Integrated STEM professional development in interdisciplinary teacher design teams: Teacher self-efficacy profiles using cluster analysis

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Abstract

This study examined teachers' self-efficacy in STEM and computational thinking (CT) and identified distinct profiles based on their self-efficacy ratings. Most teachers recognized the relevance of STEM integration, problem-based learning, computational thinking, and teamwork. However, variations in self-efficacy were observed across specific areas. These findings highlight the need for targeted interventions, particularly for teachers in cluster 3, to enhance self-efficacy in STEM and CT education. Gender differences in profile membership were also noted. This study informs effective professional development programs in these domains.

Keywords

Cluster Analysis, Self-efficacy, STEM, Computational thinking

Introduction

STEM education has gained global attention from ministries of education due to its recognition of the importance of STEM-related competencies for economic growth and global competitiveness (Kennedy & Odell, 2014).Technological advancements and societal changes have driven economic and occupational shifts, leading to the emergence of the fourth industrial revolution, also known as Industry 4.0 (Schleicher, 2019). While the term "STEM" is often used to convey innovation and excitement, it can still be perceived as disconnected subjects (Wang et al., 2011). Integrated STEM education aims to break down the perceived barriers between the four disciplines of science, technology, engineering, and mathematics, fostering students' understanding of the practical applications of STEM to address real-life technical and social challenges. However, implementing integrated STEM education is complex and challenging, as it requires more than just treating different subject areas in parallel (Knipprath et al., 2018). Despite the clear benefits of an integrated STEM approach (Becker & Park, 2011; Roberts, 2013), the implementation in practice does not always align with the intended goals. Creating meaningful connections between STEM disciplines is a challenging task that involves iteratively matching and reorganizing learning goals across different disciplines, determining appropriate sequencing of these goals, and incorporating new learning objectives (Thibaut et al., 2018). Many teachers face obstacles in adopting a more integrated STEM methodology due to these complexities (Margot & Kettler, 2019). Consequently, professional development plays a crucial role in enhancing the quality of STEM education and classroom practices (Loughran, 2014).

Similarly, the integration of computer technology and programming has had a profound impact on society and is considered a vital component for academic and professional success in the technologically advanced 21st century (Shute et al., 2017). Consequently, computational thinking (CT), a complex competency defined as a way of thinking that can be applied to various fields requiring problem-solving skills (Wing, 2008), has been recognized as a critical 21st-century skill (Angeli et al., 2016) and is increasingly being integrated into national curricula across the world (Bocconi et al., 2022; Hsu et al., 2018; Law et al., 2018; Voogt et al., 2015)

Currently the 'iSTEM inkleuren' project aims to translate scientific knowledge on integrated STEM-approaches into practice and builds on research conducted under the 'STEM@School 'project (Knipprath et al., 2018), which provides a framework and lesson materials to facilitate an integrated approach. Because short interventions have been shown to have a limited impact on teaching practices (McConnell et al., 2013), the project adopts a more demand-driven model for teacher professionalisation (i.e., teacher design team, TDT). A TDT can be described as a group of teachers who (re-)design curriculum materials together (Handelzalts, 2009). A distinctive characteristic of TDTs is the sort of design task at hand. This collaborative and inclusive approach allows for the development of innovative and contextually relevant educational practices that align with the needs and interests of the students and the broader community. STEM teacher design teams, through their professionalization efforts, can contribute to the creation and dissemination of open educational resources, collaborative projects, and community engagement initiatives, thereby fostering a more open and interconnected learning environment.

The integration of STEM and CT, like any other innovation, into education is influenced by the attitudes and perceptions of teachers (Davis, 1989). Furthermore, the perceptions and attitudes of teachers towards teaching and learning play a significant role in shaping their instructional practices and impacting the resultant learning outcomes (Tschannen-Moran & Barr, 2004; Tschannen-Moran & Hoy, 2001). As the implementation of CT ad STEM in many education systems is still in its infancy (Bocconi et al., 2022), we want to better understand how teachers that participate in iSTEM training initiative perceive and rate their ability to teach integrated STEM and computational thinking. By doing so, we aim to contribute evidence which could inform any effort of designing efficient training and proper preparation of teachers for the integration of CT in education. To guide our efforts, we formulated the following research questions:

1. What are the self-efficacy profiles of teachers participating in the iSTEM training initiative regarding their ability to teach integrated STEM and computational thinking?
2. How do teachers perceive the relevance of integrated STEM and computational thinking?
3. Are there significant differences in self-efficacy profiles among teachers based on demographics?

Method

Participants

The data for this study was collected at the beginning of the professionalization initiative through an online survey. Participants were 171 secondary school teachers from the Flemish education system who engaged in a professional development trajectory focused on interdisciplinary Teacher Design Teams (TDTs). The TDTs consisted of 4-5 teachers collaborating together. Of the participants, 86 identified as female, and 85 identified as male. The average age of the participants was 45 years, and their average teaching experience was 14 years, ranging from 0 to 30 years. Each TDT was supported by an iSTEM coach who guided the team in incorporating the principles of integrated STEM education. The online survey served as a tool to collect relevant data and insights from the participants regarding their self-efficacy and perceived relevance of STEM and computational thinking in education.

Instrument

To assess teachers' self-efficacy in teaching computational thinking, the questionnaire used in this study was adapted from the TPACK (Technological Pedagogical Content Knowledge) questionnaire developed by (Schmid et al., 2020). To measure teachers' self-efficacy specifically in teaching STEM and computational thinking, the questionnaire items related to subject content and pedagogical knowledge were modified (e.g., "I know the basic theories and concepts of computational thinking ", instead of "I know the basic theories and concepts of my teaching subject"). Additionally, items to measure perceived relevance were included in the questionnaire, drawing from the attitude questionnaire developed by Thibaut et al. (2018). These items assessed teachers' perceived relevance towards STEM integration, problem-based learning, computational thinking, and teamwork. This resulted in a 36-item questionnaire, in which participants were asked to rate each item on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Analysis

To identify different self-efficacy profiles among teachers, a two-step cluster analysis (CA) was employed. Cluster analysis is a statistical method used to group individuals based on similarities across multiple variables. In this analysis, the goal was to identify homogenous groups of teachers without any prior knowledge of the grouping structure, making it a taxonomy analysis. The two-step cluster analysis approach was chosen for this study. This approach consists of two separate steps, with the first step being the pre-clustering phase. During this step, each case is examined individually to construct a cluster features (CF) tree. The log likelihood distance measure is used to determine whether a case should form a new pre-cluster on its own or be merged with other similar cases. After scanning all cases, the resulting pre-clusters are treated as independent entities and serve as the raw data for the next step. The advantage of the two-step clustering approach is that it reduces the size of the distance matrix by basing it on the number of pre-clusters rather than the total number of cases. Additionally, the pre-clustering step automatically standardizes all continuous variables, eliminating the need for separate data transformation steps. The final number of clusters was determined using statistical metrics, such as the silhouette measure of cohesion and separation. This measure assesses how well an object is matched with its own cluster and how poorly it is matched with neighbouring clusters. Scores for the silhouette measure range from -1 to 1, with higher values indicating better cluster fit. After the pre-clustering step, an agglomerative algorithm is used to complete the clustering procedure. For a more detailed description of the methodology, references such as Meila and Heckerman (2013), and Banfield and Raftery (1993) can be consulted. The analysis was performed using IBM SPSS Statistics (Version 28). The scale variables used in the cluster analysis were extracted from the previously mentioned survey.

Results

Our analysis indicated that a three-cluster solution was the most optimal solution for the data, because it minimized the models' Bayesian inference criterion value (BIC) and the ratio of BIC change between adjacent numbers of cluster. Moreover, the model with three clusters was complies with the statistical criteria that each separate cluster should not contain fewer than 7% of the total number of respondents, and a multivariate test should indicate that the cluster solution explains at least 50% of the total variance (Tinsley & Brown, 2000). The number of respondents belonging to each of the clusters exceeded 7% of the total number of respondents (see Table 1). Table 1 also shows the cluster membership for men and women. Moreover, the data contains enough cases (N = 171) to satisfy the cases to variables assumption, as guidelines indicate a minimum of 10 cases per independent variable (Schwab, 2002). A graphic representation of the profile cluster can be found in Figure 1.

Table 1. Cluster profiles

	N_{total}	N_{male}	N_{female}	M_{age}	Self-efficacy					Perceived relevance			
					STEM content	STEM pedagogy	CT content	CT pedagogy	CT-STEM pedagogy	STEM integration	PBL	CT	Team work
Cluster 1	44	19	25	41	4,26	4,10	4,10	3,76	3,97	4,47	4,41	4,42	4,46
Cluster 2	84	38	46	48	3,72	3,28	3,28	2,88	3,23	3,97	4,03	4,01	4,14
Cluster 3	43	28	15	43	2,93	1,97	1,97	1,85	1,88	3,73	3,92	3,83	3,92
All	171	85	86	44	3,66	3,29	3,16	2,85	3,08	4,04	4,10	4,07	4,17

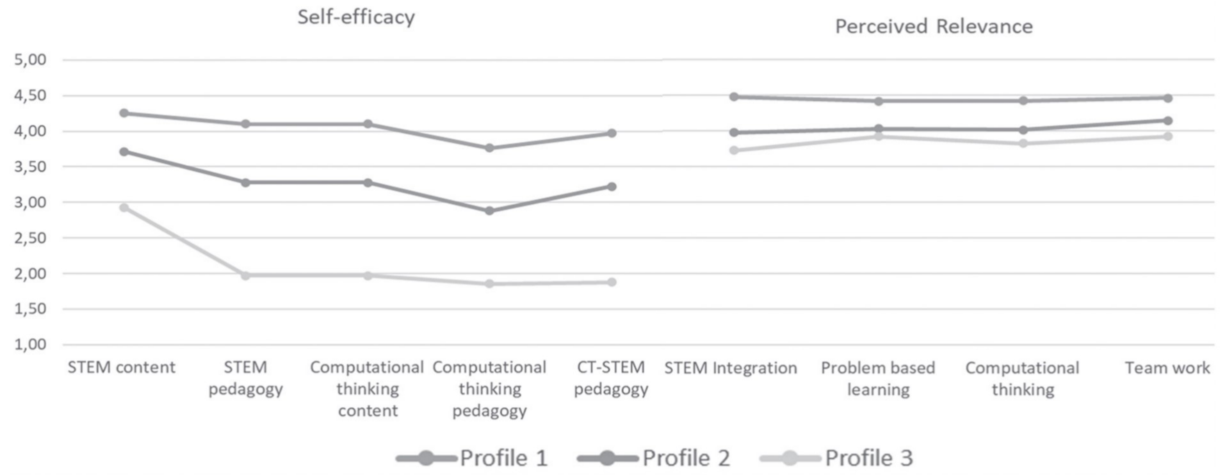

Figure 1. Profiles identified in this study

In the following section, we will present the characteristics of each cluster in detail. As the teachers' perceived relevance towards STEM integration, problem-based learning, computational thinking, and teamwork in each cluster differs marginally, we will exclude it from this comparison. We do however note regarding our second research question that overall, most teachers perceive STEM integration (*M*= 4.04, *SD*= 0.55), problem-based learning (*M*= 4.10, *SD*=0.56), computational thinking (*M*= 4.07, *SD*=0.48), and teamwork (*M*= 4.17, *SD*=0.65) as relevant educational practices.

Cluster 1 (*N* = 44, 26%) can be considered the most favourable profile cluster as teachers rate there self-efficacy regarding STEM content (*M*= 4.26, *SD*= 0.48), STEM pedagogy (*M*= 4.10, *SD*= 0.52), CT content (*M*= 3.76, *SD*= 0.51), CT pedagogy (*M*= 3.76, *SD*= 0.56), and CT-STEM pedagogy (*M*= 4.47, *SD*= 0.48) higher than teachers in cluster two and three. This cluster consists of 19 male (22%) and 25 female (29%) teachers.

Cluster 2(*N* = 84, 49%) (*N* = 43, 25%) can be considered a good but average profile cluster as teachers rate there self-efficacy regarding STEM content (*M*= 3.72, *SD*= 0.48), STEM pedagogy (*M*= 3.28, *SD*= 0.59), CT content (*M*= 3.28, *SD*= 0.62), CT pedagogy (*M*= 2.88, *SD*= 0.51), and CT-STEM pedagogy (*M*= 3.23, *SD*= 0.50) lower than teachers in cluster one but higher than teachers in cluster three. This cluster consists of 38 male (45%) and 46 female (53%) teachers.

Cluster 3 (N = 43, 25%) can be considered the least favourable profile cluster as teachers rate there self-efficacy regarding STEM content (M= 2.93, SD= 0.92), STEM pedagogy (M= 1.97, SD= 0.93), CT content (M= 1.97, SD= 0.79), CT pedagogy (M= 1.85, SD= 0.77), and CT-STEM pedagogy (M= 1.88, SD= 0.67) lower than teachers in cluster one and two. This cluster consists of 28 male (33%) and 15 female (17%) teachers.

Discussion and conclusion

The present study aimed to identify different profiles of teachers' self-efficacy in teaching STEM and computational thinking (CT). The results revealed three distinct clusters, each representing a different profile of self-efficacy. It is important to note that the perceived relevance towards STEM integration, problem-based learning, computational thinking, and teamwork did not significantly differ among the clusters. The findings suggest that teachers with profiles in Cluster 3 may have the most to gain from interventions aimed at improving their self-efficacy in teaching STEM and computational thinking. Targeted professional development programs could be designed to address the specific needs and challenges faced by teachers in this cluster. Gender differences were observed in profile membership, with more male teachers in Cluster 3 compared to the other clusters. This finding highlights the importance of considering gender-specific factors when designing interventions and support mechanisms to enhance self-efficacy in STEM and computational thinking among teachers.

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