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STEM Teachers' Digital Competence: Different Subjects, Different Proficiencies

Rui Marques Vieira [1,*], Celina C. Tenreiro-Vieira [1], Pedro Bem-Haja [2] and Margarida Lucas [1]

[1] Research Centre on Didactics and Technology in the Education of Trainers, Department of Education and Psychology, University of Aveiro, CIDTFF, 3810-193 Aveiro, Portugal; cvieira@ua.pt (C.C.T.-V.); mlucas@ua.pt (M.L.)

[2] CINTESIS@RISE, Department of Education and Psychology, University of Aveiro, 3810-193 Aveiro, Portugal; pedro.bem-haja@ua.pt

* Correspondence: rvieira@ua.pt

Abstract: STEM—science, technology, engineering, and mathematics—and STEM literacy have emerged as one (of many) concerted efforts aiming to provide the different competences required for future generations to adapt to an evolving world. Despite lacking a comprehensive framework for STEM, this concept has been studied under different perspectives, one of which is the digital competences of teachers. This study focuses on the digital competence and proficiency of 20,935 teachers, distributed across the following subjects: mathematics and natural sciences, physics and chemistry, biology and geology, and mathematics. It uses DigCompEdu as a conceptual framework to describe teachers' use of digital technologies to teach STEM subjects. The results show that biology and geology teachers achieved significantly higher digital proficiency scores when compared to teachers from the other three subjects. Physics and chemistry teachers also scores significantly higher than mathematics and natural sciences teachers. The results show the existence of significant positive correlations among all competence areas for the four STEM subjects. In conclusion, Portuguese teachers presented different levels of digital competence and perceived themselves as differently prepared for integrating digital technologies. A potential implication of this study is the need for teacher education about digital competences and a focus on producing teachers capable of dealing with STEM in their future classroom teaching and learning.

Keywords: STEM; digital proficiency; DigCompEdu; self-perception

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1. Introduction

Social, economic, and environmental change and unpredictability are an attribute of the complexity of current life on our planet both for humans and all other beings and resources with whom we must ecologically live. In recent years, such change has taken on different forms, such as more sustainable lifestyles, but also in our ways of being in or seeing the world. The COVID-19 pandemic necessitated a resizing of the competences to be mobilised in everyday work interactions alongside the move to "home offices" leveraging, on a massive scale in the Western world, connections to a globally interconnected digital network of communications.

The evolving conditions of human societies are coloured by a variety of contexts, with technology taking a prominent place. The proper use and effectiveness of technology require different competences and literacies. Such competences have been included in the educational curricula of several countries, more explicitly since the 1980s under the denomination of the science, technology, and society (STS) perspective, movement, orientation, and education. According to STS, the development of scientific knowledge is fundamental for a more democratic and sustainable citizenship in the context of volatile, uncertain, complex, and ambiguous transformations which is also strongly embedded with technology(ies) [1–4]. These authors and others such as Aikenhead [5] have sought

to understand science in interaction with technology and society, uncovering their interrelationships, controversies, and mutual influences. This implies an educational approach including topics in real contexts with personal and social meaning that contribute to a better quality of life and enable thinking about science and technology from philosophical, ethical, and cultural points of view.

Despite different perspectives and controversies, it is within this frame of reference that other movements have anchored their reasoning and reflection, as is the case of STEM (science, technology, engineering, and mathematics) movement [6,7]. The STEM movement emerged as another concerted effort on the part of companies, academia, and governments to meet the different competences required for the U.S. job market and was an initiative created in that context by the National Science Foundation (NSF) [8]. However, the current practices, educational goals, and policies of STEM education still lack a comprehensive framework [9,10].

Despite this fact, STEM has progressively been adopted in other countries, namely as a curricular guideline seeking the articulation or interconnection between the four fields/domains in education in order to develop an integrated STEM literacy [11,12]. STEM literacy is considered necessary given that achieving competences in those four separate fields does not necessarily lead to learning the concepts, skills, and dispositions identified with STEM literacy [13]. However, several authors have noted that the very concept of literacy remains a broad and ambiguous notion, as it is also dependent on the social, cultural, and environmental contexts (e.g., Yip [13]).

Nonetheless, there is broad consensus that STEM education must begin in primary schools, which presents a challenge for teachers in preparing students to become STEM-literate [14]. These authors and others (e.g., Zeidler [9]) emphasise that schools need teams of teachers working together in an integrated approach based on cross-curricular teaching and learning: "Integrated STEM education could be defined as the approach to teaching the STEM content of two or more STEM domains, bound by STEM practices within an authentic context for the purpose of connecting these subjects to enhance student learning" [12] (p. 6).

The interdisciplinary nature of STEM advocates integrative and life-long educational approaches [9,13] in an ecosystem of social networks, peers, educators, friends, and families for in-school and out-of-school learning contexts [15]. Thus, educational policies supporting teacher education are key aspects for STEM literacy [14]. These authors add that STEM educators also need to develop instructional material, namely digital, and implement teaching practices involving different ways of thinking, solving problems, and communicating.

There has been an effort in different countries to create favourable conditions for the implementation of STEM in real educational contexts. For example, in Portugal, there have been different initiatives, such as the Erasmus projects reported by Ribeiro [16]. Horta [17] described strategies and action plans set up and implemented in Portugal aiming to foster STEM competences and qualifications in primary, secondary, and higher education, such as those included in the Digital Agenda for Portugal (as a follow-up of the Digital Agenda for Europe) [18]: "In order to popularise STEM amongst the younger population and foster STEM at all levels of education, Portugal decided to work on two important aspects: the development of effective and attractive STEM curricula and teaching methods, and improved teacher education and professional STEM development" [17] (p. 2).

These proposals seek to align with the ten competence areas of the "Profile of Students Leaving Compulsory Schooling" [19] that all students must achieve after 12 years of school at the age of 18 years.

Despite these efforts, how the integrative approach can be adopted in the classroom has remained uncertain since proficient teachers require specific subject-matter and practical knowledge to teach effectively [13]. This author highlighted the need for teacher education to develop teachers' understanding, skills, and dispositions to teach STEM, including digital competence. Competence in conceptualizing and using information and digital literacy for STEM education via science, mathematics, technology, and engineering practices is necessary to this approach [20].

In this study, digital competence is conceptualised through the Digital Competence Framework for Educators (DigCompEdu) [21]. The DigCompEdu framework understands digital competence as a "comprehensive concept of teacher-specific competences in the digital age" [22]. It integrates the pedagogical and contextual competences a teacher needs in order to use digital technologies effectively to improve all areas of their professional activities.

The framework details 22 competences that are distributed across six competence areas—area 1: professional engagement; area 2: digital resources; area 3: teaching and learning; area 4: assessment; area 5: empowering learners; and area 6: facilitating learners' digital competence. Areas 2 to 5, the core of the framework, detail the pedagogical and methodological aspects specific to the teaching process (designing, implementing, and assessing). Area 1 details the digital competences needed to engage with the professional working environment, and area 6 details the digital competences required to facilitate the development of students' digital competence.

The DigCompEdu framework proposes a progression model that describes the different stages of digital competence development. These competence stages are expressed as proficiency levels, with A1 corresponding to the lowest and C2 to the highest. For each of the 22 competences, a proficiency descriptor is provided, exemplifying activities at each proficiency level. The descriptors provided by the framework were used to develop a self-reflection instrument, which is referred to ahead.

The DigCompEdu framework and its related self-reflection instrument have been increasingly used to examine teachers' digital competence [23,24], but few studies have focused on these competences across different STEM subjects. The few available studies mostly pertain to single curricular subjects, small samples, or other contexts rather than school education. For instance, Rooy [25] concluded that experienced Australian biology teachers do incorporate technologies, however limited, in order to improve the quality of student learning. In Spain, Fraile, Peñalva-Vélez, and Lacambra [26] assessed the competence level of 43 schoolteachers in initial training and found it was low in content creation and problem solving. Those authors also highlighted the urgent need to purposefully incorporate relational and didactic aspects of digital technology integration in teacher education.

While offering important insights, these studies fail to provide a more nuanced view of how digital competences are perceived by different teachers in STEM areas. Our study draws from a large sample, which constitutes a unique opportunity to focus on the differences across different STEM subjects.

2. Methodology

2.1. Aim of the Study

This research study focused on measuring the digital proficiency of a sample of Portuguese teachers and examining differences across different STEM subjects: mathematics and natural sciences, mathematics, physics and chemistry, and biology and geology. The research questions that guided our research are as follows:

RQ1: *How are the digital proficiency scores of STEM teachers distributed across subjects?*

RQ2: *What differences can be found across digital competence areas and STEM teachers?*

2.2. Sample and Procedure

This sample was drawn from a larger study conducted by the Portuguese Ministry of Education within the scope of the Digital Transition Action Plan. One of the axes of this plan corresponds to the digital capacity of teachers, which included as an initial step the diagnosis of their digital proficiency. Between January and March 2021, all teachers in primary and secondary public education (ISCED levels 1, 2, and 3) were invited to answer a self-reflection-based survey. The invitation was made by the Portuguese Directorate-General for Education, with the support of 91 School Association Training Centres, who shared the link with teachers from their associated schools. A total of 99,760 teachers (92%

of all public primary and secondary teachers in Portugal) took the self-reflection survey. The purposes of the survey were fully disclosed, and teachers gave their consent before starting it. The present sample corresponds to 21% of the total sample and was selected for the purposes of this study.

The study sample consisted of 20,935 teachers (78.7% female and 21.3% male). A total of 4285 teachers (20.47%) taught mathematics and natural sciences (M&NS) to the 5th and 6th grades (ISCED 1, second cycle CITE 1 (https://eacea.ec.europa.eu/national-policies/eurydice/content/portugal_en, accessed on 3 January 2023) and had an average of 24.1 years of teaching experience; 6807 (32.51%) taught mathematics (M), 4883 (23.32%) taught physics and chemistry (P&C), and 4960 teachers (23.69%) taught biology and geology (B&G). The latter three groups of teachers taught students from the 7th to the 12th grades (ISCED 2 and [27]). Their average teaching experience corresponded, respectively, to 23.1, 23.6, and 24.3 years. Considering that these STEM subjects—M&NS, M, P&C, and B&G—are a target variable in the present study, the demographic characteristics of these teachers are presented in Table 1.

Table 1. Demographic characteristics of the sample by STEM subjects.

	M&NS	M	P&C	B&G
Gender				
Female				
N	3455	5284	3740	4005
%	80.6	77.6	76.6	80.7
Male				
N	830	1523	1143	955
%	19.4	22.4	23.4	19.3
Age range (years)				
>25				
N	4	0	2	6
%	0.1	0.0	0.0	0.1
25–29				
N	35	13	3	21
%	0.8	0.2	0.1	0.4
30–39				
N	210	327	186	255
%	4.9	4.8	3.8	5.1
40–49				
N	1712	2966	1834	1946
%	40.0	43.6	37.6	39.2
50–59				
N	1520	2623	2353	2080
%	35.5	38.5	48.2	41.9
<60				
N	804	878	505	652
%	18.8	12.9	10.5	13.1

M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology.

According to Table 1, the majority of M&NS and M teachers are between 40 and 49 years old, and the majority of P&C and B&G teachers are between 50 and 59 years old.

2.3. Instrument

The self-reflection instrument used was developed by the Joint Research Centre of the European Commission and is based on the European Framework for the Digital Competence of Educators (DigCompEdu). It is commonly known as DigCompEdu-Check-In, and its fundamental objectives are to enable teachers to better understand the framework and to provide them with a way to self-reflect on their strengths and needs or areas for improvement in digital learning. The DigCompEdu Check-In contains 22 items that correspond to the 22 competences described in DigCompEdu. They respond to the six competence

areas described earlier in this work—area 1: professional engagement; area 2: digital resources; area 3: teaching and learning; area 4: assessment; area 5: empowering learners; and area 6: facilitating learners' digital competence.

For each item, a five-answer option is provided, which is then mapped onto the proficiency levels proposed by the framework and respective scores. They range from A1 (less than 20 points) to A2 (between 20 and 33), B1 (between 34 and 49), B2 (between 50 and 65), C1 (between 66 and 80), and C2 (above 80 points). The psychometric properties of the Portuguese version of the instrument can be found in Lucas et al. [22]. Apart from the 22 items focusing on teachers' digital competence, the instrument included items addressing gender, age, teaching experience, and subject taught.

The Portuguese Ministry of Education was responsible for ensuring the compliance with the GPDR and Ethical Procedures. Access to the full and complete anonymized database was authorized under a working contract for data analysis.

2.4. Data Analysis

To assess the differences between STEM subjects in teachers' global proficiency score, a Welsh's ANOVA was performed followed by multiple comparisons with Bonferroni correction. To understand how large these differences were, the data were then submitted to a Bayesian ANOVA following a methodology proposed by Rouder [28]. The BF_{10} was classified according to the criteria postulated by Lee and Wagenmakers [29]. To evaluate the differences between STEM subjects in teachers' competence areas, six one-way ANOVAs followed by pairwise comparisons with Bonferroni correction were carried out: one for each area of competence. Pearson's bivariate correlations were performed to explore correlations among the different competence areas and across STEM subjects.

To predict the STEM subject from each competence area controlling the remaining five competence areas, a multinomial generalised linear model was applied, using the STEM subject as the dependent variable and the competence areas as covariates.

Analyses were performed using R Core Team [30] to produce the linear models and JASP [31] for Bayesian analyses.

3. Results

3.1. Global Proficiency Score by STEM Subject

As shown in Figure 1, biology and geology (B&G) teachers achieved the highest digital proficiency score (M = 48.03, SD = 13.05, 95% [47.67, 48.39]) when compared to teachers from other subjects. Despite reaching a lower proficiency score, physics and chemistry (P&C) teachers (M = 46.91, SD = 13.24, 95% [46.53, 47.28]) score higher than mathematics and natural science (M&NS) teachers (M = 43.30, SD = 13.46, 95% [42.90, 43.71]) and mathematics teachers (M = 43.02, SD = 14.12, 95% [42.68, 43.35]).

To verify if these absolute differences reached statistical significance, a Welsh's ANOVA was performed. The result of this test shows a main effect of STEM subject with a significant fluctuation among the subjects (cf. inference on top of Figure 1).

In view of this result, and following a top-down statistical exploration, multiple comparisons with Bonferroni correction were performed. All three possible comparisons obtained statistically significant results, and the full statistical parameters can be seen in Table 2.

The results show that the proficiency score of B&G teachers is significantly higher than that of the other three groups of teachers. At the same time, the proficiency scores of P&C teachers are significantly higher than the proficiency scores obtained by M and M&NS teachers. No significant differences were obtained between the proficiency scores of M and M&NS teachers.

These results suggest that the null hypothesis (no differences among teachers from the different STEM subjects) may be rejected. Nonetheless, we wanted to further investigate how large the evidence in favour of this effect was. To test for this, the data were then

subjected to a Bayesian ANOVA following a methodology proposed by Rouder [28]. The results of this analysis are described in Table 3.

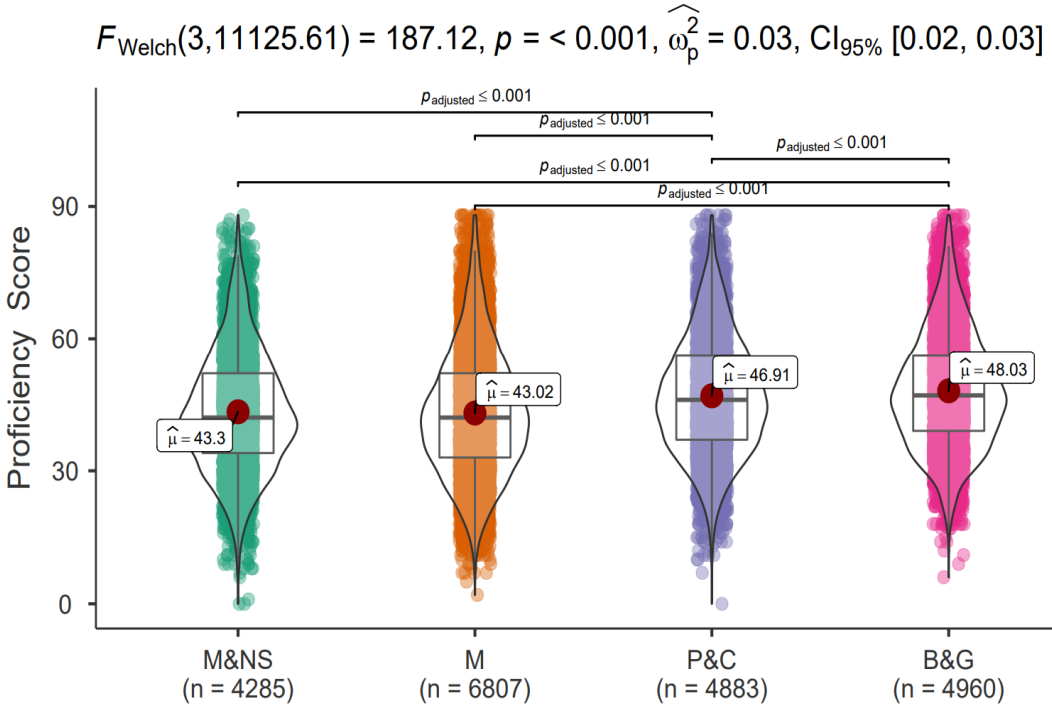


Figure 1. Violin plots with means and distribution of proficiency scores by STEM subject. M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology.

Table 2. Post hoc comparisons.

		95% CI for Mean Difference						
		Mean Difference	**Lower**	**Upper**	**SE**	***t***	***p* Bonf**	
B&G	M	5.013	4.364	5.662	0.253	19.846	<0.001	***
	M&NS	4.730	4.005	5.455	0.282	16.760	<0.001	***
	P&C	1.126	0.425	1.827	0.273	4.126	<0.001	***
M	M&NS	−0.284	−0.961	0.394	0.264	−1.074	1.000	
	P&C	−3.888	−4.540	−3.236	0.254	−15.320	<0.001	***
M&NS	P&C	−3.604	−4.332	−2.877	0.283	−12.725	<0.001	***

*** $p < 0.001$ Note: *p*-value and confidence intervals adjusted for comparing a family of four estimates (confidence intervals corrected using the Tukey method). M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology.

Table 3. Comparison between null model and STEM subject model.

Models	**P(M)**	**P(M | Data)**	**BF $_M$**	**BF $_{10}$**	**Error %**
Null model	0.500	3.874×10^{-115}	3.874×10^{-115}	1.000	
STEM subject	0.500	1.000	2.581×10^{114}	2.581×10^{114}	0.005

It is possible to verify that the alternative hypothesis (differences among teachers from the different STEM subjects) is 2.581×10^{114} times more likely than the null hypothesis. According to the classification criteria postulated by Lee and Wagenmakers [29], this effect can be classified as extreme (evidence for alternative hypothesis). Bayesian post hoc comparisons were also performed, with the results shown in Table 4.

Table 4. Bayesian post hoc comparisons.

		Prior Odds	Posterior Odds	BF 10, U	Error %
B&G	M	0.414	1.575×10^{80}	3.802×10^{80}	1.844×10^{-87}
	M&NS	0.414	4.111×10^{60}	9.926×10^{60}	8.983×10^{-69}
	P&C	0.414	76.381	184.399	3.536×10^{-9}
M	M&NS	0.414	0.016	0.038	4.719×10^{-5}
	P&C	0.414	5.193×10^{46}	1.254×10^{47}	6.363×10^{-54}
M&NS	P&C	0.414	6.109×10^{33}	1.475×10^{34}	8.155×10^{-42}

The BF10 results of the multiple comparisons show an advantage of the alternative hypothesis in all comparisons (extreme, according to Lee and Wagenmakers [29]) except for the comparison between M and M&NS teachers.

3.2. Proficiency Scores and Competence Areas by STEM Subject

As can be seen in the previous section, there were significant differences in the global score of digital proficiency obtained by the different groups of teachers. These, however, may be explained interactively by scores obtained in specific competence areas. As we see below, the differences between groups in some competence areas are indeed statistically significant, though not in all. In this case, the differences found between groups regarding the global proficiency score could be explained by a specific competence area.

To ascertain the statistical significance of differences between groups in each competence area, six one-way ANOVAs with pairwise comparisons (Bonferroni correction) were carried out. The results are shown visually in Figure 2 and Table 5. The results showed main effects of STEM subjects for all competence areas (area 1—$F(3, 20{,}931) = 52.78$, $p < 0.001$; area 2—$F(3, 20{,}931) = 96.92$, $p < 0.001$; area 3—$F(3, 20{,}931) = 234.54$, $p < 0.001$; area 4—$F(3, 20{,}931) = 40.52$, $p < 0.001$; area 5—$F(3, 20{,}931) = 90.30$, $p < 0.001$); area 6—$F(3, 20{,}931) = 351.16$, $p < 0.001$).

Table 5. Mean value of proficiency scores by competence areas and STEM subjects.

STEM Subject	Area 1	Area 2	Area 3	Area 4	Area 5	Area 6
M&NS	2.1175	2.0052	1.9575	1.9919	2.1595	1.7064
M	2.2293	2.0537	1.9381	1.9578	2.0594	1.6272
P&C	2.2724	2.1709	2.2224	2.0508	2.2402	1.9083
B&G	2.2915	2.2220	2.2609	2.0889	2.2974	1.9994

Notes: M&N, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology; area 1, professional engagement; area 2, digital resources; area 3, teaching and learning; area 4, assessment; area 5, empowering learners; area 6, facilitating learners' digital competence.

Regarding the post hoc comparisons, in area 1, significant differences among STEM subjects were found except for the comparison between the P&C and the B&G groups ($t = -1.32$, $p = 548$).

Regarding area 2, significant differences were found between all STEM subjects (all p-values < 0.003). As we can see in Figure 2, the first two competence areas have the same pattern of responses, which is different from the pattern obtained for the global proficiency score. In fact, in these two areas, M&NS achieves a lower proficiency score than M (see dashed blue square in Figure 2).

As for area 3, the pattern obtained is the inverse of that obtained for area 2 (see dashed black square in Figure 2), with M reaching the lowest result. The post hoc comparisons show that no differences were registered between M and M&NS (t = 1.23, p = 610) or between P&C and B&G (t = −2.35, p = 085).

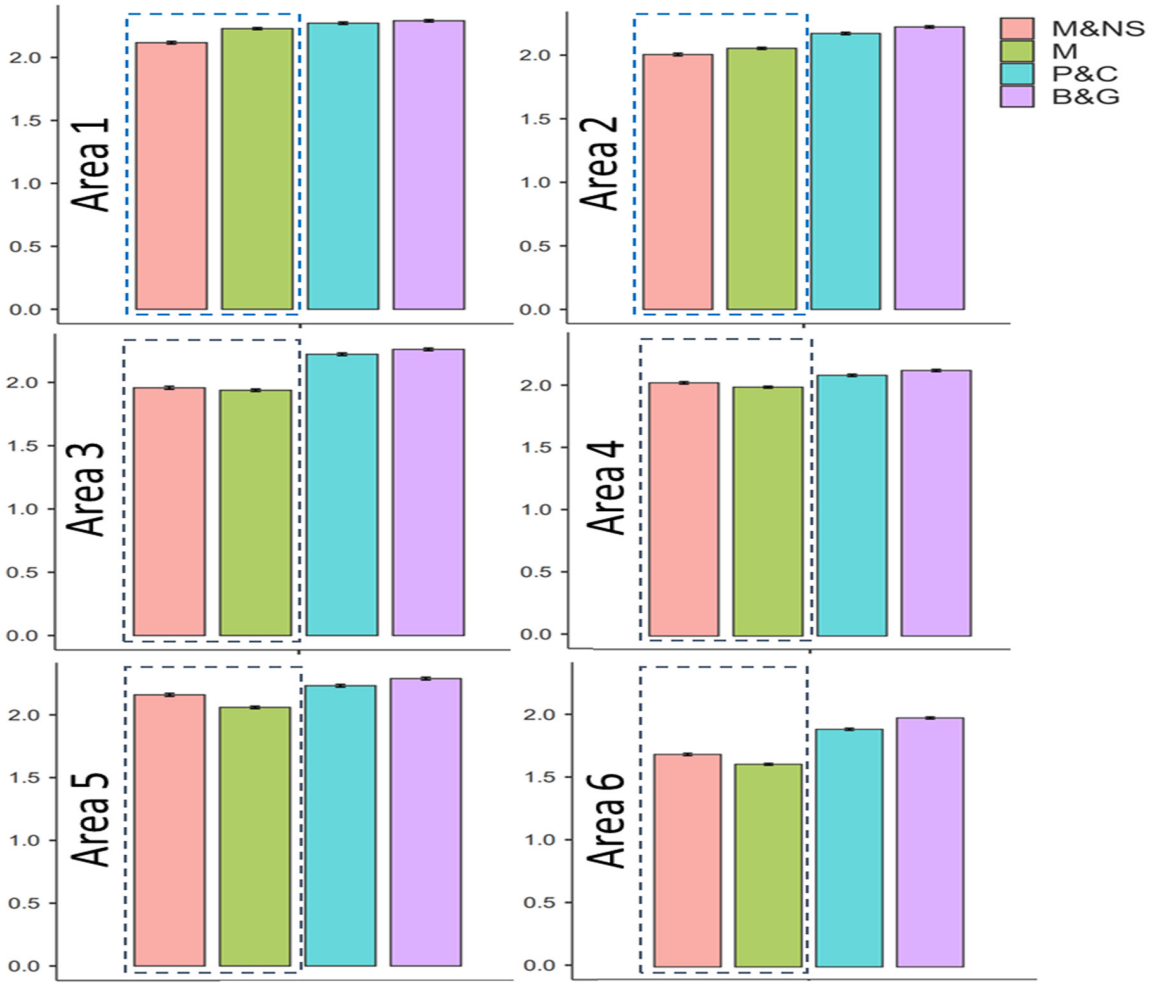


Figure 2. Proficiency scores by competence areas and by STEM subjects. Notes: M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology; area 1, professional engagement; area 2, digital resources; area 3, teaching and learning; area 4, assessment; area 5, empowering learners; area 6, facilitating learners' digital competence.

Areas 4, 5, and 6 display the same pattern as area 3 (see dashed black square in Figure 2): the same obtained in the global proficiency scores, with significant differences recorded between all STEM subjects (all p-values < 0.034).

To explore if the pattern of correlations among the different competence areas varied across STEM subjects, Pearson's bivariate correlations were performed. The correlation matrix (Figure 3) shows the correlation analysis. The results show the existence of significant positive correlations of great magnitude between all competence areas for the four STEM subjects.

The existence of high correlations between all competence areas raises the possibility that there are many shared variances and that some areas may be functioning as moderators or mediators of the relationship between others. Thus, considering these results because that we wanted to account for the interactions among competence areas, a multinomial generalised linear model was carried out using the STEM subject as the dependent variable and the competence areas as covariates. This analysis allowed to predict the STEM subject for each competence area while controlling the remaining five competence areas. The results show that the scores obtained by the teachers in area 1 (χ^2 (3)= 296.5496, $p < 0.001$), area 2 (χ^2 (3) = 19.8236, $p < 0.001$), area 3 (χ^2 (3) = 360.2793, $p < 0.001$), area 4 (χ^2 (3) = 219.4479, $p < 0.001$), area 5 (χ^2 (3) = 77.8185, $p < 0.001$), and area 6 (χ^2 (3) = 650.3029, $p < 0.001$) account for a statistically significant distinction between the different groups of teachers/STEM subjects.

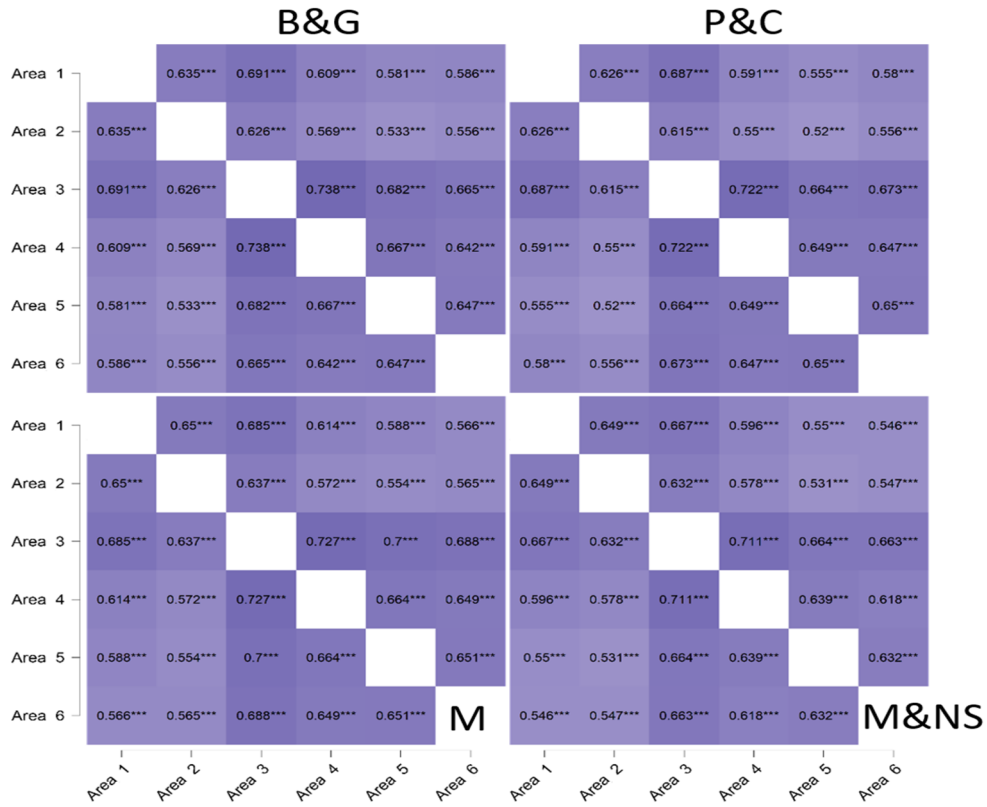


Figure 3. Correlations among the different competence areas across STEM subjects. Notes: M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology; area 1, professional engagement; area 2, digital resources; area 3, teaching and learning; area 4, assessment; area 5, empowering learners; area 6, facilitating learners' digital competence; *** $p < 0.001$.

There is a similar pattern when comparing P&C and B&G teachers. It is only possible to distinguish between them in relation to competence areas 1 (B = −0.1017, SE = 0.024, Z = −2.3901, $p = 0.017$) and 6 (B = −0.2642, SE = 0.04, Z = −2.3901, $p < 0.01$).

As shown in Figure 4 below, the differences for area 1 are mainly found in the lower values; in other words, when controlling the remaining five competence areas, teachers score lower in area 1 and are significantly more likely to teach B&G than P&C. On the other hand, it is the higher values obtained in area 6 that allow us to distinguish between these two groups. This means that when controlling for the remaining five competence areas, teachers scoring higher in area 6 are significantly more likely to be B&G teachers.

Interestingly, the results also show that both B&G and M&NS teachers can be significantly distinguished in all areas (all $p < 0.05$). In this case, the inverted pattern of area 4 (B = −0.5504, SE = 0.0493, Z = −11.1658, $p < 0.001$) with area 6 (B = 0.7003, SE = 0.0467, Z = 14.99, $p < 0.001$) stands out. In fact, when controlling for the remaining five competence areas, teachers with higher values in area 4 are more likely to be M&NS teachers than B&G teachers. Teachers with higher values in competence area 6 are more likely to teach B&G.

Similar results occur when comparing P&C with M&NS (all $p < 0.01$), except for in area 1, in which these two groups cannot be distinguished (B = 0.0144, SE = 0.0445, Z = 0.3249, $p = 0.745$). The differentiating pattern found between B&G and M&NS was also found in the comparison between P&C and M&NS. When looking at the M group, its comparison with the B&G group obtains the same pattern as with the P&C group. In fact, P&C, and B&G cannot be distinguished from the M group in areas 2 and 5 (all $p > 0.134$).

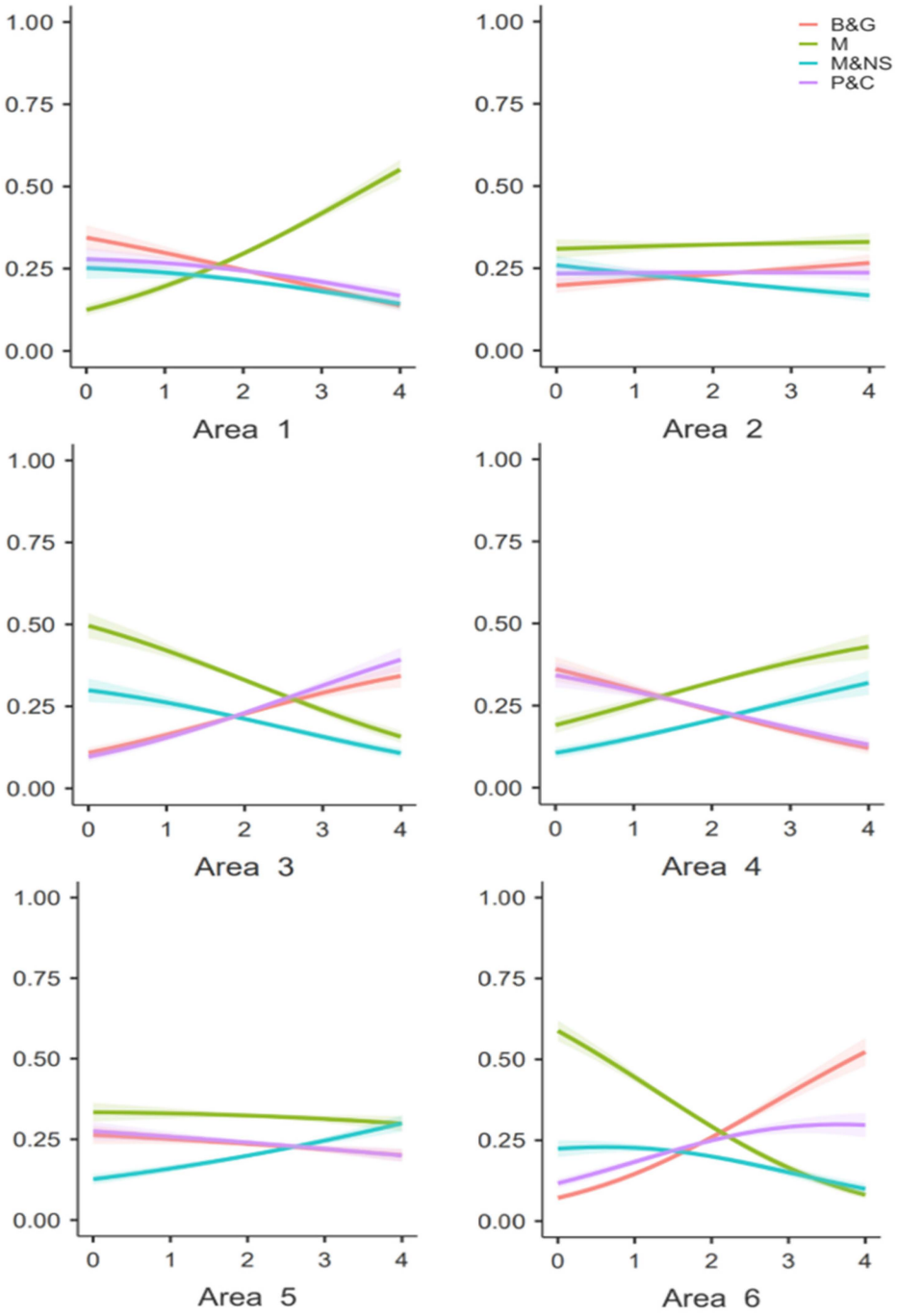


Figure 4. Multinomial generalised linear model plots with areas predicting STEM subject. Notes: M&NS, mathematics and natural sciences; M, mathematics; P&C, physics and chemistry; B&G, biology and geology; area 1, professional engagement; area 2, digital resources; area 3, teaching and learning; area 4, assessment; area 5, empowering learners; area 6, facilitating learners' digital competence.

Teachers with higher scores in areas 1 and 4 are more likely to be from M than from B&G (area 1—B = −0.60074 SE = 0.0407, Z = −14.76, $p < 0.001$; area 4—B = −0.4776 SE = 0.0447, Z = 10.68, $p < 0.001$) or P&C (area 1—B = −0.4989 SE = 0.0404, Z = −12.36, $p < 0.001$; area 4—B = −0.4433 SE = 0.0445, Z = −9.956, $p < 0.001$). On the other hand, when teachers score low in areas 3 and 6, they are more likely to teach M than B&G (area 3—B = 0.5745 SE = 0.0426, Z = 13.48, $p < 0.001$; area 6—B = 0.99 SE = 0.0428, Z = 23.21,

$p < 0.001$) or P&C (area 3—B = 0.6373, SE = 0.0423, Z = 15.058, $p < 0.001$; area 6—B = 0.7286, SE = 0.0424, Z = 17.1739, $p < 0.001$).

When comparing the M group with M&NS, it is only possible to distinguish between them in area 3 (B = −0.0309, SE = 0.0425, Z = −0.7267, $p = 0.467$) and area 4 (B = −0.0728, SE = 0.0456, Z = −1.5958, $p = 0.111$). However, relevant results can be found in area 1: When controlling for the effects of the remaining five competence areas, it is significantly more likely that teachers scoring higher in this area belong to the M group than to M&NS (B = 0.5134, SE =0.0412, Z = 12.47, $p < 0.001$). The opposite pattern was obtained for area 6, where it is more likely that teachers with higher scores belong to the M&NS group (B = −0.2925, SE = 0.0433, Z = −6.751, $p < 0.001$).

4. Discussion

Based on these results, it is evident that the digital competences of these teachers are different even though globally they consider themselves digitally proficient. These differences in their competence may come from several different factors, such as different teacher education (pathways) and length of teaching service. In Portugal, the average age of teachers is around 50 years old, with almost half being over 50, which contrasts with the OECD average of 44 years [32]. Similarly, teachers from the different groups (M&NS, M, P&C, and B&G) are likely to have different education paths (some in universities and others more often in polytechnics) and postgraduate experience, with either masters (2nd cycle of Bologna) or Ph.D. (3rd Cycle) degrees in areas more connected to digital skills, such as Multimedia in Education at the University of Aveiro (https://www.ua.pt/en/curso/276 accessed on 10 January 2023).

Based on the results obtained in this study, a possible explanatory hypothesis for the differences found is the fact that secondary school teachers (B&G and P&C) have developed more digital competences in their initial courses than those in primary education (M&NS) and/or have technological resources in their schools that allow them to make the most of these competences. Additionally, teachers can have different in-service education, which in Portugal is only compulsory for career progression and, depending on the options of each teacher, may have been more linked to technological skills or not.

However, according to the activity report for in-service education in Portugal [33], in-service training on STEM is still scarce in Portugal given that only four training actions were identified (such as "Innovative STEM practices for the development of students' technological and mathematical literacy" (in Portuguese, "Práticas inovadoras STEM para o desenvolvimento da literacia tecnológica e matemática dos alunos") (https://www.ccpfc.uminho.pt/acao-formacao/16221, accessed on 1 September 2023).

Based on the body of evidence underlying the present study and other studies such as that by Kurup et al. [14], teacher education seems to provide only limited understanding and experience with STEM. This indicates a need for very explicit professional development.

Thus, as also highlighted by Fraile, Peñalva-Vélez, and Lacambra [26], the results of this study emphasise the urgent need to purposefully incorporate relational and didactic aspects of digital competence integration into an interdisciplinary perspective of STEM and other areas.

The results of this study need to be read with a limitation in mind relating to the instrument employed, which is based on teacher self-perception. It does not measure what teachers do or are capable of when integrating digital technologies but only their self-perception, which may be under- or overestimated.

5. Conclusions

Portuguese Teachers have different levels of digital proficiency. The results show that B&G teachers achieved significantly higher digital proficiency scores when compared to teachers from three other subjects. The P&C teachers also obtained significantly higher sores than those of the M and M&NS teachers. The results also show significant positive correlations of great magnitude among all competence areas for the four STEM subjects.

One implication of this study is the need for teacher education (initial and in-service) on digital competences. All teachers, including pre-service, may lack comprehensive opportunities to improve their competences in scientific inquiry, technology, design, and engineering to teach the relevant practices proficiently [13].

It is important that teacher education focuses on empowering teachers to deal with STEM in their future classroom teaching and learning: "It is essential to formulate a course work and professional development in STEM, capable of integrating disciplines, providing an understanding of pedagogical approaches, and connecting to real-life relevance with the twenty-first century competencies" [14] (p. 1). According to these authors, future teachers have strongly held beliefs and intentions for teaching STEM in their future classrooms. The reality they face is the lack of knowledge on how to integrate science, mathematics, engineering, and technology as well as pedagogical approaches to deal with STEM based on real-life situations.

The major limitation found in this study, in addition to the one related to the employed instrument that is based on teacher self-perception, which does not measure what teachers do or are capable of when integrating digital technologies, has to do with the scarcity of studies focused on initial teacher-training courses considering the Bologna process that began in Portugal in 2007. This fact does not allow for other discussions of results that would be relevant, for instance, to verify whether the different training paths have an impact on digital competences.

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