JOURNAL OF LEARNING ANALYTICS

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Early Access Articles, 1–12. https://doi.org/10.18608/jla.2024.8079

Identification of Complex Thinking Related Competencies: The Building Blocks of Reasoning for Complexity

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Abstract

Complex thinking competency enhances the high cognitive capacities necessary for the future of education. This study aimed to analyze these capacities through its sub-competencies (critical, systemic, and scientific thinking). We worked with the Cross Industry Standard Process for Data Mining methodology, with an original database of class data of 33,319 unique students, 46 different variables, and a random identification number. The variables were sociodemographic information, academic information, subject admission, competencies, and activities. Statistical analyses identified correlations between competency and sub-competencies. The findings show that 1) critical thinking is strategic in the development of complex thinking and its sub-competencies; 2) Development of Critical Thinking skills early in the curriculum can lead to a cascade effect, enhancing competence and sub-competence development; and 3) an overall performance encompasses the semester results. The study is of value to the academic, technological, and social communities to provide opportunities for the design and implementation of challenging scenarios for the future of education.

Notes for Practice

- Critical thinking is strategic in developing complex thinking and its sub-competencies.
- Development of critical thinking skills early in the curriculum can lead to a cascade effect, enhancing competence and sub-competence development.
- Integrate challenging problems (such as those presented by the sustainable development goals of the UNESCO 2030 agenda) into the curriculum, involving interdisciplinary work and the promotion of complex thinking skills.
- Integrate strategies for developing high skills (such as case studies, challenge-based problems, and inquiry-based learning) as well as alternative assessments (such as peer assessment, external agent assessment, and self-assessment), which are in line with the encouragement of complex competences.

Keywords

Reasoning for complexity, competency-based education, educational innovation, higher education

Submitted: 08/06/2023 — **Accepted:** 29/01/2024 — **Published:** 06/03/2024

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1. Introduction

One of the few certainties of the world is that things will change, be it from technological advances, discoveries, or even politics. Our society continuously faces new challenges and problems. As changes accelerate, education must prepare the younger generations for the unknown and constant change. One of the current preparations is Education 4.0 (Mo & Beckett, 2020). Education 4.0 uses novel information and communication technologies to aid the learning–teaching process, and competencies are core components. Competency-based education models aim to train students for uncertainty in their future, giving them the competencies (theoretical knowledge, practical skills, and know-how) to ensure that they keep learning as their discipline and work grow and evolve.

Education paradigms and strategies have long followed the industry, and those paradigms are shaped by the necessities of those time periods. Ever since the first Industrial Revolution, there has been a matching educational shift accompanying the industrial ones, initially based around new accessibility of education for the general population (first and second revolutions) and then on the information and skills necessary to be competitive in the globalized, highly competitive industries of the modern age (third and fourth revolutions; Miranda et al., 2021). As mentioned previously, change is guaranteed in the present world; we can investigate the consequences of the COVID-19 pandemic to easily understand how quick some of those changes need to be. According to the learning outcomes, student roles, and the philosophy of Education 4.0 mentioned by Miranda and colleagues (2019) and by Salmon (2019), the principal objective of modern education is not simply relevant knowledge or skills, but "key competences soft and hard." What this means, together with the fact that students are now required to be active, independent learners and that self-learning is a necessity due to the constant change happening in any industry, is that not only is the development of competences imperative, but the development of higher-level competences like reasoning for complexity will only increase in importance.

One of the main challenges of competency-based education is the range of competencies that must be acquired by the student. It is no longer the case that students need only memorize knowledge or apply a set of predetermined steps; they must solve a challenge and propose a solution to a non-trivial problem. Complex thinking integrates interrelated and complementary factors into a whole (Morin, 2020a). Ramírez-Montoya and colleagues (2022) propose a niche for research on the components of Education 4.0. Beyond that, research into the components of complex thinking must occur because it is a high-level competency that comprises several components or sub-competencies, such as systemic, critical, innovative, and scientific thinking. A student must also demonstrate mastery over the sub-competencies to achieve complex thinking. These competencies are not developed in a vacuum, so students and educators must understand their correlations to improve teaching and learning.

A statistical analysis of the factors influencing the acquisition of complex thinking would give educators tools to better plan their curricula, courses, and lessons. Previous studies have approached student development of complex thinking with self-reporting assessments (Davis et al., 2023), pre-test and post-test comparisons (Gago et al., 2020), and interview questions (Lizier et al., 2018). In our study, we propose using statistical methods to better understand the relationship among the sub-competencies, which could influence curriculum design in the future. For example, if statistical analyses show the critical thinking sub-competency as significantly more correlated with the overall complex thinking competency than the others, it should have priority in its development, and universities can plan for this. This paper offers statistical insights into the relationships between complex thinking and its sub-competencies, and the tools researchers and practitioners need to further Education 4.0. These are our research questions:

R1. Does the development of a specific level of one sub-competency significantly affect the development of the others?

R2. To what extent does a sub-competency's development affect higher levels of it?

1.1. Competencies in Higher Education

Ideally, Education 4.0 would be present in all levels and styles of modern education, but it is most important in higher education since it is the last step for most students before they transition into their chosen industries and are expected to demonstrate competence in their fields. Traditional education (such as lecture-only courses), as well as vocational or trade schools, have proven insufficient regarding the development of competencies needed in the 21st century (Buckingham Shum & Deakin Crick, 2016). Lecture-only courses fail to develop much-needed practical skills, while vocational training falls short on theory. Therefore, a different approach is necessary, one where the development of knowledge, skills, and attitudes that make up the different competencies are purposefully targeted. One such approach is challenge-based learning, or challenge-based educational (CBE) models.

Challenge-based models have begun to show promise against traditional systems in terms of competence development, as can be seen in the EPICS programs at Purdue University, for example (Purdue University, n.d.). Purdue has a history of being at the vanguard of educational research, which gives added weight to their use of CBE. Before their EPICS programs, they were among the first institutions to use educational data mining (EDM) and learning analytics (LA) as part of their decision-making process, as can be seen in Arnold and Pistilli (2012). Other notable examples of challenge-based models are the Challenge Lab at Chalmers University of Technology (Holmberg, 2014) and the Green Challenge at the Technical University of Denmark (About Green Challenge, n.d.; Hussmann, 2010). A case study closer to our subject university was investigated by Professor Claudia Lizette Garay-Rondero. Professor Garay-Rondero performed a statistical analysis on the results regarding the competence level achieved by students on a course given under a challenge-based approach against a traditional classroom when teaching the Lean Manufacturing production model in Tecnológico de Monterrey (Garay-Rondero et al., 2019). Her experiment concluded that students under the challenge-based model increased their competence level by 29% compared to students in traditional classrooms.

The specific model for this research is challenge-based, with three distinct phases in its curriculum: discovery, focus, and specialization. New students have the option of enrolling in an undergraduate degree program directly or spending three or four semesters on a more general path (engineering, social sciences, biosciences, et cetera). The students who do not choose an undergraduate program must take a series of elective courses to familiarize themselves with their different options and make an informed decision about their future. During their studies, students learn the specific competences required of their major, and these competences are evaluated in every course they take, which makes up an important percentage (50–60%) of their final grade. Competences are divided into sub-competences, and these are further divided into levels of complexity that students are expected to master. For example, a student taking a programming course for the first time might develop a "Computational Thinking" sub-competence on the A (lowest) level, while one developing their end-of-course project would work on "Computational Thinking" at level C (highest).

The model focuses on preparing students for their professional life by developing the skills expected of leaders and entrepreneurs, and by developing the competencies needed for their future endeavours. These competencies are developed through four main strategies: 1) the Tec21 challenge-based learning model, 2) flexibility on how and where students learn, 3) a remarkable higher education experience, and 4) top-rated professors capable of inspiring students (Tecnológico de Monterrey, 2018). The model also contains special learning modules of varying lengths designed to bring real-life challenges to develop the necessary competencies for solving future problems. Additionally, students have the option of participating in leadership, cultural, or sports activities designed to contribute to their development of "soft" or transversal competencies (Conecta, 2018).

1.2. The Reasoning for Complexity Competency

Fostering high-level skills in university students yields problem-solving citizens. Morin (2020b) states that thinking for complexity comprises several skills and tools an individual or social agent needs to face real problems with an integrated and holistic approach. Similarly, Tobón (2021) states that complex thinking is a person's ability to apply integrative thinking to analyze and synthesize information to solve problems and develop continuous learning skills. Universities have focused on this competency comprising quantitative, qualitative, algorithmic, analogical, contextual, combinatorial, fuzzy, imaginative, provisional, heuristic, and ethical reasoning components. To better understand this competency, one must first examine its inherent complexity and components (Tecnológico de Monterrey, 2019). In this sense, developing competencies for complexity encourages high-level thinking for problem-solving.

The need to prepare students for an increasingly complex world has led to the development of several new training methodologies (e.g., Pi et al., 2022; Wang et al., 2022; Mentzer et al., 2023). Pi and colleagues (2022) provide POET, a pre-training paradigm for basic reasoning that they call simply POET-Math and POET-Logic, as well as the more complex POET-SQL. Results show that POET significantly increases student performance in natural language reasoning, such as numerical reasoning, logical reasoning and, therefore, complex reasoning. Wang and colleagues (2022) present a model geared to the Law School Admission Test (LSAT). This standardized test assesses general complex reasoning skills (analytical reasoning, logical reasoning, and reading comprehension skills). The authors propose a hybrid model, DUMA, based on modelling complex reasoning skills, especially fundamental reading comprehension and challenging logical reasoning skills. The results show improved performance in complex reasoning skills. With the Interactive Synchronous HyFlex, Mentzer and colleagues (2023) attempt to promote design thinking, both in the classroom and online, by encouraging teamwork and community interaction, shifting autonomy from teacher to learner in order to solve complex problems. Thus, focused on design work, it seeks criticism, reflection, and reasoning skills for the complexity that enhances design thinking.

It is important to note that, in the context of this specific study and educational model, the reasoning for complexity competence is classified as a transversal competency. In other words, it is what has been previously called a "soft" skill, in the sense that it requires no discipline-specific knowledge or skills and can be applied to any situation. As such, this competency is, in general, not usually the main objective of a course or challenge, but instead is progressively developed as students solve subsequently harder problems, while also defending the process they followed to do so.

Reasoning for complexity is a meta competency because it encompasses several sub-competencies. Silva Pacheco (2020) declares meta competency to include cognitive and metacognitive processes. Several smaller sub-competencies integrate a high-level or meta-level competency. Vázquez-Parra and colleagues (2022) identified three types of thinking required for the mastery of complex thinking — systemic, critical, and scientific thinking — all having valid definitions:

- *Systemic thinking* is the ability to analyze interconnected problems and situations holistically to understand all factors and inner dynamics of the situation.
- *Critical thinking* allows students to evaluate the information presented to form logical judgments and take action.
- *Scientific thinking* involves using standardized methods, strategies, and knowledge to attack problems. This type of thinking includes the development and testing of hypotheses.

As parts of a whole, all three of these sub-competencies must be attained before a student has mastered the competency. Ponce and colleagues (2022) worked with university students to develop complex reasoning skills through vehicle prototypes and integrating artificial intelligence and simulators. Roche and colleagues (2021) explored the development of complex thinking with recursive interaction between a stated problem, solution design, implementation, and evaluation. Dowd and colleagues (2018) worked with undergraduate thesis writers to identify and understand the relationships between scientific thinking and critical thinking in writing. Blatti and colleagues (2019) developed their chemistry curriculum using a systems thinking approach to consider the UN sustainability goals, green chemistry, and interdisciplinarity when integrating the competency into its classes. As with almost any topic, the correlations between these components can affect how a student progresses in each sub-competency. These correlations are the main topic of this article.

1.3. Correlations Between the Sub-Competencies

Dealing with real-world problems is a complex endeavour that often requires non-linear solutions and several approaches for understanding and resolving. It is straightforward to see that a complex problem requires all three types of thinking. Scientific thinking provides a tested and applied baseline for an initial understanding of a problem's components. Systemic thinking allows addressing the entire situation instead of just its components and gives insight into interactions among them. Critical thinking provides the necessary scrutiny and objectivity to verify that the proposed answer or solution is good (Jaaron & Backhouse, 2018; Talanquer et al., 2020; Cui et al., 2021; Sellars et al., 2018; Suryansyah et al., 2021). Understanding and solving any non-trivial problem requires a set of thinking competencies, but how do these types of thinking relate to each other? It would be naive to think that the sub-competencies develop in a vacuum. More likely, the development of one (say, critical thinking) affects the development of the others.

Regarding competency correlations, a previous study analyzed two different competencies — social entrepreneurship and reasoning for complexity — and found relationships between scientific thinking, self-control, and leadership, and between systemic thinking, social awareness, and social value (Cruz-Sandoval et al., 2023). While their approach used compositional data analysis, we investigated the internal relationships of the complex thinking competency using values assigned by teachers to students under the University's Tec21 Educational Model.

2. Methods

We followed the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology for this project (Wirth & Hipp, 2000). This methodology consists of six steps iterated throughout the project as needed, but the overall process is as follows:

- **Business Understanding:** involves analyzing and understanding the problem. We discuss this in the introduction.
- **Data Understanding:** involves identifying, collecting, and organizing needed data.
- **Data Preparation:** includes dataset cleaning, feature selection and construction, and any required rearrangement to satisfy our project needs.
- **Modelling:** involves applying the relevant algorithms and performing an initial evaluation of the results obtained. In our case, this refers to the correlation analysis performed, discussed in the results section.
- **Evaluation:** results are reviewed and considered in the context of the problem. The discussion section corresponds to this phase.
- **Deployment:** the project is launched, and the results are recorded for further iterations (not applicable in this case).

2.1. Data Collection and Ethical Considerations

The dataset came from the IFE Living Lab and Data Hub Call for Proposals, "Fostering the Analysis of Competency-based Higher Education." The dataset comprised anonymized information from undergraduate students who had taken at least one semester under the TEC21 Educational Model at Tecnológico de Monterrey in Mexico from August–December 2019 to February–June 2022 (six semesters). Tecnológico de Monterrey's Data Owners and Data Security and Information Management Departments validated privacy issues related to student data collection, curation, and publication.

2.2. Dataset Description

The original dataset consisted of class data from 33,319 unique students with 46 variables and a randomized identification number. These variables consisted of sociodemographic information (age, gender, nationality), academic information (last term average, current average, academic status), admission information (Tec system, cohort, program/school), subject information (type, modality, period), competency information (type, sub-competency, level), and activity information (title, assignments, evidence).

The dataset contained 269 distinct competencies, including our target: complex thinking. Evaluation of competencies is not performed directly under the Tec21 model. Instead, sub-competencies that include the main one are assigned to different

ISSN 1929-7750 (online).

courses/blocks. Varying amounts of sub-competencies compose the competencies, commonly two or three. Our dataset contained 789 different sub-competencies and both categorical and numerical variables.

In this study, we focused on the progress of complex thinking sub-competencies by students in the School of Sciences and Engineering at Tecnológico de Monterrey. The university evaluates the Reasoning for Complexity competency by assessing three sub-competencies: scientific thinking, critical thinking, and systemic thinking. Table 1 shows the sub-competency codes for the complex thinking competency. Each sub-competency is evaluated in ascending order of achievement levels: A, B, and C, with A the lowest (most basic level) and C the highest (most complex level).

Table 1. Sub-Competency Descriptions

Code	Sub-competency
SC1	Scientific thinking
SC2	Critical thinking
SC3	Systemic thinking

Table 2 shows the distribution of competency evaluations per semester; that is, the number of students evaluated in some complex thinking sub-competency at some level and in some formation course/block. Columns in Table 2 denote the sub-competency (see Table 1) and the corresponding achievement level (A–C). As can be seen, the initial level (A) of the three sub-competencies is mainly evaluated in the first four semesters. Meanwhile, the intermediate level (B) is evaluated in semesters four through six. The highest level (C) is barely evaluated in the fifth and sixth semesters. All bachelor's degrees have eight semesters, hence the evaluation of level C continues into the seventh and eighth semesters.

Table 2. Complex Thinking Sub-Competency Evaluations per Semester

Semester	SC1_A	SC1_B	SC1_C	SC2_A	SC2_B	SC2_C	SC3_A	SC3_B	SC3_C
1	14,408	0	0	3,406	1	0	8,201	0	0
2	7,520	4	0	6,753	12	0	5,768	5	0
3	8,320	410	0	7,209	370	0	8,015	380	4
4	2,617	3,877	0	3,226	2,835	18	3,487	2,912	41
5	463	1,743	51	895	2,098	30	920	1,202	225
6	129	1,803	319	316	1,694	38	451	708	631
Total	**33,457**	**7,837**	**370**	**21,805**	**7,010**	**86**	**26,842**	**5,207**	**901**

Sub-competency evaluation is binary. The teacher evaluates the sub-competency as 1 if the student shows some level of the corresponding sub-competency or with 0 otherwise. Given that a student can be evaluated for the same sub-competency/level in multiple courses in the same semester, we calculated an average from these marks. These averages are on a scale of 0–1, where 0 would represent that all teachers evaluated the student at 0 while 1 represents that all teachers evaluated the student at 1. Values in the middle represent a combination of 0's and 1's for that sub-competency in a given semester. The distribution of these averages is shown in Figure 1 using boxplots for the median and both upper and lower quartiles. As can be seen, in the first four semesters, level A competencies are evaluated in multiple courses with an average median of 0.8 for SC1 and 0.6 for SC2 and SC3. Likewise, the average medians of level B sub-competencies in the last three semesters are 0.7 for SC1 and 0.5 for SC2 and SC3. The empty spaces in Figure 1 represent cases where no information was available, mostly due to the sub-competencies being of a higher level than the available courses developed. Most empty spaces belong to early semesters for level C sub-competencies. The bars with missing variances represent having few cases for those sub-competencies, mostly without repeat evaluations, so the students either attained the sub-competency (1) or not (0).

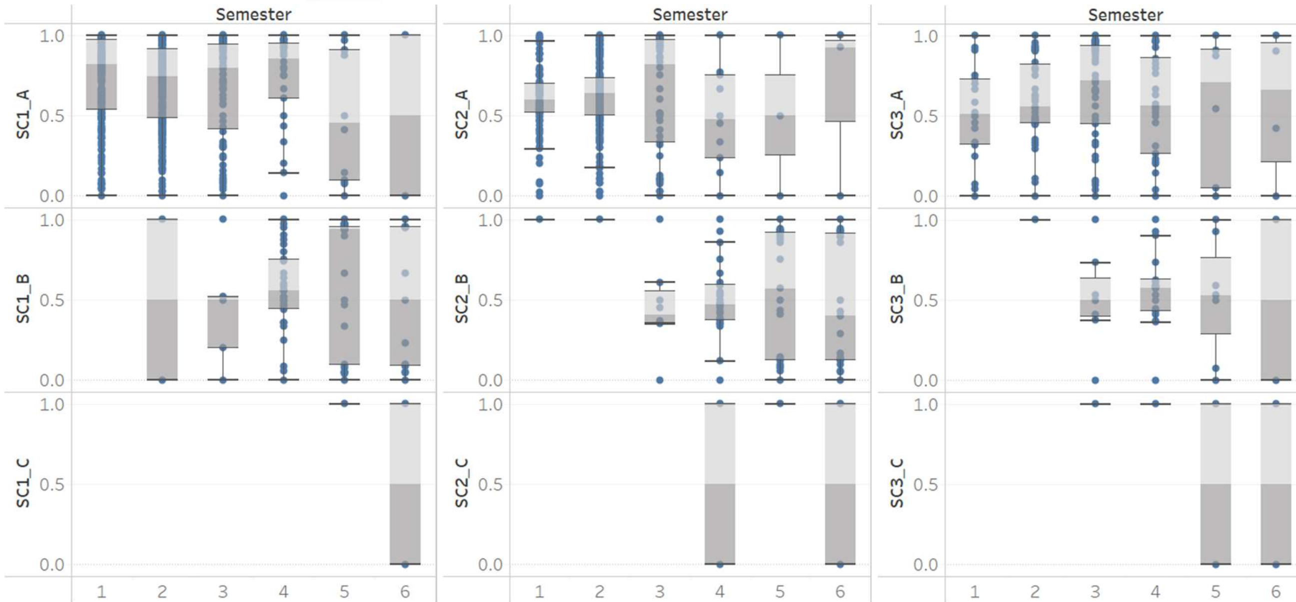

Figure 1. Distribution of sub-competency evaluations per semester.

The final analysis was performed on six sets of 15,903 row by 18 column data frames, each consisting of the previous and current competency scores for each semester from first to sixth. The process taken to arrive at these datasets is detailed below.

2.3. Data Preparation

To prepare our variables for analysis, we transformed variables with only two possible values that were not already binary into 1 or 0 (e.g., competency type, level assigned to competency, competency status in Canvas, and if the course had an associated evaluation instrument). The competency level required for each course/block is on an ordinal scale of A, B, C, which we changed to 1, 2, 3, respectively, with C/3 being the most advanced level. Blank data points were replaced by "nan" values when missing (Not a Number). We discarded features if the number of missing values was deemed too much (>30%).

The researchers arranged the original dataset in a "long" format where a single student has several rows describing their progress and grades for each activity in every class taken. To properly analyze our data, we transformed our dataset into a "wide" format, in which each student corresponds to a single row containing the following columns: 1) previous scores for our three sub-competencies (scientific, critical, and systemic thinking) for the three levels, 2) whether the student is currently on a course developing a competency and what level, and 3) the results of each student's evaluations. These totalled nine columns per section (3 competencies x 3 levels) and three sections, for a total of 27 columns.

The previously mentioned dataset was used to track sub-competency progress through their semesters. As students are not guaranteed to enroll in courses that develop the sub-competencies, it was necessary for us to keep a record of previous sub-competency scores, current enrollments, and current sub-competency achievements. To have variables representing the current sub-competency achievement level we defined *semester cumulative score* as the average of all the evaluations from the current and the previous semesters. To further track student progress, we performed a rearrangement by semester, in which each row corresponded to a student, nine features tracked previous sub-competency acquisition for specific levels and sub-competencies (3 distinct cases x 3 levels each), and another nine features tracked current acquisition. This resulted in the final datasets from which all our figures were obtained: six datasets (one for each semester from first to sixth) with 15,903 rows (one per student) and 18 columns (nine for previous sub-competence values, nine for current ones) Table 3 shows the column names, descriptions, and values.

Table 3. Variable Definitions

Variable name	Definition	Values
SC*_prev_score_**	Describes the student's cumulative scores per sub-competency* and level**	Range from 0 to 1 (where 1 indicates entire mastery of the sub-competency)
SC*_sem_score_**	Describes the student's obtained scores per sub-competency* and level** during the semester	Range from 0 to 1 (where 1 indicates entire mastery of the sub-competency)

3. Results

A correlation analysis by semester identified how much previous sub-competency scores correlated to their future achievement, which comprised the Reasoning for Complexity competency, different sub-competency levels, or the other sub-competencies. Pearson correlation was chosen for two main reasons: 1) its ability to measure the magnitude of a correlation in an easy-to-understand and interpretable manner between significantly correlated pairs (their effect size), and 2) the information obtained was perfectly paired to use this value. To show the relevant cases, we also obtained each correlation's p-value, used to decide which results to show in our figures. As we performed multiple tests, a False Discovery Rate (FDR) correction followed the Benjamini-Hochberg method. The corrected p-values were used as a "mask" for our figures since only correlation values with smaller than 0.05 corrected p-values are shown. Not shown are p-values that repeat information available from the figures themselves. Regarding the necessary assumptions for Pearson Correlation: all feature values are on ratio level, the population distribution is normal, there were no outliers in the data, the data was randomly selected, and we expect to see a linear relationship between the features. Finally, the data was perfectly paired. Therefore, all relevant assumptions of Pearson Correlation held, allowing for a direct analysis. Figures 2, 3, and 4 show the Pearson correlation values for semesters 4, 5, and 6 under the current Tec21 Educational Model; they show the degree to which our variables are linearly related.

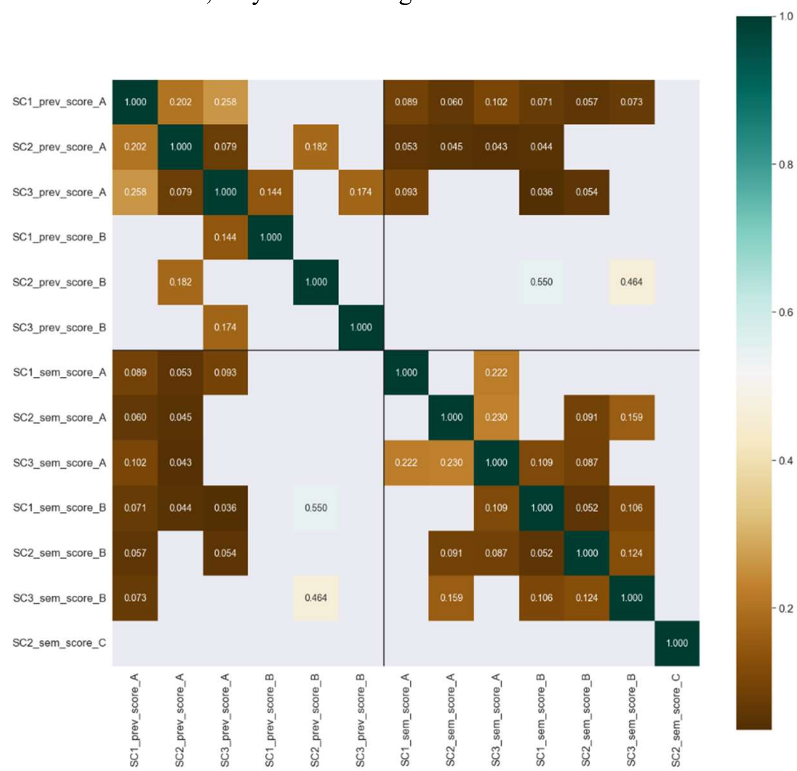

Figure 2. Correlation values with significant p-values for fourth-semester students.

In the top right and bottom left quadrants of Figure 2, we can observe relationships between previous experience and current achievements. The correlations of previous scores in sub-competency 2 (critical thinking) on level B and sub-competencies 1 and 3 (scientific thinking and systemic thinking), also on level B, are of particular interest. We observe that previous scores on critical thinking had a 0.55 correlation with current scores in scientific thinking and a 0.464 correlation with current scores in systemic thinking.

Figure 3 shows the same analysis for the fifth semester. Note that the number of rows and columns increases because there is now information regarding higher competencies and their previous scores.

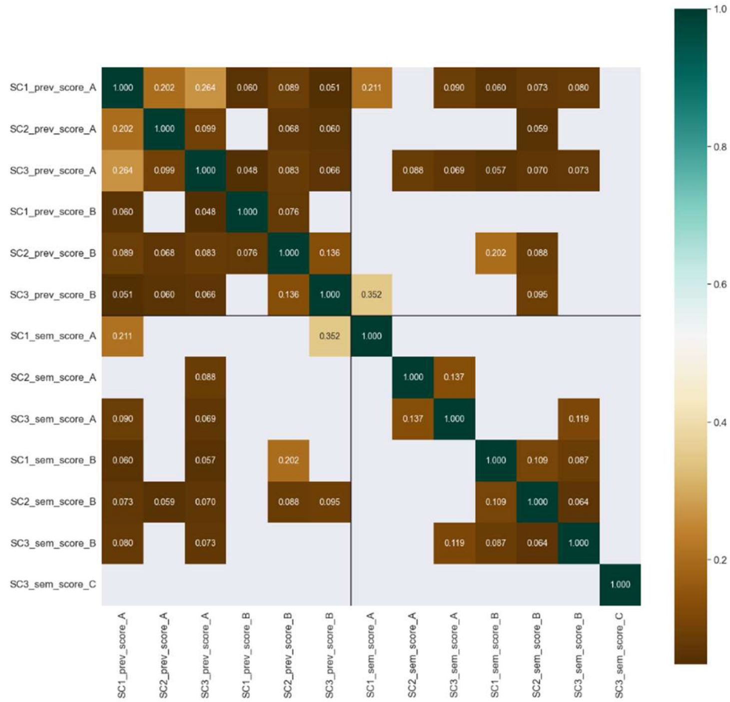

Figure 3. Correlation values with significant p-values for fifth-semester students.

We can observe in Figure 4 that the most relevant correlation corresponds to sub-competency 3 (systemic thinking) level B's previous score, and sub-competency 1 (scientific thinking) level A current score with 0.352. The next biggest correlation is between sub-competency 2 (critical thinking) level B and sub-competency 1 (scientific thinking) level B with 0.202. While the different levels inside one single sub-competency usually develop in order, different sub-competency levels can and do interact.

Notably, transversal competencies, like our target one, are usually more commonly evaluated during the middle semesters of the program; as such, there are cases (like the sixth semester) where relatively few students take courses that develop them. Figure 4 shows the correlations for the sixth semester.

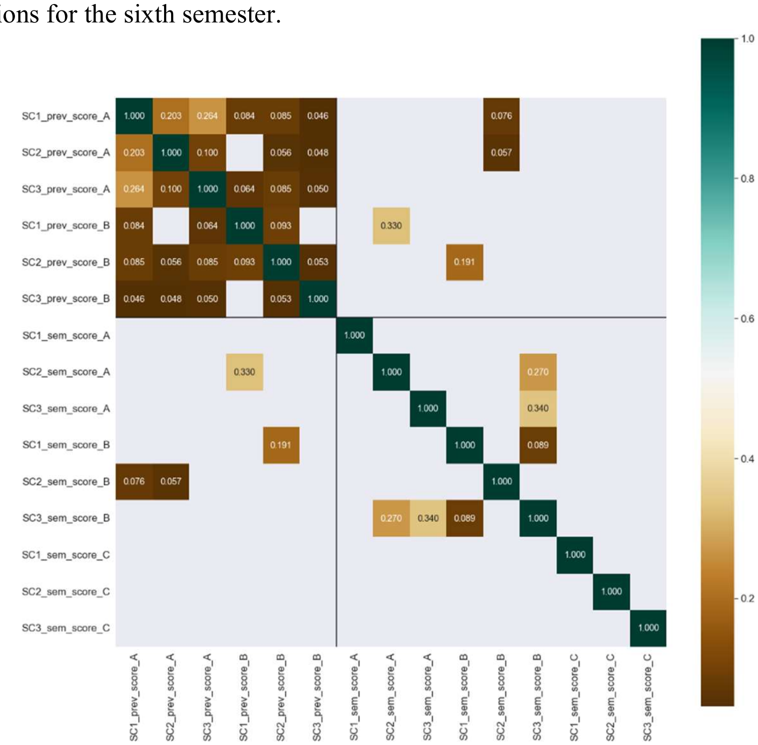

Figure 4. Correlation values with significant p-values for sixth-semester students.

We can observe two cases with relevant correlations in the sixth semester: the previous score of sub-competency 1 (scientific thinking) level B and the current score of sub-competency 2 (critical thinking) level A (0.33); and the previous score of sub-competency 2 (critical thinking) level B and sub-competency 1 (scientific thinking) level B (0.191).

While the values are not extremely high, it is noteworthy that aside from developing a sub-competency, many more factors could affect their acquisition. For example, we did not consider sociodemographic data, course grades, or other informative factors in this analysis due to our objective to isolate the factors of the competency itself.

4. Discussion

The development of competencies is a complex process that cannot and should not be assumed to occur in a vacuum. Figures 2, 3, and 4 show that the critical thinking competency has a recurring impact on other competencies. We summarize the most relevant correlation values with significant p-values in Table 4.

Table 4. Relevant Correlation Effects

Semester	Previous sub-competency	Current sub-competency	Correlation value
4th	SC2 B	SC1 B	0.550
4th	SC2 B	SC3 B	0.464
5th	SC2 B	SC1 B	0.202
6th	SC2 B	SC1 B	0.191

These results align with Cruz-Sandoval and colleagues (2023), where sub-competencies interact organically, and development in one affects the others. No other sub-competencies appear as commonly as critical thinking (SC2) with the impact shown in our study. This could indicate that critical thinking is a possible cornerstone in developing complex thinking and its sub-competencies, especially scientific thinking (SC1) and systemic thinking (SC3). These results help answer our R1 and R2 questions: the development of the critical thinking sub-competence does significantly affect other sub-competencies according to the results obtained from the dataset (R1), and no evidence was found to support the idea that previous results regarding a sub-competency's development affect higher levels of itself (R2).

It is important to mention that from all the significant correlations we found between sub-competencies, none were negative. A negative correlation would have represented that having a given sub-competency domain in the previous semester would hinder having the domain of another sub-competency by the end of the current semester. On the contrary, positive correlations (even when small) indicate that having achieved a sub-competency in a semester will facilitate achieving the same or another sub-competency in the next semester.

No single variable can fully explain the development of competency in the same way that no single characteristic can predict a student's performance in school. In sub-competencies other than critical thinking, previous scores do not strongly correlate with current scores. While the correlation values shown in Figures 2, 3, and 4 are all relevant according to the p-value analysis, many of those values are small, ranging from 0.05 to 0.10. Except for the critical thinking sub-competency and a few isolated cases, previous sub-competency scores explain only a small fraction of the current results. This is consistent with Dowd et al. (2018), as several significant correlations (according to p-values) are small in effect. It is important to note that current sub-competency evaluations in the Tec21 model were closely related to the overall grade of the course, so possibly student performance in their classes explains the remainder of the feature.

From the standpoint of correlation values, only two cases could traditionally be seen as moderate, which belong to the effects of previous scores on critical thinking with current scores in scientific thinking (0.55) and with current scores in systemic thinking (0.464). No other correlation achieves higher scores, with most cases not going above 0.1. One possible explanation is a series of courses that are deeply dependent on previously seen material regarding critical thinking skills. Cases like a series of courses given by the same professor, or courses that build heavily upon previous concepts and require a level of mastery on the basics of a topic could explain the higher correlation amounts. While this is expected on disciplinary competencies, it is a rarer occurrence for transversal ones.

As mentioned before, learning does not occur in isolation. While students perform differently in their classes, usually an overall performance encompasses their semester results. Relationships between the current scores of the different sub-competencies appear to follow the relationship between previous scores and current scores, albeit with a slightly higher average. This can be seen again in Figures 2, 3, and 4. It is important to note that these relationships depend strongly on whether the students participated in a course developing more than one sub-competency or in several courses that developed different ones. The latter was not an extremely common occurrence; therefore, the relationship is better explained by students' overall semester results than the correlations of competency acquisition.

Another relevant fact about our results is that they consider temporal precedence: we correlate the previous results of sub-competency acquisition with future ones. While not a causal relationship, this could pave the way for future work involving cause and effect relationships.

5. Conclusion

Complex thinking is a high-level competency that involves sub-competencies of critical, systemic, and scientific thinking. This study aimed to analyze the correlation of the sub-competencies to answer these research questions:

R1. Does the development of a specific level of one sub-competency significantly affect the development of the others?

R2. To what extent does a sub-competency's development affect higher levels of it?

The findings show that critical thinking has a high incidence of developing complex thinking and its other sub-competencies, primarily scientific and systemic thinking. The study also found no determinant variables driving the development of complex thinking, and there appears to be a sequence in the performance results in different courses throughout the academic trajectory.

Implications for educational practice are that a direct teaching focus on critical thinking skills could impact the development of overall competency, mainly through real scenarios where the student must make decisions and create value by analyzing a problematic situation. Also, we recommend developing critical thinking in the early semesters and following up with assessments to measure improvement. Reformulating curricula so that they purposefully develop the critical thinking sub-competency would in turn create a beneficial cascade effect regarding future development of other sub-competencies. Encouraging complex thinking requires the integration of challenging problems, strategies that encourage high abilities and alternative evaluations, which include the assessment of diverse agents. In addition, the research implies the potential of integrating different instruments to measure the level of competencies "in situ" so that mixed methods with different instruments can shed light on the design of exciting training scenarios in the future of education.

Regarding the limitations of this work, one comes from the data origin: although the data came from a large population (33,319 unique students with 46 different variables), it still originated from a single higher education institution. Even though this particular institution is comprised of several different campuses, there are institutional and sociodemographic similarities between them. This data also covers the initial semesters of a relatively new educational model, to the point that, at the time of collection, no cohort had yet graduated. As such, the educational model has not had time to properly mature, so corrections in the evaluation and teaching strategies are possible, which could in turn affect some of the relationships obtained from this study. Finally, the results uncovered here only account for sub-competency acquisition and the relationships with other sub-competences. Learning is a complex endeavour with a multitude of possible confounders. Among many other factors, human condition, the teachers of specific classes, and unmeasured or unmeasurable values could all influence the results of learning, which in turn could affect our results. Even so, we believe that this research is valuable towards better understanding competence development and could be used with confidence by stakeholders in areas like curriculum design.

Future work will include studies with data from different institutions, which would undoubtedly expand the generalizability. Such expansion would provide academics, technology developers, decision makers, and social communities interested in designing and implementing high-level learning scenarios with evidence to support the design and implementation of challenging scenarios for the future of education. Future work will also include the use of tools and techniques aimed at finding causal relationships between the sub-competencies, which would in turn better inform decision-making for stakeholders, and determine to what extent the domain of a sub-competency influences the increase in the achievement level of another sub-competency.

Declaration of Conflicting Interest

The authors declare no potential conflicts of interest in the research, authorship, and/or publication of this article.

Acknowledgments

The authors would like to acknowledge the Living Lab & Data Hub of the Institute for the Future of Education, Tecnológico de Monterrey, Mexico, for the data used in this work and provided through the Call "Fostering the Analysis of Competency-based Higher Education."

Funding

The authors would like to thank the financial support from Tecnológico de Monterrey through the "Challenge-Based Research Funding Program 2022." Project ID #I004-IFE001- C2-T3 – T, and from the Writing Lab, Institute for the Future of Education, Tecnológico de Monterrey, Mexico, in the production of this work.

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