that the student needs to improve.

For a comprehensive assessment of the outcomes, feedback was collected via Google Forms to gather students' perspectives on their engagement and understanding of the complex subject's attributes. Performance metrics and final scores were also analyzed to identify correlations between activity engagement and academic achievement.

To align the results obtained in the Module I assessment with the feedback provided by each student in their self-assessment, highlighting the use of a threshold of 60% or higher to state that a student has cultivated a specific skill, it is necessary to compare the initial assessment vector with the self-assessment vector. A Python script was used to calculate the weighted Jaccard distance, which evaluates the similarity between binary vectors while considering the order of the elements, as shown in Eq. 1:

$$D_{WJ}(V_1, V_2) = 1 - \frac{\sum_{i=1}^{n} w_i \cdot I(v_{1i} \neq v_{2i})}{\sum_{i=1}^{n} w_i} \quad (1)$$

where:

n is the length of the vectors,
v_{1i}, v_{2i} are the elements at position i in vectors V_1 and V_2,
w_i is the weight associated with the element at position i,
$I(\cdot)$ is the indicator function, equal to 1 if the condition is true, and 0 otherwise.

4. Experiment

When starting the Data Structures course, 42 students were enrolled (Figure 1), but only 20 of them responded to the form to identify themselves in relation to the characteristics of the complex subject (self-assessment). Despite a significant percentage of non-respondents, of these, 39 students completed the course and only 3 dropped out.

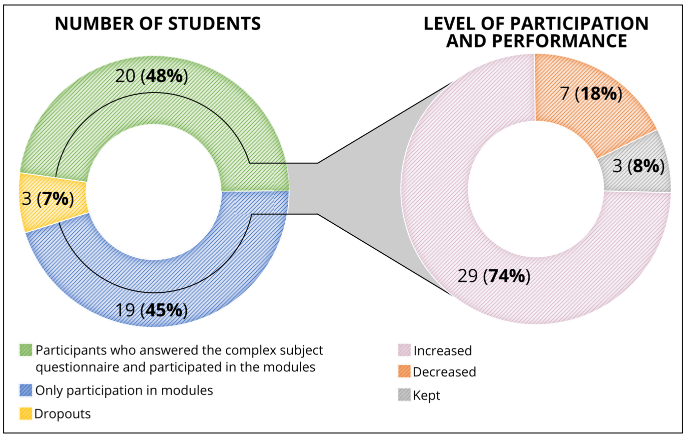

Figure 1. Comparison between the number of students and the overall level of participation and performance.

To analyze the students' profile, they responded to a pre-evaluation form composed of several objective questions related to each skill. Each question presented both a perspective stating how the student would react to a situation that highlighted a certain characteristic, and questions with an opposite perspective. A five-point Likert scale (from weak to very strong) was used to capture students' self-assessment.

Initially, students were instructed to complete all activities presented in Module I. In addition, they were informed that superior performance in the initial module would result in fewer recommended activities for the subsequent module. This reduction was implemented based on the understanding that a comprehensive assessment of competencies could be achieved through a minimum of three activities. By adopting this approach, not only was student engagement promoted, but early dropout was also mitigated [Almusaed et al. 2023, Roski et al. 2023].

To generate activity recommendations to individual students, we leverage data gathered from responses to the initial module (Module I). These responses were analyzed via an algorithm devised by Oliveira (2023), which computes the distribution of activity grades for each skill. Incorporating a weighted average when a skill pertains to multiple activities, the algorithm generates a vector. This vector, depicted in Table 2 as an example, maps the relationships between skills and completed activities, forming the foundation for recommendation computations.

For tailoring activity recommendations to each student, we employ the Decision Tree Classifier algorithm, as it provides insights into crucial resources for recommendations, identifying which skills exert the most influence on decision-making, capturing differentiated and non-linear relationships between input data (vector profile) and target variables (resources linked to each skill) [Priyanka and Kumar 2020].

The developed code employs a decision tree model to train and predict results using student data extracted from the IFTM database. Initially, the model undergoes training with data from previous years, followed by predictions on a test set to assess its accuracy. Subsequently, a DataFrame containing details about a new student, including their skill set, is generated. The code then identifies the student's areas of skill deficiency and offers recommendations (typeItem) based on these gaps. Lastly, the code generates the typeItem recommendations for the student. In essence, this code illustrates the process of training a classification model based on user skills and using it to provide personalized recommendations to new learners based on their areas of improvement.

Through the process presented above, we were able to generate and analyze the results of the recommendations and monitor engagement compared to the perception obtained from the students' self-assessment.

5. Results

Firstly, it is important to presents the results of the above calculation (Equation 1) and reveals that almost half of the students involved in the self-assessment obtained a score of approximately 60% or higher in the Weighted Jaccard Distance (Table 3). This implies a significant level of similarity between the self-assessment and the initial assessment, meaning that the recommendations arising from the initial assessment are closely aligned with students' perceptions of their skill profiles.

Table 3. Weighted Jaccard Distance for Each Student - source: the author

Id Students	1	2	3	4	5	6	7	8	9	10
Distance	0.29	0.71	0.71	0.29	0.71	0.57	0.57	0	1	0.6
Id Students	11	12	13	14	15	16	17	18	19	20
Distance	0.5	0.43	1	0.57	0.57	0.57	0.43	0.14	1	0.6

In an effort to comprehend how to enhance the initial assessment process, we conducted separate skill-based comparisons of the results. The bar chart displays orange bars representing the resul at initial evaluation (Module I) and blue bars representing the students self-evaluation about each skills. Each pair of bars (orange and blue) corresponds to evaluations for individual students (from ID-1 to ID-20, left to right). If only one bar is present, it indicates that the student either did not complete the assessment or did not receive a score in that specific evaluation.

In several skills, students tend to self-assess more positively than in the initial evaluation. This trend is particularly evident in areas like Transdisciplinarity (Figure 2), where 12 self-assessments exceeded the initial evaluation, and Flexibility, which saw 14 self-assessments surpassing the initial evaluation (Figure 3). It is worth noting that these skills showed less alignment when considering the 60% or higher threshold.

The remaining skills exhibit a stronger resemblance between the initial assessment and self-assessment when considering the 60% threshold, with a notable focus on Creativity (Figure 4) and Metacognition (Figure 5) skills. More precisely, 17 and 15 out of the twenty students demonstrated converging evaluations for Creativity and Metacognition, respectively.

Figure 2. Comparison between Self-assessment and Initial Assessment for Transdisciplinarity. - source: the author

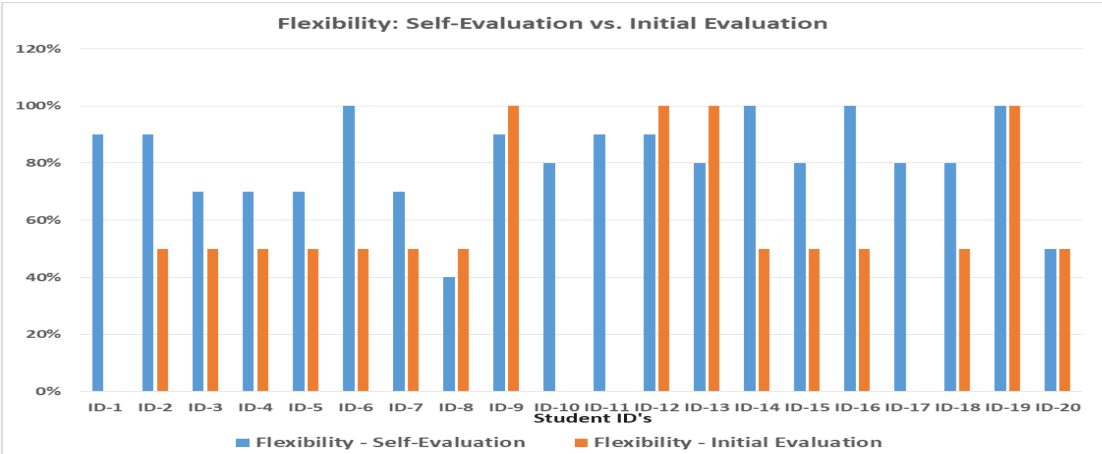

Figure 3. Comparison between Self-assessment and Initial Assessment for Flexibility. - source: the author

Considering the overall alignment between the initial assessment and self-assessment across most competencies, it is important to investigate whether there is an increase in student engagement when responding to questions in subsequent modules (2 and 3) following recommendations.

Analyzing the variation in question response rates between the initial assessment and subsequent modules reveals a notable increase in student engagement, persisting until the final module. This is visually depicted in the attached graph (Figure 6), where the gray line representing Module 3 surpasses the others (blue - Module 1, orange - Module 2). This trend is observed, as around 29 students (74%) increased their participation in the recommended activities, 7 students demonstrated a drop in participation (18%) and only 3 (8%) maintained the level of participation, which indicates a reception of positive response to recommended activities.

We highlight cases where students demonstrated, in addition to engagement, also exhibited autonomy by carrying out more activities than recommended (ID-21, ID-24, ID-27 and ID-36) [Oliveira et al. 2022]. On the other hand, students with initially

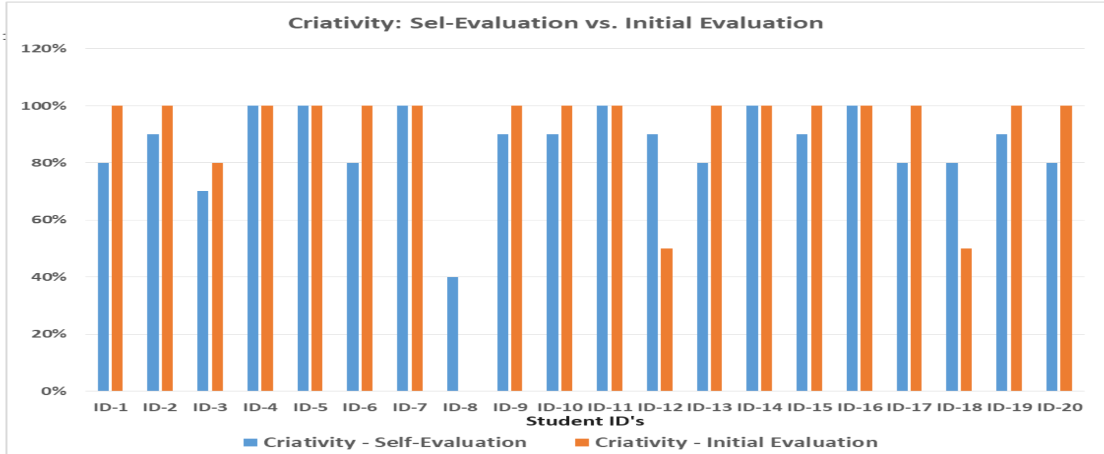

Figure 4. Comparison between Self-assessment and Initial Assessment for Creativity.

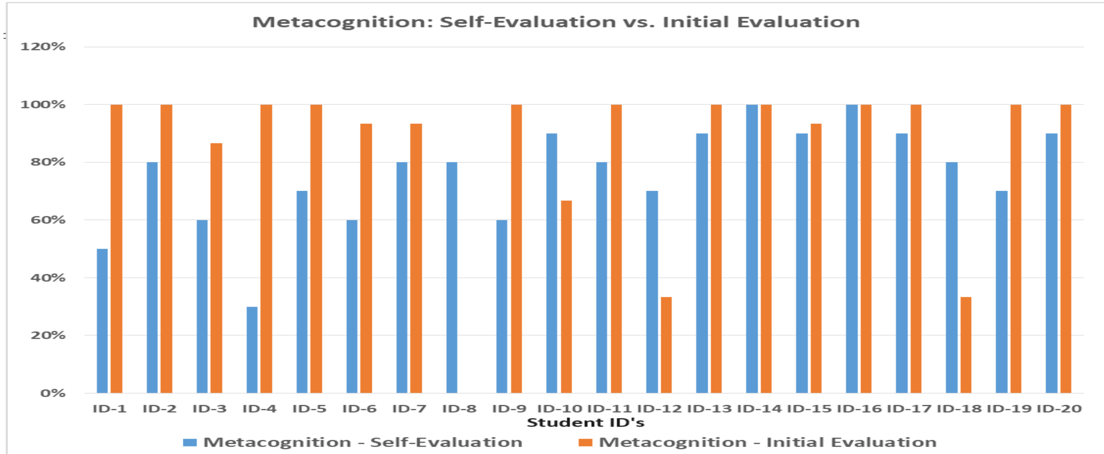

Figure 5. Comparison between Self-assessment and Initial Assessment for Metacognition. - source: the author

low participation (e.g. ID-3, ID-16, ID-23, ID-33) faced challenges in increasing their engagement levels, requiring complementary strategies beyond personalized recommendations. These strategies included contact via chat and the use of the Questions Forum for each Module and Subject. Despite their efforts, students ID-3, ID-16 and ID-23 ended up dropping out of the course.

Given that there is generally alignment between the initial assessment and self-assessment across most skills, our exploration now extends to assessing whether there is an uptick in student engagement in responding to questions from the subsequent modules (2 and 3) as a result of the activity recommendation process following the initial assessment.

To achieve this, an analysis of the variation in the percentages of questions answered between the initial assessment and the subsequent modules becomes imperative. Hence, upon examining the chart (Figure 6) below, one can observe a rise in student engagement extending to the final module (Module 3), as indicated by the gray line surpassing the others (blue - Module 1, orange - Module 2). This trend is evident in

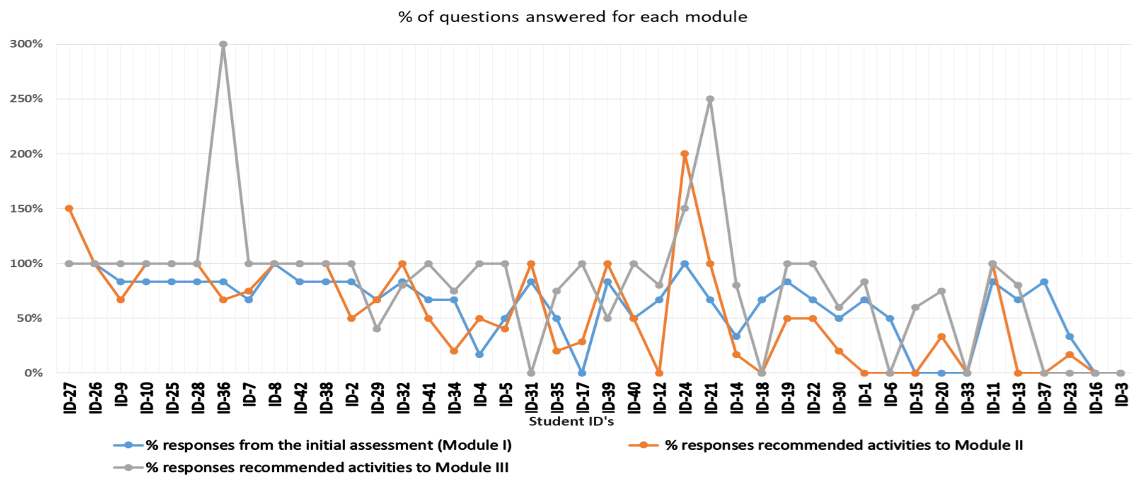

Figure 6. Percentage of questions answered for each module

over half of the students.

It is crucial to emphasize extreme cases where students exhibit not only engagement but also the development of the autonomy skill by completing more activities than recommended (ID-21, ID-24, ID-27, and ID-36) [Oliveira et al. 2022]. It is worth noting that in each module, students were expected to adhere to activity recommendations, although all activities were optional. Conversely, students with low initial participation (e.g., ID-3, ID-16, ID-23, ID-33) may encounter challenges in boosting their engagement, necessitating additional strategies beyond personalized recommendations. Notably, ID-3, ID-16, and ID-23 dropped out.

Investigating a possible correlation between the increase in questions answered from Module 1 to Module 3 (indicating student engagement) and the consequent improvement in the student's final grade, we created the graph (Figure 7), using lines of trend polynomial (4th degree) to accommodate the fluctuating nature of the data (e.g. ID-36, ID-31, ID-21 and ID-18). This analysis showed a pattern for the majority of students, such that by increasing their engagement, there was a corresponding improvement in final grades. For students above ID-37, who had less engagement at the end of the module compared to the beginning, the result was not completing the course successfully.

Upon analyzing the trendlines, a clear pattern emerges: for most students, engagement in recommended activities during the final module (depicted by the orange dashed line) surpasses their participation in the initial module (represented by the blue dashed line). Furthermore, as student engagement intensifies, there is a corresponding increase in their final grades. However, it is important to highlight an exception: starting with student ID-37, this trend is reversed, signifying reduced engagement towards the end of the module compared to the beginning. Consequently, the last three students did not successfully complete the course.

Table 4 shows the correlation between completion (c) and performance (p) of students in each module (MI, MII, MII) and overall (O). As there is no normal distribution of the quantitative data analyzed, Spearman's correlation is indicated

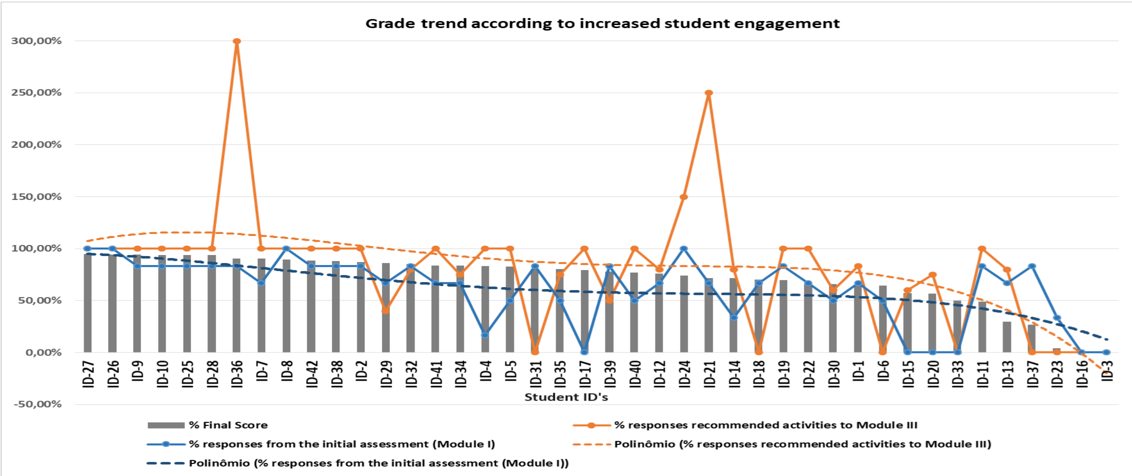

Figure 7. Grade trend according to student engagement

[Hauke and Kossowski 2011]. Furthermore, the interpretation of the correlation indices (rho) given, follows the parameters defined in [Baba et al. 2014], with a significant correlation when $p - value < 0.05$. In addition, the correlation indices Spearman's ρ are classified as: *very weak* $[0, 0.2[$; *weak* $[0.2, 0.4[$; *moderate* $[0.4, 0.7[$; *strong* $[0.7, 0.9[$; *very strong* $[0.9, 1]$.

Intuitively, a correlation is expected between a student's module completion and performance in the same module. The table 4 supports this expectation, revealing a very strong correlation between module completion and performance in Modules I, II and III, as well as completion and overall performance. Although Module I is diagnostic, the recommendations adapted to the profile of students in Modules II and III maintained a strong correlation between completion and performance. Notably, completion of Module III shows a moderate correlation with overall completion and performance. Descriptive measures, including completion and performance rates between Modules I and III, indicate a positive impact on student motivation, with completion rates of 61% and 82%, and performance rates of 58% and 74%, respectively. These findings are promising but warrant more comprehensive studies with a larger sample of students.

6. Conclusion

Starting from the benefits, this paper presents some that deserve to be highlighted. Firstly, it aligns instructional design with the principles of complex thinking theory, when analyzing students' learning requirements, aiming to promote a process intrinsically linked to students' cognitive attributes. Secondly, by categorizing and recommending activities according to specific cognitive aspects, the use of Moodle present a fundamental advantage, as it is a versatile learning management system, easily adaptable to active and student-centered teaching methodologies, offering varied learning activities to personalize teaching. Furthermore, the study demonstrates a correlation between students' self-assessment and their initial assessment, reinforcing the reliability of the recommendations, increasing students' awareness of their own abilities. The positive impact on final grades stands out as a fundamental result, indicating that there is a correlation between involvement in recommended activities and better academic performance, especially in conjunction with methodologies that emphasize student

Table 4. Spearman's correlation between completion and performance of students in each module and overall

		MI-c	MI-p	MII-c	MII-p	MIII-c	MIII-p	O-c	O-p
MI-c	Spearman's ρ	—							
	p-value	—							
MI-p	Spearman's ρ	0.957	—						
	p-value	<.001	—						
MII-c	Spearman's ρ	0.744	0.757	—					
	p-value	<.001	<.001	—					
MII-p	Spearman's ρ	0.717	0.735	0.961	—				
	p-value	<.001	<.001	<.001	—				
MIII-c	Spearman's ρ	0.476	0.434	0.643	0.61	—			
	p-value	0.001	0.004	<.001	<.001	—			
MIII-p	Spearman's ρ	0.511	0.485	0.648	0.644	0.911	—		
	p-value	<.001	0.001	<.001	<.001	<.001	—		
O-c	Spearman's ρ	-0.075	-0.116	0.078	0.12	0.645	0.577	—	
	p-value	0.637	0.464	0.626	0.448	<.001	<.001	—	
O-p	Spearman's ρ	-0.028	-0.052	0.143	0.22	0.605	0.641	0.933	—
	p-value	0.861	0.745	0.367	0.161	<.001	<.001	<.001	—

Legend:
MI-C: Module I completion | MI-P: Module I performance
MII-C: Module II completion | MII-P: Module II performance
MIII-C: Module III completion | MIII-P: Module III performance
O-C: Overall completion | O-P: Overall performance

engagement. Therefore, they demonstrate the potential of this approach to produce favorable results in students' learning outcomes.

Below are some challenges that deserve attention. As some students tend to present more positive self-evaluations in relation to initial evaluations, there is potential difficulty in achieving self-awareness about their competence, requiring further investigation into the factors that influence self-perception. Although the majority of students demonstrated improvement in engagement and performance throughout the course, students with low levels of initial participation required personalized strategies, as recommendations of labeled activities alone were not sufficient for such an improvement.

This study offers possibilities for advancing educational practices, opening up opportunities for future research. Refining the labeling process is a potential area, as Moodle offers a variety of activities that have not been used. Another important point is to align these activities with the different methodologies mentioned for the formation of the complex subject. Considering being an experimental study covering only one subject, analyzing the long-term impact, considering students' involvement in activities throughout their academic career, could provide valuable information about the sustained benefits. Furthermore, the integration of artificial intelligence (AI) technologies into the educational framework holds promise for personalized recommendations and adaptive learning, making it a promising area for future investigation.

Concluding, valuable insights into the intersection between the theory of complex thinking and the practice in distance education were presented, while also showing benefits, challenges, and avenues to explore, setting the stage for continued research aimed at refining and expanding the application of such strategies in online education.

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