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Cognitive Skills of Canadian Educators: An Analysis of PIAAC Data

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The purpose of this study was to conduct national and cross-country analyses to provide insights about educator cognitive skills in literacy, numeracy, and problem-solving within Canada and across nineteen countries using the PIAAC data. MANOVA results of profession differences within Canada demonstrated that educators outperformed other professions in general programs, health and welfare, and services but underperformed the professions in science, mathematics, and computing in all three domains. MANOVA results of educator differences across countries showed that educators in Canada outperformed those in Denmark, Estonia, the Russian Federation, and the United Kingdom in literacy, outperformed the United Kingdom in numeracy, and outperformed Denmark, Estonia, and the United Kingdom in problem-solving. Finally, multiple regression analyses identified statistically significant indicators of Canadian educators' literacy, numeracy, and problem-solving proficiencies. The results of this study reveal and suggest that the cognitive skills of Canadian educators have the potential to be enhanced.

L'objectif de cette étude était de mener des analyses nationales et internationales afin de fournir des informations sur les compétences cognitives des éducateurs en matière de littératie, de numératie et de résolution de problèmes au Canada et dans dix-neuf pays à l'aide des données de l'enquête PIAAC. Les résultats de l'analyse MANOVA des différences entre les professions au Canada ont démontré que les éducateurs surpassent les autres professions dans les domaines des programmes généraux ; de la santé et du bien-être ; et des services, mais qu'ils sont moins performants que les autres professions en sciences, en mathématiques et en informatique dans les trois domaines. Les résultats de l'analyse MANOVA des différences entre les éducateurs des différents pays ont montré que les éducateurs du Canada surpassent ceux du Danemark, de l'Estonie, de la Fédération de Russie et du Royaume-Uni en littératie, surpassent ceux du Royaume-Uni en numératie et surpassent ceux du Danemark, de l'Estonie et du Royaume-Uni en résolution de problèmes. Enfin, les analyses de régression multiple ont permis d'identifier des indicateurs statistiquement significatifs des compétences des éducateurs canadiens en matière de littératie, de numératie et de résolution de problèmes. Les résultats de cette étude révèlent et suggèrent que les compétences cognitives des éducateurs canadiens ont le potentiel d'être améliorées.

The 21st century is characterized as the era of the knowledge-based economy due to rapid changes occurring in technologies and advanced computer-based systems. As the knowledge and technology requirements of today's jobs are growing rapidly, fostering a high-quality education system that helps all students develop the knowledge and skills they need to succeed in the modern workplace is central to the future success of every country in the global economy.

Teachers are one of the most important factors of education systems because they educate students and set them up for future success.

Teachers are lifelong learners and their education path includes studying education programs, training in classrooms as a teacher candidate, and then becoming a licensed teacher. Their learning continues with job-related training and learning in content, pedagogy, and technology to improve their teaching in a technology-enhanced learning environment. Thus, teacher qualifications improve during their education and training. Even though teacher qualification is a complex construct that has been operationalized through different components such as content knowledge, pedagogical knowledge, teaching experience, and cognitive skills, researchers highlighted the need to investigate this construct because of its relationship with student achievement (Croninger et al., 2007; Manning et al., 2019). In particular, it is important to measure and understand teachers' cognitive skills because they are considered as one of the key teacher qualification criteria.

Development of Cognitive Skills

The 21st century requires people to have additional skills, not only for workplaces, but also for everyday life (Hämäläinen et al., 2019). Literacy, numeracy, and problem-solving skills are the most fundamental skills in the 21st century, and the need for them is likely to increase in the future because they are interpreted as the essential aspects of the labor force (Hämäläinen et al., 2015). These skills are important for both individuals and society because people with these skills contribute to economic growth and societal advancement (Hanushek & Kimko, 2000; OECD, 2013a). The education systems are the most important pathway for the majority of students to gain these skills (Ananiadou & Claro, 2009). Teachers have a major role in improving student learning (Hanushek et al., 2014) and thus they are essential in education systems to help students acquire knowledge, skills, and competencies. Despite the need for the development of 21st century skills for teachers, and thus for students, few teacher training programs address the 21st century skills (e.g., New Zealand and Korea), although some teaching programs such as those in Belgium and Austria target the teaching and development of pedagogical use of new technologies (Ananiadou & Claro, 2009). However, to what extent these training programs focus on teaching and development of 21st century skills is not clear (Ananiadou & Claro, 2009). Even though most teacher programs do not target 21st century skills, studies showed that they improve pre-service teachers' skills through learning activities during the program such as a technology reinforced learning environment (Nissim et al., 2016), learning-by-teaching (Aslan, 2015), or the use of learning management systems (Neghavati, 2016).

Why Teacher Cognitive Skills Matter?

To understand student learning (i.e., knowledge, skills, and competencies), teacher effectiveness should be investigated. Teacher effectiveness refers to pedagogical approaches to facilitate and enable student learning and ultimately to improve education (Klassen & Tze, 2014; Seidel & Shavelson, 2007). In the literature, there are two common ways of measuring teacher effectiveness: student achievement and teacher qualifications.

Regarding the first method, student achievement test scores are used as a direct measure of teacher effectiveness (Meyer, 2017; Thompson & Cook, 2014). Education policymakers assume that teacher effectiveness is measurable through their student achievement on examinations

(Pratt, 2016). However, assessing teacher effectiveness based on the student achievement on examinations is itself opposed to the nature of the educational process (Meyer, 2017). When teachers are forced to think about their teaching in relation to student achievement on examinations, this might have negative results because teachers become framed (e.g., good teachers and bad teachers) by student achievement. The use of examination results goes beyond the purpose of education and they become a position that is privileged over educational values and practices. Teachers *teach to the test* in a very direct manner, meaning that they tailor their teaching to meet the requirements of the examinations because they know that student test results are being used against them (Jones, 2007; Pratt, 2016; Tanner, 2013). Therefore, the extent to which student test results are, or are not, measures to teacher effectiveness is controversial.

In contrast to the use of student test results as a direct measure of teacher effectiveness, alternatively, teacher qualifications have been investigated as an indicator of teacher effectiveness and their importance for student learning has been highlighted (e.g., Hanushek et al., 2019; Metzler & Woessmann, 2012). Teacher cognitive skills are an important component of teacher effectiveness because high-quality teaching requires high cognitive skills. Studies reported that teachers' individual qualifications affect their teaching effectiveness and student learning (Hanushek et al., 2019; Hill et al., 2019). Metzler and Woessmann (2012) studied teachers' skills and found them to be linked to productivity in the education systems. Particularly, good teachers enhance their student learning (Hanushek et al., 2019) and teacher cognitive skills have been recognized as an indicator to explain teacher effectiveness and the differences in student performances in a global context (Hanushek et al., 2014).

Literature showed different results regarding the relation between teacher cognitive skills and teacher effectiveness. Many studies investigated teacher skills measured by scores on standardized tests (e.g., teacher licensure tests) and found a relationship between teacher cognitive skills and teacher effectiveness (Andrew et al., 2005; Boyd et al., 2008; Corcoran & O'Flaherty, 2018; D'Agostino & Powers, 2009; Goldhaber et al., 2013; Goldhaber et al., 2017; Jacob et al., 2018; Memory et al., 2001). Hanushek et al. (2014) investigated teacher cognitive skills and student performance and found an association between them. In another study, Hanushek et al. (2019) provided systematic evidence to show that teachers' cognitive skills impact student achievement. They explained the differences in student performance across countries through the differences in the cognitive skills of teachers. In summary, the literature has shown that teacher cognitive skills explain at least in part teacher effectiveness and student achievement, and the use of student test scores as a direct measure of teacher effectiveness has a negative impact on teaching and learning. Therefore, it is important to assess teacher cognitive skills directly, as a way to measure teacher effectiveness.

Cognitive Skills in the 21st Century

Technological developments have been reshaping education in the 21st century. Over the last decade, different educational technologies have been available to be used in education settings such as digital learning platforms and intelligent tutoring systems. The use of technology in education requires changes in foundational skills such as literacy, numeracy, and problem-solving. That is, the way teachers read or write texts, apply mathematical information, or solve problems has been reshaped in the 21st century through computers and the internet. Regarding literacy skills, teachers need to have skills to read or write digital texts such as creating, critiquing, analyzing, and evaluating digital content. Numeracy skills in the digital environment require more skills than basic numeracy skills to be able to apply and communicate mathematical information such as designing infographics. Technology makes problem-solving easier in some cases, but it also leads to the necessity of possessing new forms of problem-solving skills (Hämäläinen et al., 2017). Problem-solving in technology-rich environments is beyond basic problem-solving because teachers need to know how to search and locate information on the web and how to extract and organize information from the web (Vörös & Rouet, 2016). In addition to the effects of digital technologies on teachers' cognitive skills, digital technologies make information and communications technology (ICT) skills essential to teachers. Teachers need to possess the ICT knowledge and skills to use ICT tools or applications because they support and enhance their cognitive skills and classroom teaching (Ananiadou & Claro, 2009).

Measurement of the Cognitive Skills

As literacy, numeracy, and problem-solving skills are increasingly important skills, it is important to measure these cognitive skills. Furthermore, it is important to measure these skills in the context of ICT because digital technology is an essential part of every aspect of human lives in the 21st century (Liao et al., 2019). To measure these skills, the most known assessment is the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC was developed by the Organisation for Economic Co-operation and Development (OECD) to measure adults' skills in literacy, numeracy, and problem-solving in technology-rich environments through computer-based assessment (OECD, 2013b) providing information about cognitive skills and focusing on education and employment (OECD, 2016). Regarding studies with a focus on teacher cognitive skills through PIAAC data, Golsteyn et al. (2016) focused on literacy and numeracy skills and found that teachers significantly outperform other professions on both skills across the countries where the Canadian sample was excluded from the study. In another study, Cai and Gut (2018) focused on literacy and problem-solving skills and studied four countries from the PIAAC: the United States, Canada, Finland, and Japan. They found that teachers in Canada outperform other professions (i.e., other non-education fields) in their country in literacy. Regarding cross-country analyses, their results demonstrated that Canadian educators showed significantly lower performance in literacy than Finnish and Japanese educators while showing significantly higher performance in problem-solving than American educators.

We have adopted the definitions of literacy, numeracy, and problem-solving in technology-rich environments by the OECD as we used PIAAC data in this study. Literacy is defined as "understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" OECD (2012, p. 20). The definition of numeracy skills is "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (OECD, 2012, p. 34). Problem-solving in technology-rich environments is defined as "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2012, p. 47). In addition, following Cai and Gut's (2018) study, we referred to adults whose response was "teacher training and education science" to the question "What was the area of study, emphasis or major for your highest level of qualification?" as *educators*. Similarly, we referred to adults whose responses were not "teacher training and education science" as *non-educators*.

Current Study

As summarized above, digital technologies have been reshaping education and the cognitive skills of educators. It is highly important to measure and understand educators' skills. However, there is a limited number of research studies on the educators' performances in literacy, numeracy, and problem-solving domains. Past research on teacher cognitive skills investigated the relationship between teacher cognitive skills and student achievement (e.g., Hanushek et al., 2014; Hanushek et al., 2019) or teacher cognitive skills and teacher effectiveness (e.g., Corcoran & O'Flaherty, 2018; D'Agostino & Powers, 2009). Other studies examined teacher cognitive skills across countries but focused on only two cognitive skills (e.g., Cai & Gut, 2018; Golsteyn et al., 2016). The purpose of this paper is to delve into the basic cognitive skills of educators whose area of study is teacher training and education science through PIAAC data by conducting national and cross-country analyses with a focus on the Canadian sample, the country with the largest PIAAC sample. The research questions are (1) whether there are differences between the performances of educators and non-educators in Canada in literacy, numeracy, and digital problem-solving domains, (2) whether educators in Canada perform differently from the educators in the other countries in literacy, numeracy, and digital problem-solving domains and (3) what factors predict Canadian educators' literacy, numeracy, and digital problem-solving performances.

Method

Dataset

We studied the PIAAC data collected in the twenty-four countries by the OECD from 2011 to 2012 (round 1) to understand the basic cognitive skills of adults whose area of study was teacher training and education science. The public-use data files are available on OECD's official website. The PIAAC included adults aged 16–65 and addressed three skills: literacy, numeracy, and problem-solving in technology-rich environments. This makes PIAAC unique because one can have information on three basic skills only using data from one assessment.

PIAAC consists of a detailed background and skill use survey and an assessment of literacy, numeracy, and problem-solving in technology-rich environments skills and predominantly collects data using ICT skills (Liao et al., 2019). However, it should be noted that 21st century technology has made computer skills essential for cognitive skills but the purpose of PIAAC is not to measure the familiarity with ICT but to assess their ability to use digital resources to locate, access, and process information critically and effectively in purposeful tasks (Vörös & Rouet, 2016).

In terms of the data collection, first, face-to-face interviews were conducted to collect information for the background questionnaire, and then assessments were administered to the respondents. The PIAAC assessment was administered through two modes of administration: computer and paper-and-pencil. For the participants who had no computer experience or did not want to take a computer-based assessment, proficiency scores in problem-solving are not available and thus they were not included in the analyses. Proficiency in each domain is measured on a scale of 500 points where higher scores refer to higher proficiency (OECD, 2016).

Data Analysis

We used the survey data and assessment data from the PIAAC with a focus on educators within Canada and across different countries. The purpose of our study is to provide some insights into the cognitive skills of Canadian educators by conducting national and cross-country analyses. We conducted this study in three phases and our research questions were:

1. Do educators perform differently from the non-educators in literacy, numeracy, and digital problem-solving domains in Canada?
2. Do educators in Canada perform differently from educators in the other countries in literacy, numeracy, and digital problem-solving domains?
3. What factors can predict educators' literacy, numeracy, and digital problem-solving performances?

Comparison of Performances of Educators and Non-Educators in Canada

We compared literacy, numeracy, and digital problem-solving performances of educators with non-educators in Canada (see Table 1). Respondents who had plausible values in each domain were included in the analysis. We used a one-way multivariate analysis of variance (MANOVA) to understand whether there are differences in three domains of different professions' performances in Canada. The assumptions of MANOVA (i.e., adequate sample size, two or more continuous dependent variables, independent variable with two or more levels, independence of observations, absence of univariate and multivariate outliers, multivariate normality, absence of multicollinearity, linearity, homogeneity of variance) were checked.

Comparison of Educators' Performances across Countries

The target population for this research question consisted of educators who were residents of one of the countries that participated in PIAAC data collection in the first round. There were twenty-

Table 1

Number of Respondents for Each Profession in Canada

Profession	Number of respondents
General programs	5,082
Teacher training and education science	1,275
Humanities, languages, and arts	1,383
Social sciences, business, and law	3,133
Science, mathematics, and computing	1,863
Engineering, manufacturing, and construction	2,164
Agriculture and veterinary	234
Health and welfare	1,835
Services	1,195
Total	18,164

four countries in the first round and one of them, Australia, was excluded from the analysis because of the lack of dataset for this country on the OECD's official website. Also, three countries, Spain, France, and Italy were excluded from the analysis due to a lack of data regarding the digital problem-solving domain. In the analysis, we included respondents who took each assessment (see Table 2) and used the merged dataset (i.e., the datasets of countries in the first round were merged into one dataset). We used one-way MANOVA to understand whether there are differences in literacy, numeracy, and problem-solving performances of educators across countries. The assumptions of MANOVA were checked.

Identifying Factors of Educators' Performances

Even though our first attempt was to perform hierarchical linear modeling (HLM) because of the data structure of educators nested within countries, we adopted multiple regression because of the given low ICC value (i.e., interclass correlation coefficient) of around 0.02 according to the preliminary analysis of HLM. We used hierarchical multiple regression to find out what factors are highly associated with the performances of Canadian educators and predict their literacy, numeracy, and digital problem-solving proficiency levels. The assumptions of multiple regression

Table 2

Number of Educators in PIAAC Across Countries

Country	Number of respondents
Austria	207
Belgium	296
Canada	1,275
Czech Republic	212
Denmark	658
Estonia	223
Finland	196
Germany	169
Ireland	232
Japan	257
Korea	232
Netherland	241
Norway	307
Poland	299
Russian Federation	233
Slovak Republic	194
Sweden	298
United Kingdom (England and Northern Ireland)	449
United States	278
Total	6,256

(i.e., linearity, multivariate normality, multicollinearity, homoscedasticity) were checked. We included all Canadian educators and did multiple imputations by Predictive Mean Matching (PMM) to deal with missing data, resulting in a total sample size of 1,448.

With respect to the dependent variables, we used educators' proficiencies in literacy, numeracy, and digital problem-solving. Table 3 presents the descriptions of categorical variables in the regression models. To determine which factors to enter into the model as the first layer variables, we used previous research studies to identify factors that were found to be related to adults' skills (see Table 4). These variables selected based on the literature were entered into the model first, followed by the second layer variables including those that have not been studied in the literature. In terms of the second layer variables, we used both life-related and work-related factors to explain the performances of Canadian educators because we assumed that their knowledge and skills are related to both their personal lives and work (Hämäläinen et al., 2015). We focused on these main groups to select the second layer variables: background variables, work-related variables, and everyday life-related variables. Table 4 summarizes the first layer variables and Table 5 demonstrates the second layer variables for each dependent variable in the regression model. Regarding the categorical variables, they were recoded into a set of binary variables (i.e., dummy coding) before entering into the models (see Table 3).

Table 3

Descriptions of Categorical Variables in the Regression Models

Categorical variables	Category	Description
Gender		
	1	Male
	2	Female
Education level		
	1	Lower secondary or less
	2	Upper secondary
	3	Postsecondary
	4	Professional degree
	5	Bachelor degree
	6	Master/research degree
Education level of parents		
	1	Neither parent has attained upper secondary
	2	At least one parent has attained secondary and postsecondary, non-tertiary
	3	At least one parent has attained tertiary
Number of books		
	1	10 books or less
	2	11–25 books
	3	26–100 books
	4	101–200 books
	5	201–500 books
	6	More than 500 books
Level of computer use		
	1	Straightforward

Table 3 (continued)

Categorical variables	Category	Description
(Level of computer use, continued)		
	2	Moderate
	3	Complex
Solve simple problems		
	1	Never
	2	Less than once a month
	3	Less than once a week but at least once a month
	4	At least once a week but not every day
	5	Every day
Solve complex problems		
	1	Never
	2	Less than once a month
	3	Less than once a week but at least once a month
	4	At least once a week but not every day
	5	Every day
Related work experience in years		
	1	None
	2	Less than 1 month
	3	1 to 6 months
	4	7 to 11 months
	5	1 to 2 years
	6	3 years or more
Paid work		
	1	Has not paid work in past 5 years
	2	Has had paid work in past 5 years
Monthly income		
	1	Lowest decile
	2	9th decile
	3	8th decile
	4	7th decile
	5	6th decile
	6	5th decile
	7	4th decile
	8	3rd decile
	9	2nd decile
	10	Highest decile
AET for job-related reasons		
	1	Did not participate in formal or non-formal AET for job-related reasons
	2	Participated in formal or non-formal AET for job-related reasons
AET for non-job-related reasons		
	1	Did not participate in formal or non-formal AET for non-job-related reasons
	2	Participated in formal or non-formal AET for non-job-related reasons

Note. AET: Adult Education and Training

Table 4

List of Variables Found Related to Literacy, Numeracy, or Problem-Solving in the Literature

Control variables	Literacy	Numeracy	Problem-solving
Gender		x	x
ICT at work			x
ICT at home			x
Numeracy at work			x
Numeracy at home			x
Reading at work			x
Reading at home			x
Writing at work	x		
Number of books			x
Education level of parents			x
Education level	x	x	x
Level of computer use	x	x	x
Solve simple problems	x	x	x
Solve complex problems	x	x	x
Related work experience in years	x	x	x
Paid work	x	x	x
Monthly income	x	x	x

Note. ICT: Information and Communications Technology

Table 5

List of Variables Used in the Regression Model as the Second Layer Variables

Variables	Literacy	Numeracy	Problem-solving
Gender	x		
ICT at work	x	x	
ICT at home	x	x	
Numeracy at work	x	x	
Numeracy at home	x	x	
Reading at work	x	x	
Reading at home	x	x	
Writing at work		x	x
Writing at home	x	x	x
Number of books	x	x	
Education level of parents	x	x	
AET for job-related reasons	x	x	x
AET for non-job-related reasons	x	x	x

Note. ICT: Information and Communications Technology; AET: Adult Education and Training

Regarding the prediction of literacy performances, education level, related work experience, use of writing skills at work, level of computer use, solve simple and complex problems, paid work and monthly income were entered into the model first as the first layer variables (Liao et al., 2019). After that, gender, education level of parents and number of books (background variables); the use of ICT, numeracy and reading skills at work, and adult education and training for job-related reasons (work-related variables); the use of ICT, numeracy, reading and writing skills at home, and adult education and training for non-job-related reasons (everyday life-related variables) were entered into the model as the second layer variables.

In terms of prediction model of numeracy performances, gender, education level, related work experience, level of computer use, solve simple and complex problems, paid work and monthly income were entered into the model first as the first layer variables (Liao et al., 2019). The Education level of parents and number of books (background variables); the use of ICT, numeracy, reading and writing skills at work, and adult education and training for job-related reasons (work-related variables); the use of ICT, numeracy, reading, and writing skills at home, and adult education and training for non-job-related reasons (everyday life-related variables) were entered into the model as the second layer variables.

Finally, we entered sixteen variables as the first layer variables into the regression model of problem-solving performances because most of the research studies in the literature investigated the problem-solving domain. It was found in the literature that the use of ICT skills at work and in everyday life (Desjardins & Ederer, 2015; Hämäläinen et al., 2015), the use of numeracy skills at work and in everyday life, the use of reading skills in everyday life (Hämäläinen et al., 2015), education level of parents, related work experience, reading skills at work, gender, paid work, level of computer use, monthly income, solve simple and complex problems (Liao et al., 2019), the education level (Cai & Gut, 2018; Liao et al., 2019) and the number of books (Hämäläinen et al., 2019) had an association with problem-solving proficiency. We entered these sixteen variables as the first layer variables and selected only four variables as the second layer variables which were the use of writing skills at work, and adult education and training for job-related reasons (work-related variables); the use of writing skills at home, and adult education and training for non-job-related reasons (everyday life-related variables).

Results

Results From MANOVA Among Professions

A one-way MANOVA was performed to determine the differences of performances on literacy, numeracy, and problem-solving domains across various professions using PIAAC assessment. The correlations among the dependent variables were as follows: the correlation between literacy and numeracy is .83; the correlation between literacy and problem-solving is .8; and the correlation between numeracy and problem-solving is .73. There was a statistically significant difference among the professions on the combined dependent variables (literacy, numeracy, and problem-solving), *Pillai's Trace* = .128, $F(24,54465) = 100.74$, $p<.001$. The multivariate effect size was small and estimated at 0.043, which implies that 4.3% of the variance was accounted for by different professions.

The statistically significant one-way MANOVA was followed up by univariate one-way ANOVA examining, separately, each dependent variable to identify the specific dependent variables that contributed to the overall significant result. The univariate tests showed that there was a statistically significant difference in literacy $F(8,18155) = 160.33$, $p<.001$, $\eta^2 = .066$, numeracy $F(8,18155) = 147.92$, $p<.001$, $\eta^2 = .061$, and problem-solving $F(8,18155) = 86.942$, $p<.001$, $\eta^2 = .037$ among professions.

We performed a Games-Howell post-hoc test as multiple pairwise comparisons to determine which professions were different. There were statistically significant differences between educators and the following professions on the performances in all three domains: general programs; science, mathematics, and computing; engineering, manufacturing, and construction; health and welfare; services. In addition, significant differences were found between educators and the professions in the areas of humanities, languages, and arts, and agriculture and veterinary on the problem-solving domain.

Regarding the literacy domain, among all professions, educators (*M* = 291, *SD* = 41.86) underperformed the professions in the area of science, mathematics, and computing (*M* = 296, *SD* = 43.05) but outperformed the other professions: general programs (*M* = 268, *SD* = 41.79), engineering, manufacturing, and construction (*M* = 280, *SD* = 44.58), health and welfare (*M* = 281, *SD* = 42.67), and services (*M* = 267, *SD* = 42.66). Regarding numeracy proficiency, educators (*M* = 280, *SD* = 44.36) had higher performances than the professions in the areas of general programs (*M* = 261, *SD* = 45.25), health and welfare (*M* = 273, *SD* = 46.94), and services (*M* = 263, *SD* = 44.08) but lower performances than other professions in the areas of science, mathematics, and computing (*M* = 294, *SD* = 47.40), and engineering, manufacturing, and construction (*M* = 287, *SD* = 48.46). Finally, regarding educators' problem-solving performances (*M* = 284, *SD* = 40.63), they outperformed the professions in the areas of general programs (*M* = 273, *SD* = 42.46), engineering, manufacturing, and construction (*M* = 278, *SD* = 45.44), agriculture and veterinary (*M* = 273, *SD* = 40.79), health and welfare (*M* = 277, *SD* = 43.29), and services (*M* = 269, *SD* = 40.95) but underperformed other professions in humanities, languages, and arts (*M* = 289, *SD* = 40.16), and science, mathematics, and computing (*M* = 297, *SD* = 41.24).

Results From MANOVA Among Countries

A one-way MANOVA was performed to determine the differences in educators' performances on literacy, numeracy, and problem-solving domains in PIAAC assessment among nineteen countries. The correlations among the dependent variables were as follows: the correlation between literacy and numeracy is .8; the correlation between literacy and problem-solving is .76; and the correlation between numeracy and problem-solving is .69. The results showed that there was a statistically significant difference across countries on a linear combination of the literacy, numeracy, and problem-solving performances of educators, *Pillai's Trace* = .18, $F(54,18711) = 22.419$, $p<.001$. The multivariate effect size was medium and estimated at .061, which implies that 6.1% of the variance was accounted for by countries.

Follow-up univariate tests showed that there was a statistically significant difference in literacy $F(18,6237) = 19.3$, $p<.001$, $\eta^2 = .053$, numeracy $F(18,6237) = 22.3$, $p<.001$, $\eta^2 = .061$, and problem-solving $F(18,6237) = 12.9$, $p<.001$, $\eta^2 = .036$ of educators across countries. We performed a Games-Howell post-hoc test to determine which countries were different. Overall, a significant difference in the educators' performances was found between Canada and the United Kingdom on all three domains. There were statistically significant differences between Canada (*M* = 291, *SD* = 41.86) and the countries Denmark (*M* = 273, *SD* = 36.85), Estonia (*M* = 279, *SD* = 38.03), Finland (*M* = 309, *SD* = 41.62), Japan (*M* = 303, *SD* = 33.56), Norway (*M* = 299, *SD* = 33.67), the Russian Federation (*M* = 276, *SD* = 39.01), and the United Kingdom (*M* = 280, *SD* =

41.71) on the educators' performances in the literacy domain. Among these countries, educators in Canada outperformed in the literacy domain compared to the educators in Denmark, Estonia, the Russian Federation, and the United Kingdom.

Other significant differences were found between Canada (M = 280, SD = 44.36) and the countries Austria (M = 302, SD = 36.86), Belgium (M = 300, SD = 34.48), Czech Republic (M = 296, SD = 36), Finland (M = 305, SD = 40.22), Germany (M = 302, SD = 38.33), Japan (M = 293, SD = 37.85), the Netherlands (M = 292, SD = 39.72), Norway (M = 299, SD = 38.94), Slovak Republic (M = 291, SD = 35.31), Sweden (M = 296, SD = 41.90), and the United Kingdom (M = 271, SD = 46.15) on the educators' performances in the numeracy domain. Canadian educators performed better in the numeracy domain than only the educators in the United Kingdom. Regarding the problem-solving domain, there were statistically significant differences between Canada (M = 284, SD = 40.63) and only four countries Austria (M = 294, SD = 34.55), Denmark (M = 272, SD = 38.04), Estonia (M = 256, SD = 39.60), and the United Kingdom (M = 274, SD = 38.09) on the educators' performances. Only the educators in Austria outperformed in the problem-solving domain compared to Canadian educators.

Results from Regression

Results for the Literacy Domain

First, we performed hierarchical multiple regression for the outcome variable literacy performances to develop a model for predicting Canadian educators' literacy performances. The first model (Model 1) included variables: the use of writing skills at work, education level, level of computer use, solve simple problems, solve complex problems, related work experience in years, paid work, and monthly income. Overall, the first model was statistically significant, $F(30,1417) = 8.862$, $p<.001$, $R^2 = .158$. In the next step (Model 2), we added the following variables: gender, the use of ICT skills at work and home, numeracy skills at work and home, reading skills at work and home and writing skills at home, number of books, education level of parents, adult education and training for job-related reasons and non-job-related reasons. Overall, the second model was statistically significant, $F(47,1400) = 9.718$, $p<.001$, $R^2 = .246$. By adding the second layer variables, the R^2 increased by .088 and the model showed a statistically significant change according to the corresponding F-statistic and p-value, $F(17,1400) = 9.613$, $p<.001$.

Results for the Numeracy Domain

Second, we performed another hierarchical multiple regression to examine whether Model 2 explained the Canadian educators' numeracy performances better than Model 1. Model 1 consisted of variables gender, education level, level of computer use, solve simple and complex problems, related work experience in years, paid work, and monthly income. Model 1 was statistically significant, $F(30,1417) = 10.48$, $p<.001$, $R^2 = .182$. In Model 2, we entered the following variables into the model: the use of ICT skills at work and home, numeracy skills at work and home, reading skills at work and home and writing skills at work and home, number of books, education level of parents, adult education and training for job-related reasons and non-job-related reasons. Model 2 was statistically significant, $F(47,1400) = 11.8$, $p<.001$, $R^2 = .284$. The variables in the second model explained an additional 10.2% of the variance in numeracy performances and it was statistically significant, $F(17,1400) = 11.732$, $p<.001$.

Results for the Problem-Solving Domain

One final hierarchical multiple regression was performed to predict Canadian educators' problem-solving performances. We entered sixteen variables in Model 1 and three variables in Model 2. The variables in the first model were gender, the use of ICT skills at work and home, numeracy skills at work and home and reading skills at work and home, number of books, education level of parents, education level, level of computer use, solve simple and complex problems, related work experience in years, paid work and monthly income. Overall, the first model was statistically significant, $F(43,1404) = 6.857$, $p<.001$, $R^2 = .174$. In Model 2, we entered the variables: the use of writing skills at work and home, adult education, and training for job-related reasons and non-job-related reasons into the model. Model 2 was statistically significant, $F(47,1400) = 7.101$, $p<.001$, $R^2 = .193$. R^2 went up from 17.4% to 19.3% (Model 1 to Model 2) and the change was statistically significant, $F(4,1400) = 8.213$, $p<.001$, which implies that when we controlled these sixteen variables, 1.9% of the variance explained by the use of writing skills at work and home, adult education and training for job-related reasons and non-job-related reasons.

Table 6 summarizes the significant variables in the regression models for each outcome variable. According to the regression results of Model 2 in the three sets of analyses, all three outcome variables had eleven significant predictors in common: gender, education level, solve complex problems, related work experience in years, monthly income, the use of numeracy skills at home and reading skills at work, number of books, education level of parents, adult education and training for job-related reasons and non-job-related reasons. In addition to these common significant predictors, each outcome had two additional significant predictors. Solving simple problems was a significant predictor for only the numeracy domain. The use of ICT skills at work significantly predicted the problem-solving domain. The use of ICT skills at home was a significant predictor for both literacy and problem-solving domains. Finally, the use of writing skills at work was a significant predictor for both literacy and numeracy domains. Five predictors did not significantly predict any outcome variables: level of computer use, paid work, the use of numeracy skills at work, reading skills at home, and writing skills at home.

Regarding regression coefficients (see Table 7 for unstandardized regression coefficients), Canadian educators who had a higher level of education, parents with a higher level of education, a higher number of books, solved complex problems more frequently, used numeracy skills at home more frequently, attended job-related and non-job-related education and training tended to have higher scores in the three domains. However, Canadian educators who used reading skills at work tended to have lower scores in the three domains. Also, the negative coefficient for gender in the regression indicates that being a female is associated with a decrease in performance relative to males. We also found negative coefficients for work experience and monthly income. These negative coefficients indicate that Canadian educators who had short work experience (i.e., 1 to 6 months or 1 to 2 years) might get a score lower than the educators who had no experience. Similarly, for example, the performances of educators with monthly income at the 8th decile were not better than the educators with monthly income at the lowest decile for all domains.

Discussion

In this study, we examined the profession differences in the average PIAAC scores within Canada and country differences in the average scores of educators. Also, we identified factors that influence Canadian educators' literacy, numeracy, and problem-solving performances. Among

Table 6

Hierarchical Regression Analyses of Literacy, Numeracy and Problem-Solving Performances

	Literacy		Numeracy		Problem-solving	
Predictor variables	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Gender		1	1	1	0	1
Education level	1	1	1	1	1	1
Level of computer use	1	0	0	0	0	0
Solve simple problems	1	0	1	1	0	0
Solve complex problems	1	1	1	1	1	1
Related work experience in years	1	1	1	1	1	1
Paid work	1	0	1	0	0	0
Monthly income	1	1	1	1	1	1
ICT at work		0		0	1	1
ICT at home		1		0	1	1
Numeracy at work		0		0	0	0
Numeracy at home		1		1	1	1
Reading at work		1		1	1	1
Reading at home		0		0	0	0
Writing at work	0	1		1		0
Writing at home		0		0		0
Number of books		1		1	1	1
Education level of parents		1		1	1	1
AET for job-related reasons		1		1		1
AET for non-job-related reasons		1		1		1
R^2	.158	.246	.182	.284	.174	.193
R^2 change	.158	.088	.182	.102	.174	.019

Note. The number 0 indicates that this continuous variable or any level of this categorical variable was not significantly different from 0 at the significant level of .05. The number 1 indicates that this continuous variable or at least one level of this categorical variable was significantly different from 0 at the significant level of .05. ICT: Information and Communications Technology; AET: Adult Education and Training.

nineteen countries, educators in Canada outperformed the educators in Denmark, Estonia, the Russian Federation, and the United Kingdom in the literacy domain, and the educators in the United Kingdom in the numeracy domain. Finally, regarding the problem-solving domain, Canadian educators underperformed educators only in Austria. In addition, similar to the findings of Cai and Gut (2018), our results revealed that Canadian educators showed lower performance in literacy than Finnish and Japanese educators. However, unlike their study, we did not find a significant difference between Canadian and American educators in the problem-solving domain. Our results supported the literature to a certain extent regarding the profession differences (Cai & Gut, 2018; Golsteyn et al., 2016). Even though Golsteyn et al. (2016) excluded

Table 7

Unstandardized Regression Coefficients of Common Significant Predictors of Literacy, Numeracy and Problem-Solving Performances in the Final Regression Model

Significant predictors	Literacy	Numeracy	Problem-solving
Intercept	215.50**	208.84**	235.53**
Gender 2	-5.04*	-11.47**	-5.15*
Education level 4	23.24**		18.56*
Education level 5	32.31**	28.14**	19.04*
Education level 6	33.95**	25.31**	18.44*
Solve complex problems 3	11.71**	9.57*	11.76**
Solve complex problems 4	10.34*		9.86*
Related work experience in years 3		-7.11*	-6.48*
Related work experience in years 5	-6.50*		-8.04**
Monthly income 2			-13.42*
Monthly income 3	-16.70**	-23.10**	-19.35**
Monthly income 4			-12.39*
Monthly income 5		-15.00*	-14.11*
Monthly income 10			-14.60*
Numeracy at home	5.73**	8.28**	3.65*
Reading at work	-4.24**	-3.68*	-3.05*
Number of books 3	11.66**	12.73**	11.67**
Number of books 4	11.91**	18.27**	11.35**
Number of books 5	18.60**	20.92**	17.35**
Number of books 6	12.67*	11.26*	
Education level of parents 2	6.09*	5.77*	8.18**
Education level of parents 3	7.11*	7.94*	9.69**
AET for job-related reasons	11.81**	9.66**	13.86**
AET for non-job-related reasons	11.47**	10.82**	11.84**

Note. See Table 3 for the descriptions of categorical variables. All numbers shown in the table are significant regression coefficients. The missing cells or missing categories indicate insignificant regression coefficients and therefore are not reported. A positive coefficient indicates that as the independent variable increases, the dependent variable also tends to increase. A negative coefficient indicates that as the independent variable increases, the dependent variable tends to decrease. $*p < .05$; $**p < .01$. AET: Adult Education and Training.

the Canadian sample from their analyses, the general trend in their study showed that educators performed better than other professions in literacy and numeracy. Unlike their results, our study showed that within Canada, educators outperformed other professions in the numeracy domain except for professions in the areas of science, mathematics, computing, engineering, manufacturing, and construction. In contrast to the studies of Cai and Gut (2018) and Golsteyn et al. (2016), in the literacy domain, we found that educators outperformed other professions except for professions in the areas of science, mathematics, and computing. One interesting conclusion from our results is that educators showed lower performances than professions in the areas of science, mathematics, and computing in all three domains, including the literacy domain, which is surprising considering these professions' quantitative training backgrounds.

Our regression results supported the literature to a certain extent (Cai & Gut, 2018; Hämäläinen et al., 2015; Liao et al., 2019) and showed that gender, education level, complex problem solving, related work experience in years, monthly income, the use of numeracy skills at home and reading skills at work, number of books, and education level of parents are significant indicators of Canadian educators' performances in all three domains. Similar to other studies (Desjardins & Ederer, 2015; Hämäläinen et al., 2015), we found the uses of ICT skills at work and home are significant predictors of the problem-solving domain. The use of writing skills at home was also found a significant predictor of the literacy domain, parallel to the results of Liao et al. (2019). However, even though previous researchers reported solving simple problems as a significant indicator of all three domains (Liao et al., 2019), we found that it was only a significant predictor of the numeracy domain. Different from the findings of Liao et al. (2019), we found that the use of writing skills at work was a significant predictor not only for the literacy domain but also for the numeracy domain. Finally, although Liao et al. (2019) reported the level of computer use and paid work as significant indicators of all three domains, our results showed that these two variables did not significantly predict any domain proficiency of educators. In addition to the literature, our results demonstrated that adult education and training for job-related reasons and non-job-related reasons are significant indicators of Canadian educators' performances in all three domains and that the use of ICT skills at home is a significant predictor of literacy domain.

Conclusion

The results of this study contributed to the literature by providing important insights about Canadian educators through national and cross-country analyses. Despite the vast literature on the association between student achievement, teacher effectiveness, and teacher cognitive skills, there has been no research on teacher cognitive skills in all three domains: literacy, numeracy, and problem-solving. Given the importance of teacher cognitive skills on teacher effectiveness, this study showed that there are differences between the cognitive skills of educators and other professions, that educator cognitive skills vary across countries, and that several indicators can help predict educators' proficiencies in literacy, numeracy, and problem-solving. Therefore, the results of this study show the performance differences of educators in cognitive domains and the need to improve their proficiencies in these domains. These results are important to policymakers to design teacher education pre-service and in-service programs to help improve teacher cognitive skills, which, in turn, enhance their teaching effectiveness, and ultimately result in higher student achievements.

Educational accountability systems use student achievement scores to monitor teacher effectiveness, which might lead to the negative consequences of "teaching to the test". Instead, emphasis should be placed on the investigation of educators' cognitive skills and the improvement of these skills with curriculum and activities such as job-related training to enhance educator cognitive skills, resulting in improvement of their teaching effectiveness and student achievement. Student achievement is significant for every country in a global context because students who are educated by high-quality education systems will likely succeed in future workplaces. Therefore, teachers with a high level of cognitive skills are essential to high-quality education systems.

Our results are informative for policymakers who aim to increase the quality of education systems and teacher effectiveness. Our main suggestion is that differences between educators and non-educators within Canada and differences among educators across countries can inform educational policymakers to implement different strategies to minimize the cognitive skill gap and improve educators' cognitive skills. The indicators of higher literacy, numeracy, and problem-solving proficiency of educators can be used by policymakers to design more effective teacher workforce, education, and training programs. For example, education level has been found as a significant predictor of higher proficiency in all domains. Policymakers can support teachers to continue higher education to enhance their cognitive skills. For another example, adult education and training both for job-related and non-job-related reasons have been found as a significant predictor of higher proficiency levels for all three domains. Educational policymakers can consider this important indicator of teacher cognitive skills and provide continuing education through short or part-time courses to sustain their cognitive skill development. These courses can offer writing, reading, numeracy, and ICT activities, which are also found as significant indicators of teacher cognitive skills in this study. More effective education and training programs can equip educators with higher cognitive skills, resulting in higher-quality teaching.

Limitations and Future Research

Despite the given significant insights about educators, there are some limitations to our study. First, we conducted this study with the main focus on educators in Canada and therefore did not investigate the differences between educators and non-educators in other countries. Future research studies could investigate this. Second, we only focused on the countries that took part in the first round of PIAAC. Future studies need to conduct cross-country analyses considering the second and third rounds. Last, we removed four countries from our analyses, one for unavailable data, and three for the lack of problem-solving data. The data for these countries also needs to be investigated to have a better understanding of educators' cognitive skills across countries.

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