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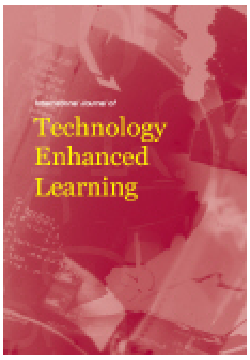

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Latent profiles of computational thinking in first-year university students in Peru

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Abstract: This study aims to classify computational thinking (CT) among first-year Peruvian university students. A sample of 730 students was analysed, focusing on five key dimensions – abstraction, decomposition, algorithmic thinking, evaluation, and generalisation – using a validated CT evaluation tool and the 'mclust' package in R. Four distinct CT profiles were identified, each highlighting unique strengths and weaknesses: Profile 1 exhibited high levels of CT skills, especially in evaluation and algorithmic thinking; Profile 2 showed moderate levels with a balanced distribution across dimensions; Profile 3 indicated significant weaknesses, particularly in decomposition; and Profile 4 had the lowest overall CT skills. Demographic variations explored through SPSS version 27 revealed significant differences in CT profiles based on the type of secondary school attended, with public school students excelling in abstraction. These findings contribute to the discourse on CT, offering practical guidance for educators to tailor interventions and enhance CT skills among university entrants.

Keywords: computational thinking; CT; latent profile analysis; LPA; higher education; abstraction.

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1 Introduction

In our swiftly evolving world, the rapid advancement of information and communication technologies, propelled by scientific and technical development, is reshaping societal structures and work paradigms (Rodríguez del Rey et al., 2021). The pervasive influence of these technologies demands a proactive exploration of their possibilities for developing a modern person (Soboleva et al., 2021).

This paradigm shift necessitates an evolution in teaching methodologies to equip students for adaptability in the face of constant change. The global challenge of enhancing the quality of education, crucial for cultivating competent professionals in today's society (Rodríguez del Rey et al., 2021), is particularly pronounced in higher education. Here, both students and lecturers must augment their digital competencies to meet the dynamic demands of the changing labour market (Ter Beek et al., 2022). Amidst this landscape, computational thinking (CT) emerges as an essential set of skills. As artificial intelligence burgeons, the development of CT becomes not only pedagogically imperative but strategically crucial. These skills empower students to navigate evolving technological landscapes and responsibly harness the potential of artificial intelligence.

CT, a term in use since the 1950s, encapsulates the emphasis on structured and algorithmic thinking to produce appropriate output from given inputs, problem – solving, and coding (Angeli and Giannakos, 2020). While it has roots in earlier decades, the last few years have witnessed a remarkable resurgence in its significance, spurred by the rapid evolution of technology. Various definitions exist for CT, reflecting its diverse dimensions. The most common definition of CT is a multi-faceted model of thinking, encompassing abstraction, decomposition, algorithmic thinking, evaluation, and generalisation (Tsai et al., 2021). This definition emphasises the thinking processes over the computing aspect (Li et al., 2020a). However, it is important to note that professionals may practice a more advanced form of CT (Denning and Tedre, 2021b). Despite the prevalence of this definition, there is still a lack of consensus in the literature, with some studies operationalising CT as a composite of programming concepts (Ezeamuzie and Leung, 2022).

Although there is not consensus regarding its definition, recent endeavours underscore the revitalisation of CT, aiming to democratise CT as a critical facet for learners to navigate the modern challenges (Angeli and Giannakos, 2020). Furthermore, CT is asserted by many investigators as a universally applicable set of attitudes and skills essential for all individuals (Rodríguez del Rey et al., 2021).

CT is pivotal in today's technology-driven landscape, empowering students to solve intricate problems by leveraging computing resources (Guggemos et al., 2023). This dynamic paradigm supplements human imagination (Rodríguez del Rey et al., 2021), and equips learners with tools to engage with advanced technological developments (Soboleva et al., 2021). Integrating CT into education is crucial for cultivating professional competencies needed in the digital society (Soboleva et al., 2021), with a global emphasis on assessing it either as a holistic measure or as an array of sub-skills (Angeli and Giannakos, 2020).

However, despite its significance, the specific development of CT demands further investigation, particularly in regions like Peru (Rodríguez del Rey et al., 2021). Beyond computing, CT extends its impact across disciplines, enhancing problem-solving, logical thinking, and digital literacy (Li et al., 2020a; Yuliana et al., 2020). In essence, the development of CT is a vital educational pursuit, equipping students with critical thinking skills for the complexities of the 21st century. Therefore, the assessment of CT also gains relevance.

Assessing CT skills encompasses diverse methods, including performance-based assessments, coding tests, problem-solving tasks, and project-based assignments (Salehi et al., 2020). Among these, the CT Test developed by Román-González (2015) stands out as a versatile instrument designed for secondary students. This performance test incorporates fundamental computing concepts such as basic sequences, loops, iteration, conditionals, functions, and variables, requiring no prior knowledge in programming, thus ensuring flexibility in its application. Notably, studies by Korkmaz et al. (2017) have yielded scales with robust psychometric properties, exemplified by Korkmaz's scale, comprising 29 items across five factors. Additionally, the computational thinking scale (CTS) developed by Tsai et al. (2021) emerges as a pivotal tool, validated for assessing thought processes in problem-solving contexts. This scale delves into critical dimensions like abstraction, decomposition, and algorithmic thinking. Its applicability spans students from middle school levels and beyond, irrespective of the inclusion of computer programming tasks. The CTS by Tsai et al. (2021) emerges as a reliable and comprehensive examination tool, contributing significantly to the assessment and understanding of CT skills in students. Furthermore, the CTS collaborates by opening the possibility of carrying out studies on levels of CT among the student community. Particularly, this tool may be used for the identification of latent profiles in CT.

The application of latent profile analysis (LPA) to discern CT profiles offers valuable insights into the diverse types of computational thinkers, an aspect that has been relatively unexplored in CT research (Guggemos et al., 2023). Uncovering distinct CT profiles holds immense significance, as it enables the provision of personalised guidance and support tailored to individual cognitive strengths and weaknesses. This person-centred approach, widely adopted in various research domains, can be instrumental in addressing the unique learning needs of students. In the context of this study, the identification of CT profiles among Peruvian university students holds particular relevance. These insights not only contribute to a deeper understanding of the diverse skillsets within the student population but also shed light on their preparedness for the challenges of modernity. By revealing the specific CT profiles prevalent among Peruvian students, this research endeavours to inform educational strategies that align with the evolving demands of contemporary society.

Consequently, the primary objective of this work is to identify latent CT profiles among Peruvian university entrants using the CTS developed by Tsai et al. (2021). This scale comprehensively measures CT through five distinct mental processes – abstraction, decomposition, algorithmic thinking, evaluation, and generalisation. To achieve this, a diverse sample of Peruvian university entrants from various institutions was meticulously collected. The data was then thoroughly analysed using the mclust package in R for LPA, enhancing the depth of our investigation (Scrucca et al., 2023). As a secondary objective, the statistical package for the social sciences (SPSS) (version 27) was employed to explore the competency levels across these mental processes, considering different demographic aspects and enabling insightful comparisons. The outcomes of this study significantly contribute to a nuanced understanding of students' preparedness as they transition from basic to professional education, facilitating the formulation of targeted measures to foster and optimise CT skills among university entrants.

2 Theoretical framework

2.1 Computational thinking

In the new era of technologies and communications, it is required that skills of different forms of thinking (critical, mathematical, and algorithmic, among others) combine and give rise to a new way of reasoning: CT (Rodríguez del Rey et al., 2021). CT has garnered significant attention in educational research as a concept encompassing a range of understandings and skills essential for modern students engaged in problem-solving activities using computational concepts. Although its definition is not entirely new, the discourse surrounding CT has evolved, reflecting a multifaceted understanding of its components and applications.

Wing (2010) provides a foundational definition of CT as the cognitive processes involved in formulating and solving problems in a manner conducive to execution by an information-processing agent, encompassing algorithmic thinking, parallel thinking, as well as compositional reasoning and pattern matching. This definition underscores CT as a multifaceted concept incorporating knowledge of computational concepts, practical application, and the cultivation of new computational perspectives, as emphasised by Denning and Tedre (2021a). Additionally, Rodríguez del Rey et al. (2021) state that CT is a collection of understandings and skills required for new generations of students, proficient not only at using tools but also at creating them and understanding the implications of their capabilities and limitations. Furthermore, they state that logical, systemic, and algorithmic thinking are present in CT. According to Rodríguez del Rey et al. (2021), CT is a cognitive process executed by humans to solve problems using computational concepts, which involves decomposition, pattern recognition, algorithm design, abstraction, data representation, problem decomposition, algorithmic thinking, and generalisation of patterns, simulation, and evaluation. They also emphasise that the implementation of analytical thought in education courses will successfully affect the comprehension of CT.

The integration of CT into disciplinary education represents a growing trend, offering both challenges and opportunities (Li et al., 2020b). The significance of CT transcends traditional disciplinary boundaries, finding relevance in various domains beyond computer science and mathematics, as emphasised by Andrian and Hikmawan (2021), Soboleva et al. (2021), and Yadav et al. (2017). Such skills are crucial for tomorrow's professionals, enabling effective problem-solving using technology across diverse fields (Rodríguez del Rey et al., 2021). However, it is important to note that while computers can often serve as a framework for CT skills, caution must be exercised to ensure that CT is not merely conflated with programming or instructional technology, as highlighted by Rodríguez del Rey et al. (2021). This holistic approach to CT is essential for addressing the demands of the digital era and ensuring that students acquire the skills needed for success and professional self-realisation in a technologically driven society (Soboleva et al., 2021).

The development of CT in students is important for a country’s competitiveness (Soboleva et al., 2021). In Peru, research indicates significant disparities in CT attainment between urban and rural areas, with prior secondary education instruction serving as a determining factor (Nunez et al., 2020). Moreover, initiatives leveraging educational robotics have demonstrated efficacy in enhancing CT skills, particularly in regions with limited access to education and technology (Paucar-Curasma et al., 2022). Nevertheless, challenges persist, as evidenced by the uneven development of CT skills across different demographic groups and geographic regions within Peru. Vulnerable communities often face barriers hindering their access to quality education and technology, exacerbating existing disparities (Nunez et al., 2020). Addressing these disparities necessitates comprehensive educational interventions that prioritise the integration of CT into disciplinary curricula, with an emphasis on practical applications tailored to diverse contexts (Li et al., 2020b).

2.2 CT measuring

When it comes to measuring CT, researchers have devised various instruments, ranging from scales to tests, to assess this multifaceted concept. These measurement tools are crucial for gauging the proficiency of individuals in CT skills. For instance, Weintrop et al. (2021) underscore the significance of educators comprehending the manifestations of CT in student performance and highlights diverse assessment approaches. Furthermore, they state that proper measurement of CT skills is particularly vital for first-year university students as it provides insights into their preparedness for the demands of higher education and the evolving job market. Accurate assessment allows educators to identify areas of strength and weakness in students' CT abilities, enabling targeted interventions and tailored instructional strategies to enhance their skill development. Moreover, effective measurement of CT facilitates the evaluation of educational initiatives aimed at integrating CT into curricula, thereby ensuring the attainment of learning objectives and the cultivation of essential competencies for future success in a technology-driven world.

Diagnostic tools serve as valuable instruments for capturing students' proficiency levels without the need for specific prior knowledge, such as familiarity with a particular programming language (Guggemos et al., 2023). Weintrop et al. (2021) and Tang et al. (2020) both stress the importance of employing a variety of assessment methods to encompass the complexity of CT, with Weintrop et al. (2021) emphasising the pivotal role of teacher competencies in this endeavour. To address this need, some researchers have developed performance tests designed to measure CT skills. Sondakh et al. (2020), for instance, proposes a holistic assessment instrument tailored for undergraduate students, encompassing both skills and attitudes, while Basu et al. (2021) focus on creating separate assessments targeting programming concepts and general CT practices for upper elementary students. These studies collectively highlight the necessity for a comprehensive and diversified approach to assessing CT. Conversely, Román-González (2015) has devised a CT Test tailored for students aged 12–13, albeit applicable to university students as well. Based on the CT Framework established in 2013, this test serves as a reference for designing and evaluating CT resources. It boasts validation by content experts, features items spanning various difficulty levels, and demonstrates robust psychometric properties.

On the other hand, a range of studies have delved into the development and validation of scales aimed at measuring CT, which serve as self-assessment instruments. For instance, Ertugul-Akyol (2019) crafted scales featuring multiple dimensions, including abstraction, decomposition, algorithmic thinking, evaluation, and generalisation. Similarly, Kiyici and Kahraman (2022) conducted a meta-analytic reliability generalisation study, revealing high reliability for both the overall scale and its sub-dimensions. Meanwhile, Kılıç et al. (2021) honed in on programming-oriented CT, devising a scale comprising three subscales: conceptual knowledge, algorithmic thinking, and evaluation. Together, these studies offer a robust framework for evaluating CT skills. Conversely, Korkmaz et al. (2017) formulated a CT scale comprising 29 items and identified five distinct factors: creativity, cooperativity, algorithmic-critical thinking, and problem-solving. Geared towards measuring students' CT prowess, this scale boasts commendable reliability and validity. However, its scope remains confined to the sub-skills delineated by the International Society for Technology in Education (ISTE) in 2015.

Among the array of assessment tools, one of the most recent and thoroughly validated instruments is the CTS developed by Tsai et al (2021). Distinguished by its comprehensive approach and consideration of additional dimensions compared to its predecessors, the CTS comprises 19 items measuring processes across five dimensions. Utilising a two-dimensional conceptual framework to analyse definitions (domain-specific vs. domain-general) and assessments (outcome vs. process), this scale offers a nuanced understanding of CT. Specifically, the CTS allows for the assessment of students' habits, tendencies, or dispositions in utilising the general mental tools of CT. Given its robust properties and formulation, this study employs the CTS as the primary instrument to assess and analyse the CT abilities of first-year students.

3 Methodology

A cross-sectional methodological approach was employed for this study, involving a sample group comprising 730 entrants from two universities: Universidad Católica de

Santa María (UCSM) and Universidad Católica San Pablo (UCSP), located in Peru. The participants were administered the CT test during the initial week of their academic term. The CT test utilised in this study was the CTS developed by Tsai et al. (2021), administered to students through a questionnaire format using Microsoft Forms. Prior to participation, all students were duly informed about the purpose of the study and provided their consent for data usage. LPA was performed using the 'mclust' package within the R software (Scrucca et al., 2023). Additionally, for demographic comparisons, data analysis was conducted using the SPSS version 27. Further elaboration on these methodological aspects is provided in the subsequent subsection.

3.1 The computational thinking scales instrument

The instrument applied is the CTS developed Tsai et al. (2021). It was designed and validated to assess students' CT competencies from a computer literacy perspective, and was developed based on a two-dimensional conceptual framework, analysing the definitions (domain-specific vs. domain-general) and assessments (outcome vs. process) of CT. The CTS covers five dimensions: abstraction, decomposition, algorithmic thinking, evaluation, and generalisation, with a total of 19 items.

The CTS assesses students' habits, tendencies, or dispositions to utilise the general mental tools of CT in various problem-solving contexts, regardless of the involvement of computer programming tasks. Its validity and reliability make it suitable for assessing CT competencies for all students above the middle school level in any learning context.

3.2 Study group and data collection

During the inaugural week of classes in March 2024, a cohort of 730 first-year students from two Peruvian universities participated in the completion of the CTS. The CTS was administered through a Microsoft forms online questionnaire, which was made readily accessible to the students with the assistance of faculty members. All participants were briefed on the purpose of the study and provided their informed consent for the utilisation of their responses. Alongside the 19 items comprising the CTS, the questionnaire also gathered demographic information including age, university, type of secondary school attended (state or private), and the area of study pursued at the university level.

3.3 Latent profiles identification

For the identification of CT profiles through LPA, we used the 'mclust' R-package (Scrucca et al., 2023). Missing data are not present. Since there may be careless responding, we used the Careless package and Mahalanobi's Distance to identify 'string responding', with a cap string responding maximum of 10. Consequently, the number of registers for the process changed to 705. The Bayesian Information Criteria (BIC) was applied to identify the best model. Furthermore, the bootstrap likelihood ratio test (BLRT) was executed, since it compares model fit between k-1 and k cluster models. Besides, to verify that the profiles are significantly different from each other, the MANOVA test was applied. The LPA was executed considering that the profiles should be of proper size and show clear shape differences.

3.4 Data analysis

The collected data was processed using SPSS v. 27 to analyse the results of the CTS and make comparisons based on demographic aspects: gender, type of secondary school attended, and area of studies. To identify any differences between the results per demographic factor, the ANOVA test was conducted with a significance level of 5%.

4 Results

Correlations, means, and standard deviations for the study variables are presented in Table 1. The variables under consideration represent the mean of points (0–5) obtained in each category of the CTS developed by Tsai et al. (2021). Significant associations were found among all variables, indicating strong interrelationships between the different dimensions of CT assessed. These results suggest that students who perform well in one dimension, such as abstraction or algorithmic thinking, are likely to perform well in the others as well.

Table 1 Correlation matrix and descriptive statistics

	Variable	*1*	*2*	*3*	*4*	*5*	*M*	*SD*
1	Evaluation	-					3.72	0.81
2	Abstraction	0.71*	-				3.82	0.54
3	Decomposition	0.29*	0.46*	-			3.49	0.91
4	Generalisation	0.32*	0.70*	0.31*	-		3.80	0.85
5	Algorithmic thinking	0.39*	0.61*	0.35*	0.34*	-	3.90	0.76

Note: *p < 0.01.

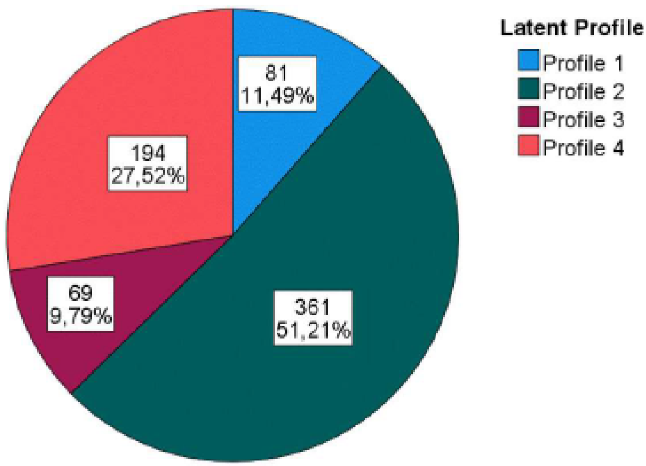
Source: Self-made

4.1 Latent profile analysis

The execution of the R program using the mclust package resulted in the selection of an ellipsoidal distribution model with equal shape and orientation, identifying four latent classes of CT. The Bayesian Information Criterion (BIC) was applied to determine the best model, and the bootstrap likelihood ratio test (BLRT) was performed to compare the model fit between k-1 and k cluster models, thereby confirming the classification of students into four latent CT profiles. Additionally, MANOVA was conducted to verify that the profiles were significantly different from each other. Levene's test confirmed the variance differences among the factors, and the inter-subject effects further validated the overall differences between groups. The student's distribution by profile is presented in Figure 1. It is worth remembering that the sample of 730 students reduced to 705 due to the identification of careless responding, which was achieved with the careless package and Mahalanobi's distance on R.

In the next step of the LPA, the general patterns of the profiles were presented. For this purpose, means and standard deviations of the study variables were examined across the latent profiles and presented in Table 2. Additionally, Figure 2 displays the standardised means of the studied variables per profile, offering a clear visual representation that facilitates easier comparison between the profiles. As shown in the table and figure, the latent profiles exhibited distinct characteristics regarding the study variables. Profile 1, which includes 81 students, is characterised by the highest means in all study variables, particularly in algorithmic thinking (M = 4.72, SD = 0.31) and evaluation (M = 4.66, SD = 0.32). This profile demonstrates a robust level of CT skills across all dimensions. In contrast, Profile 2, with 361 students, shows moderate levels in these variables, with notably lower means in decomposition (M = 3.65, SD = 0.72) and algorithmic thinking (M = 3.93, SD = 0.59), suggesting a balanced but less pronounced competency in CT.

Figure 1 Proportion of students in each latent profile (see online version for colours)



Source: self-made

Table 2 Descriptive statistics by latent profile

Variable		*Profile 1*		*Profile 2*		*Profile 3*		*Profile 4*	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	Evaluation	4.66	0.32	3.67	0.62	4.01	0.63	3.33	0.98
2	Abstraction	4.32	0.35	3.87	0.47	3.87	0.38	3.51	0.57
3	Decomposition	3.96	0.79	3.65	0.72	2.26	0.71	3.43	0.98
4	Generalisation	4.36	0.56	3.91	0.66	4.33	0.60	3.17	0.96
5	Algorithmic thinking	4.72	0.31	3.93	0.59	3.75	0.68	3.54	0.91

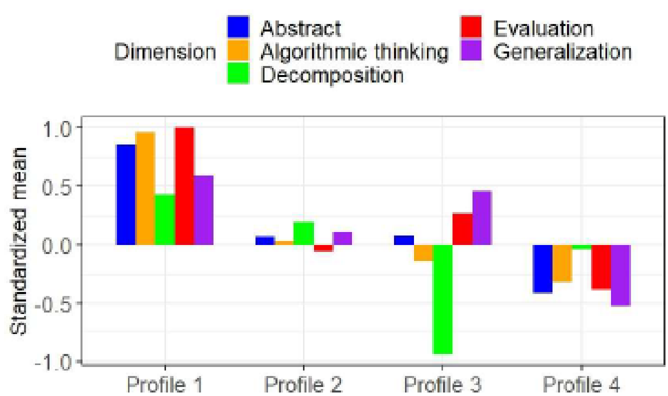
Source: Self-made

Profile 3, comprising 69 students, presents an interesting contrast with significantly lower means in decomposition (M = 2.26, SD = 0.71), indicating a potential area of weakness. However, it shows relatively higher means in generalisation (M = 4.33, SD = 0.60), suggesting specific strengths in certain CT dimensions. Finally, Profile 4 includes 194 students and is marked by the lowest means across all variables, especially in evaluation (M = 3.33, SD = 0.98) and generalisation (M = 3.17, SD = 0.96). This profile indicates the lowest overall CT skills. The graphical representation in Figure 2 visually reinforces these differences, highlighting the distinctive characteristics of each profile and the variation in standardised means across the dimensions of CT.

In the final stage of the analysis, the relationships between the identified latent profiles and demographic variables -gender, area of study, and type of school- were examined using Chi-square tests. The results indicated no significant association between the latent profiles and either gender or area of study on first year students. This suggests that CT profiles are not influenced by these demographic variables. However, a significant relationship was found between the latent profiles and the type of school ($p < 0.05$), indicating that the type of school attended by students (public or private) is related to their CT profiles. The distribution of students by type of school attended and latent profile is presented in Table 3. This relationship suggests that the educational environment provided by different types of schools might influence the development of CT skills.

Although the latent profiles show a higher representation of students from private schools (63.4%) compared to public schools (36.6%), it is noteworthy that 45.7% of students in Profile 1, which corresponds to those with high levels of CT skills, come from public schools. On the other hand, Profile 3 has the highest proportion of students from private schools. This suggests that certain characteristics associated with this profile are more common among private school students.

Figure 2 Standardised mean scores by latent profile and CT dimension (see online version for colours)



Source: Self made

Table 3 Distribution of profiles by type of school

Type of school	*Profile 1*		*Profile 2*		*Profile 3*		*Profile 4*		*Total*
	N	*%*	*N*	*%*	*N*	*%*	*N*	*%*	
Public	37	45.7%	141	39.1%	19	27.5%	61	31.4%	258
Private	44	54.3%	220	60.9%	50	72.5%	133	68.6%	447
Total	81	100%	361	100%	69	100%	194	100%	705

Source: Self-made

Additionally, while no significant relationships were found between the type of school and the dimensions of evaluation, decomposition, generalisation, and algorithmic thinking, a significant relationship was observed with the dimension of abstraction ($p < 0.05$). Students who attended public schools ($M = 3.85$, $SD = 0.56$) scored higher in abstraction compared to those who completed their secondary education in private schools ($M = 3.81$, $SD = 0.52$).

5 Discussion

This study aimed to unveil the classification of CT among first-year Peruvian university students. To achieve this objective, a sample of 730 first-year students was analysed. Focused on five key dimensions – abstraction, decomposition, algorithmic thinking, evaluation, and generalisation – the investigation employed a validated CT evaluation tool and the 'mclust' package in R. The application of the Careless package and Mahalanobi's distance in R to identify 'string responding' reduced the data to 705 students. Analysis of model tests revealed that a four-class solution best fit the data. Unveiling four distinct CT profiles, each highlighting unique strengths and weaknesses, the findings provide crucial insights into the initial CT levels of students entering university.

Specifically, members of Profile 1 exhibited higher levels of abstraction and algorithmic thinking but lower levels of decomposition and evaluation. This suggests a strength in understanding and applying algorithms but a relative weakness in breaking down problems and assessing solutions. Profile 2 members showed a balanced distribution across all dimensions, indicating a well-rounded CT skillset. Profile 3 members had lower scores in all dimensions, indicating a need for substantial improvement across the board. Lastly, Profile 4 members excelled in evaluation and generalisation but had lower scores in abstraction and decomposition, suggesting proficiency in assessing and generalising solutions but challenges in initial problem breakdown and abstraction.

Demographic variations were explored through SPSS version 27, enriching the comprehensive understanding of CT across diverse student populations. The findings indicated significant differences in CT profiles based on the type of secondary school attended. Notably, while there is a higher representation of private school students overall, a substantial proportion of students with high CT skills (Profile 1) come from public schools. This suggests that public school students may have certain strengths in CT despite the general trend. This result was unexpected and is in partial contradiction with the findings of Rodríguez del Rey et al. (2021), who state that students from private schools generally exhibit higher CT scores compared to those from public schools. Nevertheless, it is worth noting that there are not enough investigations of CT in the Peruvian context. Additionally, the significant relationship found between the type of school and the abstraction dimension highlights that public school students excel in this specific aspect. These insights underscore the need to further investigate the educational and environmental factors that contribute to these differences in CT profiles.

These results significantly contribute to the discourse on CT, offering practical guidance for educators aiming to tailor interventions and elevate CT skills among early university students nationwide. The identification of distinct CT profiles among Peruvian students highlights the importance of personalised educational strategies. For example, students in Profile 1 might benefit from exercises focused on decomposition and evaluation, while those in Profile 3 require comprehensive support across all dimensions of CT.

CT is pivotal in today's technology-driven landscape, empowering students to solve intricate problems by leveraging computing resources (Guggemos et al., 2023). The integration of CT into education is crucial for cultivating professional competencies needed in the digital society (Soboleva et al., 2021), with a global emphasis on assessing it either as a holistic measure or as an array of sub-skills (Angeli and Giannakos, 2020).

6 Conclusions

Based on the comprehensive analysis of CT among first-year Peruvian university students, this study identified four distinct CT profiles using the Mclust package in R. The profiles revealed unique strengths and weaknesses, with Profile 1 students excelling in abstraction and algorithmic thinking but needing improvement in decomposition and evaluation. Profile 2 showed a balanced CT skillset, Profile 3 indicated a need for significant improvement across all dimensions, and Profile 4 demonstrated proficiency in evaluation and generalisation but faced challenges in abstraction and decomposition. These findings underscore the necessity of tailored educational strategies to address the specific needs of each CT profile, thereby enhancing the overall CT competencies of university entrants.

Demographic variations revealed significant differences in CT profiles based on the type of secondary school attended. Despite a higher representation of private school students, a substantial proportion of students with high CT skills (Profile 1) came from public schools, highlighting potential strengths in the public school system. Additionally, public school students excelled in the abstraction dimension, suggesting the need for further investigation into the educational and environmental factors influencing these outcomes. These insights contribute to the broader discourse on CT, emphasising the importance of personalised educational interventions. Given the multifaceted nature of CT, a single instrument may not comprehensively capture all its dimensions; hence, a system of various assessments is recommended. This study represents an initial step in measuring CT levels among university entrants in Peru, providing a foundation for future research and educational practice.

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