

Teaching computational thinking to preservice teachers: The importance of the order of presentation of activities

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ABSTRACT

Background: In recent years, computational thinking has been widely included in school curricula, but specific didactics are still lacking. In addition, emotions affect learning, and there is a gender gap in technology-related issues. **Objectives:** We wanted to test the effects of the order in which examples are discussed in class (mathematical versus everyday) and the role gender plays in the emotions and performance of primary school preservice teachers when designing flowcharts. Design: We used a quantitative approach with two factors and repeated measures in one of them. **Setting and Participants:** Data were gathered from 121 preservice primary teachers enrolled in their first year of a teacher education program at a Spanish university. **Data collection and analysis:** We measured emotions with a questionnaire and performance by evaluating the flowcharts produced by the students. Afterwards, we used logistic regression and analysis of variance, respectively. **Results:** The group where the mathematical example was discussed first outperformed the other group and was less likely to feel despair, but there were no differences in other emotions. Women were more likely to experience negative emotions during the assessment, but there were no gender differences in performance. **Conclusions:** This study shows that, in the context of teaching and learning computational thinking, the order in which solved examples are discussed in class, whether mathematical or everyday-life examples, affects students' performance and the emotions they experience. As a direct application, these results suggest discussing mathematical examples first when teaching to preservice teachers.

Keywords: computational thinking; emotion; preservice teachers; sequencing classroom activities; gender.

Ensino do pensamento computacional a futuros professores: A importância da ordem de apresentação das atividades

RESUMO

Contexto: Nos últimos anos, o pensamento computacional tem sido amplamente incorporado aos currículos escolares, mas ainda faltam didáticas

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específicas. Além disso, as emoções afetam a aprendizagem e há diferenças de género em questões relacionadas com a tecnologia. **Objetivos:** Pretendemos testar os efeitos da ordem em que os exemplos são discutidos na aula (matemáticos versus da vida quotidiana) e o papel do género nas emoções e no desempenho dos futuros professores do ensino básico ao desenhar fluxogramas. **Desenho:** Utilizámos uma abordagem quantitativa com dois fatores (dois níveis cada um) e medidas repetidas num deles. **Ambiente e participantes:** Os dados foram recolhidos junto de 121 futuros professores do ensino primário inscritos no primeiro ano de um programa de formação de professores numa universidade espanhola. **Coleta e análise de dados:** Medimos as emoções por meio de um questionário e o desempenho por meio da avaliação dos fluxogramas produzidos pelos alunos. Posteriormente, utilizámos a regressão logística e a análise de variância. **Resultados:** O grupo em que o exemplo matemático foi discutido em primeiro lugar teve melhor desempenho e foi menos propenso a sentir desespero, mas não houve diferenças nas demais emoções. As mulheres eram mais suscetíveis de sentir emoções negativas na situação de avaliação, mas não havia diferenças de género no desempenho. **Conclusões:** No ensino-aprendizagem do pensamento computacional, a ordem em que os exemplos são discutidos na aula, sejam matemáticos ou da vida quotidiana, afeta o desempenho e as emoções do alunado. Como aplicação direta, sugere-se discutir, primeiro, os exemplos matemáticos na docência com futuros professores.

Palavras-chave: pensamento computacional; emoção; futuros professores; sequenciação de atividades em sala de aula; género.

INTRODUCTION

Computational thinking (CT) has been of increasing interest to educators, legislators, and researchers in recent years (see Iravan et al., 2024, for a review); furthermore, it has been included in primary and secondary school curricula in many countries. Wing (2006) defined CT as the mental process of devising strategies and explicit paths to solve problems by relying on techniques from computational science and programming, thereby integrating human thinking with computers' features. Other authors have highlighted this approach in contemporary education from the early years (Kafai & Burke, 2014) and argued that including CT in educational curricula is essential to prepare students for a digitised economy (e.g., Phillips, 2009; Resnick et al., 2009).

Developing student's CT means developing their ability to solve problems, analyse complex processes and take reasoned decisions, and it allows them to better understand how everyday technological devices and applications work. The inclusion of CT activities in primary and secondary schools' classrooms has increased in the last decade. Indeed, the European Commission's report "Reviewing Computational Thinking in Compulsory

Education” (Bocconi et al., 2022) noted that PC has been widely integrated into compulsory education across the European Union. In Spain, González and Marañón (2021) highlighted the explicit inclusion of the CT in the current primary and secondary school curricula. Specifically, the educational regulations (Real Decreto 157/2022, 2022; Real Decreto 217/2022, 2022) state that students must develop problem solving and critical thinking abilities by means of CT. Given that preservice teachers will be responsible for implementing the curriculum, CT is currently being introduced into preservice teacher training in Spain, making it important to develop criteria for teachers’ education (Berciano et al., 2024).

THEORETICAL BACKGROUND

CT and its relationship with mathematical thinking and everyday life

Several authors have emphasised the relationship between CT and skills such as abstraction, problem decomposition, algorithmic thinking and generalisation (Angeli et al., 2016; Wing, 2006, 2011). Abstraction (A) is the process of removing irrelevant aspects of a problem to simplify it while preserving essential information (Khalid et al., 2021). This allows students to focus on the suitable components of the problem. Problem decomposition (PD) means dividing complex problems into more manageable parts, which in turn eases their analysis and solution. Algorithmic thinking (AT) means designing an ordered sequence of concrete steps to solve a problem, while remaining flexible enough to modify those steps if necessary. Lastly, generalisation (G) involves identifying strategic patterns in problem solving and applying them to new situations, thus extending the scope of the solution process. Looi et al. (2018), focusing on CT in the field of education, add evaluation (E) as the ability to identify and correct errors.

CT and mathematical thinking are closely linked, as both focus on problem solving through logical reasoning and structured analysis of the situation at hand. This link becomes important in primary education in particular, because at this stage students begin to develop the basic skills which allow to systematically analyse and solve problems. Indeed, Weintrop et al. (2016) claim that integrating CT and mathematics promotes a deeper understanding of mathematical concepts. In this vein, the Spanish primary school curriculum considers the CT as a part of mathematical thinking and states that both must be addressed jointly. Such integration is supported by prior research (e.g., Freina et al., 2019; Seckel et al., 2022).

Another key aspect of CT is its applicability to everyday life—indeed, this is encouraged in the Spanish curriculum (Real Decreto 157/2022, 2022; Real Decreto 217/2022, 2022). Moreover, there is a correlation between CT and solving everyday problems (Chiazzese et al., 2019), and everyday life situations are a key aspect of CT (Sukkamart et al., 2024; Ezeamizi et al., 2022). Students tend to perceive everyday life and mathematical problems as different settings, and the applicability to a wide range of settings is a key feature of CT. Thus, these two types of examples are used in the literature to develop students' CT (Ezeamizi et al., 2022; Sukkamart et al., 2024; Threekunprapa & Yasri, 2020).

Emotions and mathematics

Many studies have emphasised the importance of emotional self-regulation in improving students' performance in mathematics, especially when facing complex challenges (e.g., Trías, Mels, & Huertas, 2021). However, traditionally, formal education has prioritised knowledge transmission, often at the expense of students' motivation and their perceptions of the relevance of mathematics. Such a disconnect, together with the abstract nature of mathematics and its perception as a difficult, impractical, or boring subject, fosters fear and emotional blockages towards mathematics (Bekdemir, 2010).

But negative emotions are key factors in academic failure in mathematics (Blanco et al., 2010). By contrast, positive emotions such as cheerfulness, interest, or satisfaction can promote students' intrinsic motivation and their willingness to participate actively in the teaching and learning process (Fredrickson, 2001; Quintanilla & Gallardo, 2022). In addition, the influence of an emotionally positive environment extends beyond classrooms because emotions towards mathematics affect students' future career choices (Boekaerts, 2011).

Concerning preservice teachers, many begin their undergraduate studies with negative emotions towards mathematics, which can adversely affect their education and future teaching practices (Bekdemir, 2010; Panero et al., 2023). These students show feelings of inferiority (Alsina & López, 2019), impotence (Satyam, 2020; Jenßen et al., 2022) and anxiety towards mathematics. These emotions trigger negative answers and mental blockages when doing activities and exams in mathematics classes, which reduces their performance and self-confidence due to the accumulation of distress and negative experiences (Ashcraft & Krause, 2007; Bekdemir, 2010). The integration of CT and mathematics allows us to address these emotional issues by providing a more dynamic and applied approach (Grover & Pea, 2013; Weintrop et al., 2016).

Emotions and gender

Prior research has not found meaningful cognitive differences between women and men, but women tend to experience higher anxiety towards mathematics (Gonzalez-Dehass, 2024). Social expectations and gender stereotypes contribute to this difference because women frequently face cultural pressure suggesting that they are less competent in mathematics than men (Beilock et al., 2010). Addressing this anxiety by means of suitable teaching interventions may help close this gender gap (Devine et al., 2012) and foster broader involvement of women in mathematics-related areas (Beilock et al., 2010).

CT teaching and learning

Currently, CT-specific didactics has not been established as a formal discipline, and there is limited research about teachers' initial and lifelong education (Adell et al., 2019). This situation has led to a lack of criteria for how to teach and assess CT across the different stages of education. A key point in designing teaching interventions is to determine the best order in which to present activities to students. Some studies suggest that it is better to focus on the teaching of CT in real-world contexts. This would help to perceive the usefulness of mathematics in everyday life and foster the development of critical and analytical thinking (Wing, 2006; González & Marañón, 2021). Moreover, students' ability to abstract improves when they learn to identify patterns and simplify complex problems in familiar contexts (Khalid et al., 2021). However, there is no consensus on whether it is more effective to move from concrete to abstract or vice versa (Roth & Hwang, 2006).

Cognitive load theory suggests that learning is more effective when students' cognitive load is appropriately managed depending on the teaching phase. Cognitive load means the amount of mental effort required to process new information (Sweller, 1988; Sweller et al., 2019). There are three types of cognitive load: the intrinsic load is the difficulty inherent in what is being learned, the extrinsic is that due to the teaching materials and procedures, and the germane load is that the individual devotes to the construction of mental schemas and the learning of the content (Ngu et al., 2014; Sweller, 1988; Sweller et al., 2019).

Cognitive load is determined by the number of elements an individual must process simultaneously, but once the content at hand is mastered, it is possible to process several interrelated elements as a single one (Ngu et al., 2014). Therefore, instruction design should follow two general principles. One

principle is to reduce the extrinsic load so that the individuals can devote their cognitive resources to the intrinsic and germane load. The other principle consists of minimising the cognitive load at the beginning of instruction and progressively increasing it as the individual gains expertise and can process more elements as a single one (Ngu et al., 2014; Sweller, 1988; Sweller et al., 2019). In relation to these principles, it would be more interesting and easier for students to understand mathematical concepts contextualised in everyday situations rather than presented in a purely mathematical context (Seeley, 2016). Everyday life activities would involve a low cognitive load, but linking them with abstract notions would give them meaning and sense, so making it possible to manage more elements as a unit. Hence, starting with examples from everyday life in the initial steps of instruction would ease subsequent learning and foster a deeper, more durable understanding of more abstract concepts (Boaler et al., 2016).

The role of flowcharts in CT

Flowcharts provide a clear and structured representation of processes and algorithms, support students in the process of devising a solution in terms of algorithms and can be considered as a learning scaffolding, so they are used to develop students' CT (Threekunprapa & Yasri, 2020; van Zadelhoff et al., 2021; Zhang et al., 2023). In addition, creating flowcharts promotes students' understanding of computer science and programming concepts (Threekunprapa & Yasri, 2020; van Zadelhoff et al., 2021; Zhang et al., 2023), thus covering the key aspects of CT as described by Wing (2006). Although creating flowcharts is challenging for students, the literature reports that both teachers and students find flowcharts useful for decomposing complex tasks into sequences of subtasks and for understanding algorithms and code (van Zadelhof et al., 2021).

In addition, due to the abstract and language-independent nature of flowcharts, students' learning or misunderstanding of CT concepts and their CT skills can be assessed by analysing the flowcharts they create (Rahimi et al., 2017; van Zadelhof et al., 2021). Specifically, given a student-generated flowchart, its specific features unveil the student's misconceptions and her command of CT skills (Looi et al., 2018). This is the approach we use in this paper to assess students' CT skills, which the literature highlights as the key features of CT (see the beginning of the Theoretical Background).

Long-term memory

Long-term memory can be defined as the mental system that stores information for extended periods, ranging from hours to years. It is a main

component of lifelong learning because it enables the construction of new knowledge based on previous knowledge by providing access to it when needed (Bjork & Bjork, 2011). Unlike working memory, which stores information for short periods and has limited capacity, long-term memory has a large storage capacity, enabling us to accumulate knowledge and experiences over the years (Sweller et al., 2019).

Several principles influence the functioning of long-term memory. According to the distinctiveness effect, information that is unique or inconsistent with prior information or experiences is easier to identify and retrieve from long-term memory than information that is consistent (Hunt & McDaniel, 1993; Howe, 2006). The emotional intensity linked to an event also plays a role in long-term memory. The events linked to intense emotions are better and more clearly remembered (Cahill & McGaugh, 1995; Tyng et al., 2017); moreover, emotional arousal influences cognitive processing and attention (Storbeck & Clore, 2008). In particular, the ability to focus and process information can increase during intense emotional situations, making it easier to recall that information accurately in the future.

The primacy effect postulates that, given a sequence of information elements, the first element is better remembered because it has more opportunities to be processed and transferred to long-term memory (Atkinson & Shiffrin, 1968; Yeh & Chen, 2022). By contrast, the recency effect establishes that elements presented at the end of a sequence are better remembered because they remain in working memory at the time of retrieval (Yeh & Chen, 2022).

Understanding long-term memory works and how the principles described above interact, allows for the determination of the best order in which to present classroom activities to students (Fiorella & Mayer, 2013). The proper integration of these principles into teaching practice would make learning more effective and long-lasting.

METHODOLOGY

Objectives

Our general objectives are, on the one hand, to study the effect (if any) of the order in which examples are discussed on the emotions experienced by students during the teaching and the assessment sessions about basic computational thinking, and on the learning outcomes. On the other hand, we study whether there are differences depending on gender or whether gender interacts with the effect of the order in which examples are provided. In turn,

this would facilitate the design of optimal instruction sequences. The general objectives are concretised in the following research questions.

- (RQ1) Do differences exist in the emotions experienced by the students during a teaching session depending on
 - a. whether the basic concepts of computational thinking are taught by using an everyday example first and subsequently a mathematical example, or vice versa?
 - b. the student's gender?
- (RQ2) Do differences exist in the emotions experienced by the students during an assessment session about computational thinking depending on
 - a. the order in which illustrative examples were presented to them in a previous teaching session?
 - b. the student's gender?
- (RQ3) Do differences exist in the learning outcomes about the ability to apply basic notions of computational thinking in a mathematical context depending on
 - a. the order in which illustrative examples are discussed in a previous teaching session?
 - b. the student's gender?

Materials and Methods

We used a between-between, 2-way design with two crossing factors: order of examples (OE) and gender. The OE factor has two levels: the mathematical example first and the everyday example first. The gender factor has two levels: woman and men.

Participants

The sample consisted of 121 students in the first year of a Bachelor in Primary School Education, with a variety of prior studies that allowed them to enrol. Specifically, 5 (4.96%) students had access through vocational education after compulsory education, and the remaining students had a High School Diploma: 25 (20.66%) in Science and Technology, 84 (69.42%) in Social Sciences, and 5 (4.96%) in Humanities. They were in two classes at a Spanish public university, taking a subject aimed at qualifying them to teach

mathematics in primary education. Algebraic and computational thinking were topics in this subject. Moreover, regardless of their prior studies, participants have studied compulsory mathematics and technology subjects during the compulsory grades of secondary education, which aimed to qualify them to solve the kinds of tasks in the instruments of this experiment.

The faculty government assigns students to classes in alphabetical order, without considering their academic abilities or prior studies. The classes were randomly assigned to different levels of the order-of-examples factor beforehand, so from now on, we will refer to them as the mathematics example first class and the everyday example class, respectively.

Instruments and procedures

The quasi-experiment comprised two 90-minute sessions: the exposition and assessment sessions. The teaching procedure was designed to meet the criteria of didactic suitability proposed by Font et al. (2010) and Godino et al. (2023). During the exposition session in both classes, as part of the subject content, one of the researchers presented the fundamentals of flowcharts for 80 minutes using two worked examples. Each class was split into 3 subsets of about 20 students, this being the customary procedure for practical sessions in the subject the participants were studying. During the exposition, the students interacted with the researcher by asking doubts, making comments, or answering questions about the matter at hand, which confers interactional suitability upon the session (Font et al., 2010). Two tasks are addressed during the exposition session. One of them uses an everyday example that connects the abstract concepts of CT to well-understood concrete actions, making the former easy to apprehend and, in turn, conferring epistemic and affective suitability on the teaching procedure (Godino et al., 2023). The other task tackles an abstract mathematical task, which increases cognitive activation, in such a way that the two examples, taken as a sequence, provide cognitive suitability (Godino et al., 2023).

In the mathematics first class, the first example dealt with the addition of numbers (Figure 1a), and the second with the process of eating up to four yogurts with or without honey in each one to the choice of the consumer (Figure 2).

Figure 1

Algorithms to add numbers. Panel a: Flowchart to calculate the sum of the first N odd numbers, where N can be any natural number chosen by the user. Panel b: Example of a valid flowchart to calculate the sum of the first 40 natural numbers.

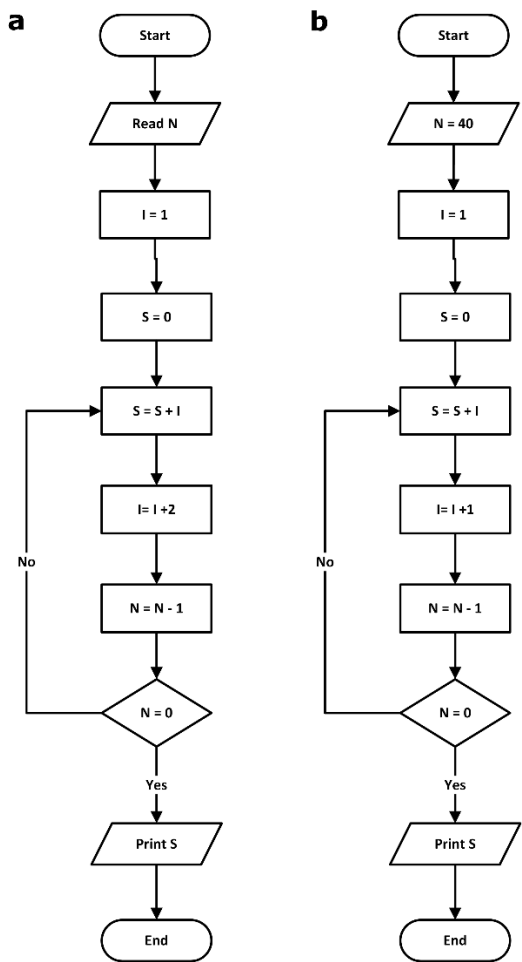
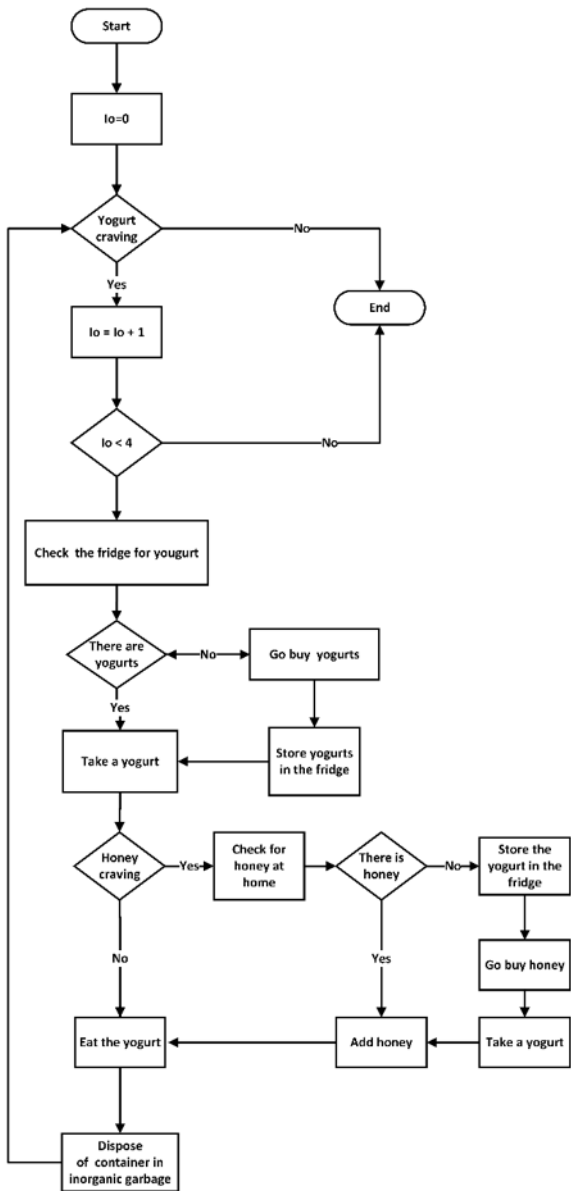


Figure 2

Process of eating up to four yogurts with or without honey in each one to the choice of the consumer



In the everyday life first class, the same two examples were discussed, but in reverse order. Both examples included conditionals and at least one variable used as a counter to limit the range of other variables.

Right after the exposition, we applied an adapted version of the Mood Map instrument for the diagnosis of emotional reactions and the subject's self-evaluation developed by Gómez-Chacón (2000). This consists of 14 binary-response items, each asking whether the participant experienced a specific emotion during the class session. We used an on-line version of the questionnaire, but the students filled it out in the classroom.

In the assessment session, that was held one week later, students in both classes were asked to individually design, in a paper and pencil setting, a flowchart to carry out a numeric computation (Figure 1b), analogous to that discussed in the mathematics worked examples, and we gathered the sheeves with the students' productions. After that, the students filled out the same online questionnaire as in the exposition session.

Students must explicitly consent to the analysis of their answers (for each online questionnaire and the flowchart design separately). Therefore, the final samples for the online questionnaire we analysed in the exposition session consisted of 46 women and 14 men in the first mathematics class, and 48 women and 13 men in the everyday example first class. In the assessment session, the sample sizes for the online questionnaire were 45 women and 14 men in the first mathematics class, and 48 women and 13 men in the other class. The analysis of the written flowchart was conducted with 31 women and 11 men in the first mathematics class, and with 37 women and 10 men in the other class.

Codification and statistical analysis

We analysed the answers to each binary item in the online questionnaire by applying logistic regression. The student's answer was the dependent variable; the order of examples and the gender were the covariates. The base levels were mathematics first for the order-of-examples factor and women for the gender factor. We followed the modelling strategies given by Kleinbaum and Klein (2010) and Field et al. (2012). Thus, we followed a hierarchical backward elimination and assessed the interaction by means of the likelihood ratio test. Secondly, at each step, we assessed confounding by comparing the ORs of the full and reduced models, deleting the confounder only if there was a meaningful change in the ORs.

Regarding the assessment of the students' CT skills, we adopted the Looi et al. (2018) approach, analysing the flowcharts produced by the students in the assessment session following the criteria in Table 1.

Table 1

Codification criteria for the flowcharts produced by the students

Criterion	Score
1. It has a start	0.5
2. It uses a variable to track the number to add at each step	1
2.1 The number to add is initialised outside of the loop	1
2.2 It updates the value of the number to add at each step	1
3. It uses a variable to update the value of the partial sum	1
3.1. The partial sum begins outside the loop	1
3.2. It updates the partial sum variable	1
4. It uses a finite loop with input and output	1
5. It includes a condition such that:	1
a) The condition is correct in the context of the problem	
b) It has an output for the Yes and another for the No	
5.1. The condition is fitted in the loop	1
6. It outputs the final value of the sum (regardless of whether the latter is correct or not)	1
7. The algorithm has an end	0.5
8. The algorithm is finite	1

A cumulative grade for each flowchart was obtained by adding the corresponding score when a criterion was met, and 0 otherwise (see Figure 3 and Figure 4 for examples of codifications).

Figure 3

First example of a flowchart created by a student

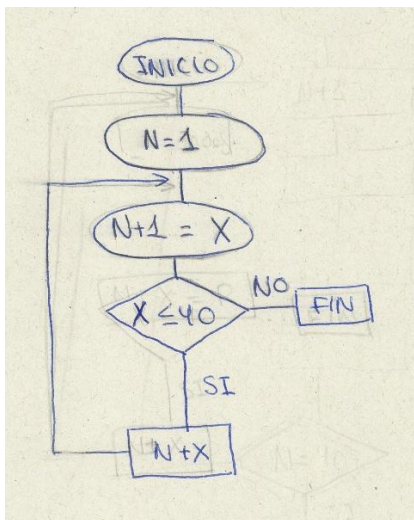
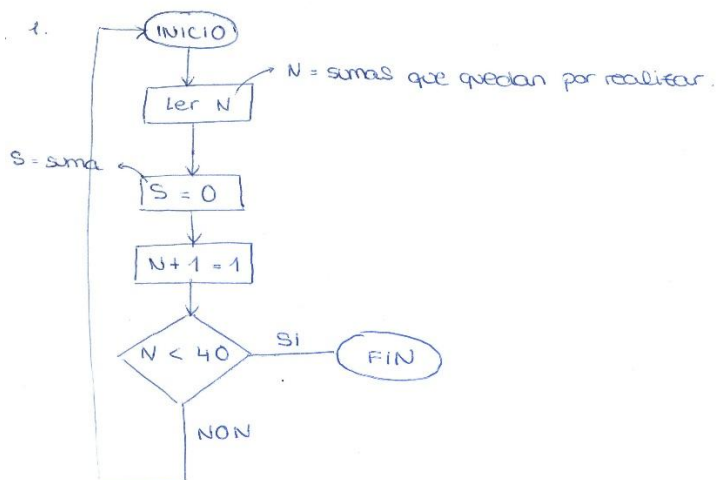


Figure 4

Second example of a flowchart created by a student



As the cumulative grade ranges from 0 to 12, we defined the variable G (grade) by normalising it to $[0,10]$, with this being the value associated with each student. The grade variable G was analysed using a 2-way analysis of variance with the same factors as in the logistic regression.

The codification of the diagram in Figure 3 (Mathematics example first) has a total score of 5 out of 12. The algorithm defines a variable N outside the loop, but N is not updated, and therefore the algorithm is not finite. Furthermore, the meaning of N could be mixed up with another variable (n) that the individual could define (badly, anyway) to keep track of the sum and uses in the conditional. To compute the sum, it would be necessary to clearly define and update each variable.

The algorithm begins with a start node (0.5 pts) and defines a variable N to track the number to be added (1 pt), which is done outside the loop (1 pt). It defines a condition that assesses whether a variable is less than or equal to 40, and two exits to be taken depending on whether the condition is true (1 pt). This is done inside a loop (1 pt), but the variables are not updated. The algorithm finishes in an end node (0.5 pts). The loss of seven points is because the variable N is not updated (item 2.2) and the variable to keep track of the sum is wrongly defined (items 3, 3.1 and 3.2), which in turn makes the condition to be is badly integrated (item 5.1), the solution not shown (item 6) and the algorithm not-finite (item 8).

The codification of the diagram in Figure 4 (Everyday example first) has a total score of 5 out of 12. This algorithm defines two variables, N and S , but this is not done outside the loop, which, in addition, is poorly defined. The individual seems to intend to update N when including the node ($N = N + 1$), but the node is not well-defined, so the variable is not updated. To compute the sum, in addition to defining the loop and updating N correctly, it is necessary to update the sum each time N increases.

The algorithm starts with a starting node (0.5 pts) and defines N to keep track of the number to be added (1pt). We also find a variable S to track the sum, and S is initialised at 0 (1 pt). However, this is not done outside the loop because the wrongly defined loop encompasses the whole algorithm. The algorithm defines a conditional sentence which assesses whether a variable is less than or equal to 40. This conditional has two exits to follow depending on whether the condition is true (1 pt), and it is correctly integrated into the algorithm (1 pt). The algorithm ends by defining an ending node (0.5 pts).

The loss of 7 points is due to the variables N and S not being initialised or updated outside the loop (items 2.1, 2.2, 3.1, and 3.2). In addition, the loop is incorrectly defined (item 4), and since N is not updated, the algorithm is not guaranteed to terminate (item 8).

We based the statistical analysis of the variable G on the recommendations and R functions provided by Wilcox (2022) to select the most suitable version of analysis of variance (ANOVA)- type procedures and effect sizes, depending on the features of the sample distribution. We refer the reader to the Results section for the details. Data were analysed using R (Version 4.3.3). We took a p-value of 0.05 as a decision criterion in every case.

RESULTS AND ANALYSES

Emotions experienced by students

In all cases of the regression analysis, our initial model includes the order of examples (exposure variable), the gender (control variable), and the interaction between the exposure and the control variable. However, the log-likelihood ratio test indicated no interaction for any emotion, neither in the exposition nor in the assessment session. Hence, we subsequently ran the analysis for a model with just two independent variables, which we called Model 2. Regarding confounding, given that we analysed 14 emotions, we show details only for those for which Model 2 predicts the experience. Regarding the exposition session, Model 2 is significant in predicting three emotions (Table 2).

Table 2

Fit indices for Model 2 for each emotion in the exposition session

Emotion	Model $X^2(2)$	p	AIC	R^{2a}	R_{CS}^{2b}	R_N^{2c}
Despair	7.470*	0.024	158.24	0.047	0.060	0.082
Relief	8.976*	0.011	164.76	0.010	0.072	0.095
Pressure	10.947**	0.004	151.3	0.070	0.087	0.119
Brain teaser	5.142	0.076	161.58	0.032	0.042	0.057

Note. $X^2(2)$ = likelihood ratio test comparing Model 2 and the base model.

^a R^2 = Hosmer–Lemeshow. ^b R_{CS}^2 = Cox–Snell. ^c R_N^2 = Nagelkerke.

*p < .05. **p < .01.

Table 3

Logistic regression coefficients and odds ratios for each emotion in the exposition session

Emotion	Variable	B	SE	95% for OR		
				LL	OR	UL
Despair	Intercept	-0.86	0.30			
	Order of examples	0.91*	0.39	1.16	2.471	5.41
	Gender	-0.62	0.48	0.20	0.540	1.32
Relief	Intercept	-0.006	0.285			
	Order of examples	-0.555	0.285	0.271	0.574	1.198
	Gender	1.128*	0.455	1.298	3.090	7.855
Pressure	Intercept	-0.6248	0.305			
	Order of examples	0.553	0.400	0.798	1.739	3.857
	Gender	-1.533**	0.581	0.060	0.216	0.614
Brain teaser	Intercept	-0.003	0.286			
	Order of examples	0.764*	0.385	1.018	2.147	4.631
	Gender	0.160	0.587	0.701	1.687	4.330

$p < .10$. * $p < .05$. ** $p < .01$

In addition, for the brain teaser perception, Model X2(2) is not significant ($p = 0.076$), although the 95% CI for the odds ratio is [1.018, 4.631] for the order of examples. This suggests that the model has no practical relevance regarding this emotion.

Regarding the assessment session, Model 2 has significance as a predictor for eight emotions (Table 4), but in all cases, gender was the only significant predictor (Tables 5-6).

Table 4*Fit indices for Model 2 for each emotion in the assessment session*

Emotion	Model $X^2(2)$	p	AIC	R^{2a}	R_{CS}^{2b}	R_N^{2c}
Curiosity	8.444*	0.015	161.77	0.051	0.068	0.091
Good spirits	10.928**	0.004	129.06	0.082	0.087	0.130
Despair	10.989**	0.004	136.17	0.078	0.088	0.127
Relief	9.632**	0.008	124.33	0.075	0.077	0.118
Pressure	17.7040***	0.0001	118.68	0.136	0.137	0.207
Boredom	4.604	0.100	149.66	0.031	0.038	0.053
Great	10.936**	0.004	81.519	0.127	0.087	0.170
Pleasure	9.444	0.009	126.94	0.072	0.076	0.114
Confidence	8.164	0.017	95.75	0.084	0.066	0.118

Note. $X^2(2)$ = likelihood ratio test. R^2 = Hosmer–Lemeshow. R_{CS}^2 = Cox–Snell. R_N^2 = Nagelkerke

* $p < .05$. ** $p < .01$. *** $p < .001$

Table 5*Logistic regression coefficients and odds ratios for the emotions in the assessment session. First part.*

Emotion	Variable	B	SE	95% for OR		
				LL	OR	UL
Curiosity	Intercept	0.362	0.290			
	Order of examples	-0.611	0.382	0.254	0.543	1.14
	Gender	1.149*	0.514	1.209	3.154	9.337
Good spirits	Intercept	1.549	0.358			
	Order of examples	-0.069	0.450	0.384	0.933	2.272

Despair	Gender	1.580***	0.479	1.906	4.857	12.635
	Intercept	1.246	0.331			
	Order of examples	0.253	0.431	0.553	1.289	3.030
	Gender	-1.517**	0.470	0.086	0.219	0.548
Relief	Intercept	1.734	0.377			
	Order of examples	0.135	0.460	0.465	1.145	2.860
	Gender	1.517**	0.486	1.760	4.557	11.970
	Intercept	2.169	0.429			
Pressure	Order of examples	-0.729	0.486	0.179	0.483	1.226
	Gender	-1.993***	0.505	0.049	0.136	0.360
	Intercept					

Note. $p < .10$. * $p < .005$. ** $p < .01$. *** $p < .001$

Table 6

Logistic regression coefficients and odds ratios for the emotions in the assessment session. Second part

Emotion	Variable	B	SE	95% for OR		
				LL	OR	UL
Boredom	Intercept	-1.335	0.334			
	Order of examples	0.845*	0.411	1.055	2.328	5.325
	Gender	0.282	0.480	0.502	1.325	3.362
	Intercept					
Great	Order of examples	0.669	0.620	0.141	0.512	1.682
	Gender	1.861**	0.603	1.989	6.433	21.990
	Intercept					

Pleasure	Intercept					
	Order of examples	-0.383	0.453	0.276	0.682	1.653
	Gender	1.418**	0.482	1.604	4.128	10.732
Confidence	Intercept					
	Order of examples	-0.715	0.561	0.154	0.489	1.433
	Gender	1.418*	0.556	1.368	4.130	12.448

p < .10. *p < .005. **p < .01. ***p < .001

In addition, although Model 2 was not significant to predict boredom ($X^2(2) = 4.604$, $p = .1$), the CI for the ORs point out that the probability of experiencing boredom is higher in the everyday example first case. In the case of boredom, the p-value of $X^2(2)$ is 0.1, and the 95% CI of the ORs ([1.055, 5.325]) for the order of examples is close to 1, so the predictor significance of the model would be of no practical relevance.

Flowcharts produced by the students

Overall, students performed poorly when designing a flowchart analogous to the one discussed in the exposition session a week earlier (Table 7). In particular, we obtained $M = 2.705$, $SD = 0.484$ for the women ($N = 31$), and $M = 4.72$, $SD = 1.078$ for the men in the mathematics first group ($N = 11$); and $M = 1.91$, $SD = 0.385$ for the women ($N = 37$), and $M = 2.058$, $SD = 0.414$ for the men in the everyday example first group ($N = 10$).

Regarding the assessment of the parametric assumptions, the subsample of women in the mathematics first class had outliers and was positively skewed, while the other subsamples were not, the women's subsamples distributions were not normal, and the Levene test indicated heterogeneity ($F = 2.727$, $p = 0.049$). Thus, we followed Wilcox (2022) and used a robust version of the 2-way ANOVA based on trimmed means and percentile bootstrap. We obtained that the factors do not interact and just the order of examples has an effect, with a moderate effect size (Table 7).

Table 7*Results of the robust 2-way ANOVA*

Factor	Grade variable			
	G			
	Ψ^a	95% CI	ξ^b	KMS
Order of examples	4.26**	[1.09, 7.43]	.35	.27
Gender	-2.37	[-5.45, 0.65]		
Interaction	-2.41	[-5.78, 0.62]		

* $p < 0.05$. ** $p < 0.01$.

Note. ^a Ψ = estimator of the difference between factor levels' trimmed means calculated by the r-function `bbmcppb`, which controls Type 1 errors –with the Rom's method– and provides confidence intervals; CI = confidence interval; ^b ξ = explanatory measure of the effect size given by Wilcox and Tian (2011), KMS = robust measure of effect size given by Kuliskaya et al. (2008).

Effect sizes calculated by the r-function `twowayESM`.

CONCLUSIONS

This section is devoted to answering the research questions, discussing some plausible explanations for the results, and deriving teaching implications. Regarding the first research question (RQ1), firstly, we found that the gender and the order of examples do not interact. This suggests that when designing teaching interventions aimed at optimising the emotions experienced by the students during the teaching sessions, the optimal order in which concepts are exemplified, if it exists, does not depend on the student's gender. This facilitates the design and implementation of teaching interventions in usual group classes. Secondly, we found that the two-factor model improves prediction of students' probability of feeling despair ($\chi^2 = 7.470$, $p = 0.024$). In particular, the estimated odds of a student experiencing despair increase more than twice when the everyday example is discussed first (OR = 2.471, CI = [1.160, 5.410]), which is considered a small-to-moderate effect size. We must also mention that our results suggest that something similar happens regarding the emotion of racking one's brain during the teaching session. The statistical results are not conclusive ($\chi^2 = 5.142$, $p = 0.076$), but they suggest that discussing the mathematical example first is at least as good as discussing the everyday example first (OR = 2.147, CI = [1.018, 4.631]).

As a plausible explanation, given the participants' mathematical background (see the Participants subsection), the mathematical example should trigger cognitive conflict for most of them due to its abstract features. But the participants know that this content is part of the subject, and therefore a potential topic on the exams they must pass. Thus, the awareness of a lack of command and of an individual's expectations could trigger negative emotions.

On the contrary, the everyday example should not trigger such a cognitive conflict, as it is straightforward to interpret the flowchart steps in terms of real actions. Thus, the linked emotions should be more positive. Therefore, when the mathematical example is the first one, the more positive emotions are the last to be experienced. In this regard, the recency effect implies that these are better remembered when answering the questionnaire at the end of the session (Yeh & Chen, 2022). Hence, concerning the emotions after the exposition session, our results suggest that the recency effect outweighs the primacy effect. Indeed, besides the statistical differences in the emotions of despair and racking one's brain, the ORs (Table 3) suggest a higher probability of feeling positive emotions and a lower probability of feeling negative ones if the mathematical example is discussed first.

The model with the variables “order of examples” and “gender” also improves the prediction of the probability that a student experienced relief and pressure. Specifically, men are more prone to feel relief (OR = 3.090, CI = [1.298, 7.855]) and less to feel pressure (OR = 0.216, CI = [0.060, 0.614]) regardless the Order of examples. The results regarding gender differences agree with those reported in the literature (Devine et al., 2012; Else-Quest, 2010; Gonzalez-Dehass et al., 2024).

Regarding the emotions after the assessment session (RQ2), our results, taken together, show that in this case, the emotions attached to the fact of being assessed are too strong for the order of exposition in the first session to have any effect. This is in line with the link between negative emotions and assessment situations reported in the literature (González-DeHass et al., 2024), to the extent that the fact of being assessed can even trigger anxiety and fear, and that once this is repeatedly experienced, the individual tends to suffer it again in each new assessment situation. However, we found differences by gender. In particular, men were more prone to feel curiosity ($\chi^2 = 8.444$, $p = 0.015$), in good spirits ($\chi^2 = 10.928$, $p = 0.004$), relief ($\chi^2 = 9.632$, $P = 0.008$), great ($\chi^2 = 10.936$, $p = 0.004$), pleasure ($\chi^2 = 9.444$, $p = 0.009$) and confidence ($\chi^2 = 8.164$, $p = 0.017$), and less to feel despair ($\chi^2 = 10.989$, $p = 0.004$) and pressure ($\chi^2 = 17.740$, $p = 0.0001$). Hence, men were more prone to experience

positive emotions and less prone to experience negative ones than women in the assessment situation, which aligns with prior research (Beilock et al., 2010; Bekdemir, 2010). It is worth noting that the students knew they were participating in an experiment and were told that their output would not count for evaluation purposes. Thus, our results show that the mere fact of being requested to reveal their skill to the researchers means a change in the emotions' configuration, because gender did not affect the exposition session, but it did in the assessment session.

Regarding the third research question (RQ3), the scores were low (the mean across all subgroups was below 5 out of 10), indicating a poor command of the basics of flowchart design. Given the simplicity of the task, this suggests a lack of command of the rudiments of CT beyond everyday life activities. This is an issue because the participants were Primary School preservice teachers, so they are expected to teach the rudiments of CT to children. The task in the assessment session was not oriented towards primary school children—it could be too difficult for them—but preservice teachers should command the topic they teach at a higher level than children do. Indeed, teachers must understand and articulate the connections between what they teach and what students are expected to learn in the future, at least within compulsory education, and approach the subject in a way that facilitates such learning. Indeed, Carrillo-Yáñez et al. (2018) claim that this type of knowledge for teaching is necessary as part of the knowledge of the structure of mathematics. Therefore, our results suggest that it would be advisable to strengthen the teaching of CT in Spanish secondary schools and bachelor's degrees in primary education to meet the educational needs of future generations (Adell et al., 2019; Freina et al., 2019; Berciano et al., 2024).

Concerning the differences in learning outcomes in the ability to apply basic notions of computational thinking in a mathematical context across levels of the factors (RQ3), our results show that the factors do not interact and that gender does not have an effect. Hence, men are more likely than women to experience positive emotions when demonstrating their skills, although this is not because they performed better than women. Even more, we found that women experienced more negative emotions in the assessment session (see above), and anxiety tends to worsen performance.

This aligns with prior studies reporting that men tend to be more confident when solving academic tasks or being assessed, regardless this is factual or not (Devine et al., 2012). This could be due to different social and cultural constructs of gender (Beilock et al., 2010; Good et al., 2012). As a

teaching implication, women's self-esteem and self-perception should be enhanced in teaching sessions involving CT at all educational levels to counteract that social construction. Moreover, negative experiences in mathematics classes must be avoided from the early years, because they are linked to pre-service teachers' mathematics anxiety, and teachers' behaviour and teaching approach is one of the causes (Bekdemir, 2010). In the case of women, such negative situations would add to and potentially deepen the gap due to gendered social constructs, so it is advisable to support women in mathematics classrooms (Good et al., 2012). This is a relevant matter because, although the number of women graduating with STEM degrees has increased over the past decade, the gender gap persists (Castro-Núñez & Santero-Sánchez, 2023).

On the other hand, there are differences depending on the order of instruction ($\Psi = 4.26$, $p = .005$, $CI = [1.09, 7.43]$), with a moderate effect size ($\xi = 0.35$, $KMS = 0.27$). Specifically, mathematical example first students statistically outperformed the everyday example first students. These results partially disentangle the issue of teaching and learning from concrete to abstract or from abstract to concrete (Roth & Hwang, 2006). Regarding this, at first glance, our results seem to contradict the design principle of cognitive load theory, which advises progressively increasing cognitive load requirements as instruction and students' expertise progress (Ngu et al., 2014; Sweller et al., 2019). However, the contradiction is just apparent, and there is a plausible explanation.

In this regard, the mathematical example raises a cognitive conflict that students seek to overcome. Indeed, given the participants' profile (see above), it would not be obvious to them that the inner principles of numeric algorithms are analogous to those of everyday life protocols. Therefore, it would be difficult for them to process the mathematical example solely through Piagetian assimilation based on the previous everyday example. Moreover, students tend to classify problems and choose resolution strategies based on the surface (mathematics/everyday life) rather than the mathematical structure (Bassok, 1990; Gómez-Ferragud et al., 2013).

During the exposition, apart from the individual's intrinsic motivation, the awareness that this content must be mastered to pass the subject would lead students to engage in sense-making. In the mathematical example, first group, on the one hand, the everyday example comes immediately after the first one, without a pause in between, so the sense-making of the mathematical example is still running, at least at the beginning. Furthermore, the teacher/researcher

and the everyday example itself explicitly point out the analogy between the examples' rationale and inner principles. Again, given these students' profiles, an algorithm for the systematic addition of numbers is unusual and distinct from the mathematical topics they have been exposed to. Therefore, the distinctiveness principle (Hunt & McDaniel, 1993; Howe, 2006) would apply. In addition, as discussed above, the mathematics example would initially trigger negative emotions, so the emotional arousal would potentially increase attention during the subsequent discussion of the everyday example (Storbeck & Clore, 2008). For all these reasons, the students would make sense of the mathematical example by means of the everyday example, in a gap-filling process. For example, the students can make sense of the counter for the already added numbers and the condition on its maximum value by using the counter for the already eaten yoghurts and the maximum number of yoghurts allowed, respectively. On the contrary, in the everyday example first, since it could be seen as banal, the distinctiveness principle would make it harder to recall it later, to overcome the cognitive conflict raised by the mathematical example. Consequently, discussing the mathematical example first would imply a better understanding and, therefore, a better performance in the assessment session.

As a teaching implication, our results indicate that when designing teaching activities to teach the basics of CT and flowchart design in bachelor's degree programs for primary school teachers, scheduled in weekly sessions, it is advisable to present abstract examples first. The latter would also help foster more positive emotions in students' memories of the classes.

Regarding the study limitations, our study encompasses just one exposition session, because this was the scheduled time for CT in this bachelor's degree subject. It would be enlightening to study the order of examples and the concrete-abstract and vice versa sequencing of examples in wider ranges. In addition, a larger sample size would be necessary to increase the reliability of our results. Regarding emerging lines of research, qualitative analysis of think-aloud protocols could shed light on students' sense-making processes through everyday examples when dealing with mathematical flowcharts. Finally, the study about the influence of the order in which teaching activities are presented to students could be extended to other aspects of CT or other academic topics.

AUTHORS' CONTRIBUTIONS STATEMENTS

CS conceived the idea presented, designed and conducted the experiments, gathered, curated, and analysed the data, interpreted the results, developed the conclusions and discussion, and revised the entire article. MS

elaborated the theoretical framework and the reference list, managed and coded the data, and revised the whole article. Both authors actively collaborated on the discussion of the results and reviewed and approved the final version of the work.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study will be made available by the corresponding author, [CS], upon reasonable request.

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APPROVAL BY AN ETHICS COMMITTEE

This study was approved by the Bioethics Committee of the University of Santiago de Compostela on 27 October 2023 (Approval code: USC 47/2023).

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