21st Century Skills for All: Adults and Problem Solving in Technology Rich Environments

Abstract: The current Information Society requires new skills for personal, labor and social inclusion. Among the so-called 21st Century Skills (Care, Griffin & Wilson 2018) is Problem Solving in Technology Rich Environments (PS-TRE), a skill evaluated in PISA and PIAAC tests (OECD 2016). This skill, although currently receiving considerable attention in compulsory education, has not received the same level of thought in adult education. In this article, the presence of the PS-TRE skill among adults of working age (25-65 years) in Europe is analysed in relation to the factors that potentially affect a higher level of PS-TRE proficiency. This analysis is carried out using structural equations modelling, taking into account socio-personal and educational factors, as well as the use of different skills at work and in daily life. The results indicate that educational attainment and the use of different skills (reading, numerical skills, ICT-related skills) at home and at work, as well as participation in non-formal education activities, decisively relate to a higher level of PS-TRE. This result is positively mediated through risk factors such as being older or being a woman. This study concludes that it is necessary to reinforce these skills, not only in children, but also in the adult population, in order to avoid social and labour exclusion.

Keywords: *problem solving, adult education, technology, 21st century skills, inclusive education*

Introduction

In recent years, technological revolution has invaded all domains of public and private life. This resulted into a new type of society, the Information Society (Castells 2002). Currently, access to and efficient use of ICT are essential for effective participation in society, both at work and in other social spheres. Technological tools are needed to solve everyday problems, an increasingly important skill labelled ‘Problem Solving in Technology Rich Environments’ (hereinafter PS-TRE) (OECD 2009). PS-TRE has been considered as one of the so-called 21st Century Skills (P21-Partnership for 21st Century Learning 2017; Care, Griffin & Wilson 2018; Griffin, McGaw & Care 2012), being indispensable "to prepare children, youth and adults comprehensively for twenty-first century citizenship and life" (Care, Griffin & Wilson 2018 p.4). Due to its relevance, PS-TRE is now part of the Organisation for Economic Cooperation and Development’s (OECD) Programme for International Student Assessment (PISA), carried out with 15 years-old students, and the Programme for the International Assessment of Adult Skills (PIAAC), carried out with 16-65 years old adults (OECD 2016).
PS-TRE has also been equated with Computational Thinking (Akcaoglu & Koehler 2014; Trawick 2017; Hämäläinen et al. 2015; Yadav et al. 2017), which, in recent years, has been highly promoted as a transversal competence to acquire during Primary and Secondary Education (Voskoglou & Buckley 2012; Bocconi et al., 2016). This impulse is given, according to Bocconi et al. (2016), not only because it prepares children and young people to think differently, to express themselves through a variety of media, to solve real-world problems and to analyze everyday issues from a different perspective, but also because it prepares them to boost economic growth, and to take up future jobs based on Information and Communication Technologies (ICTs). However, according to Vanek (2017), this indispensable skill for active participation in work and beyond, has not yet strongly featured in adult education strategies, including workplace training. This is quite paradoxical, since technological environments are already part of the entire economic and social sphere, including the need to solve everyday problems within these environments. As highlighted by Vanek (2017) and Iñiguez-Berrozpe, Valero-Errazu & Elboj-Saso (2018), lacking PS-TRE skills can exclude adults from the labour market and active participation in society.

In this article, we present a review of previous research in this area, and we analyse PS-TRE skills among adults of working age (from 25 to 65 years old) in Europe through microdata provided by the PIAAC survey (OECD 2016). A multivariate analysis using structural equations modelling (SEM) is performed to determine which factors affect the proficiency score in PS-TRE among the adults. As will be discussed below, this model, including its relevant factors, has been constructed in accordance to previous work by Scandurra and Calero (2017). The results show that, education and skills in all its levels (achieved level of formal education, skills used at home and at work, participation in adult education and training -AET-) decisively influence or mediate between other variables such as gender or age, in obtaining higher proficiency scores in PS-TRE. Given these findings, it is recommended to support further adult education and training initiatives in this area in order to promote social and labour market inclusion for all. This will hopefully eliminate the risk that certain groups in the adult population (especially older adults, women, ethnic minorities, etc.) are excluded from the Information Society, representing a sort of Social Darwinism.

Literature Review

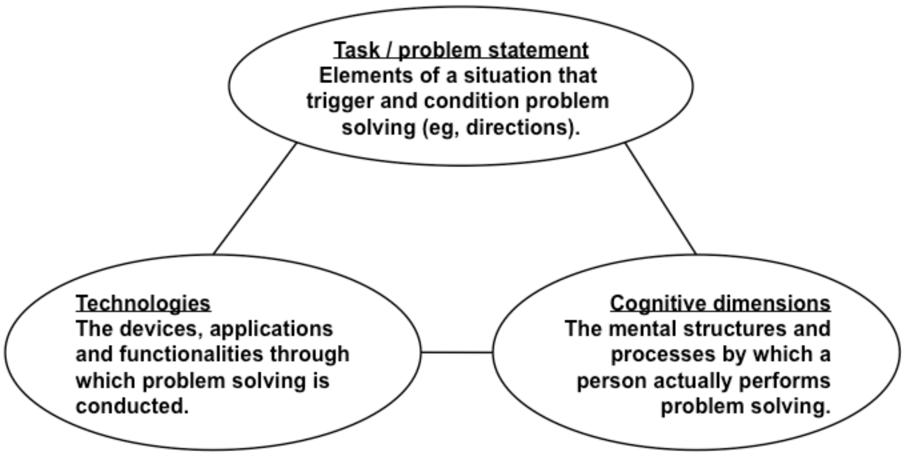
Conceptualization

Before proceeding with the analysis of adults’ PS-TRE from a theoretical and empirical point of view, it is necessary to establish its conceptual delimitation. Given our work uses data collected by the OECD’s PIAAC, we present their definition of problem solving as published in OECD (2009 p.15):

> “From a cognitive perspective, problem solving involves a complex hierarchy of processes and skills. The core characteristic of problem solving is that it is impossible for a person to achieve the goal through routine actions. In problem

solving, one has to reflect on the situation in order to identify the proper arrangement of decisions and actions that may lead to a solution. Thus, the status of problems is conditional and based on a person's familiarity with the problem or category of problems. Some activities initially experienced as problem solving may become routine activities over time with learning and practice"

In this study, we use the PIAAC PS-TRE variable, based on its 10 plausible values, as our outcome variable (OECD 2013). PS-TRE has been defined as the use of digital technology, communication tools and networks to acquire and evaluate information, to communicate with others and to perform practical tasks (OECD 2009 p.9). This concept has been used in the PIAAC survey (OECD 2016) as the variable to measure the technological and ICT competence applied by adults to solve everyday tasks or problems. It is part of the cognitive direct skills measures undertaken in PIAAC, together with literacy and numeracy (OECD 2009; Vanek 2017; Rampey et al. 2016; Reder 2015). Vanek (2017) highlights that the PS-TRE skill, instead of simply evaluating the use of common technologies, measures the efficient and creative application of technology in everyday tasks, both at home and at work. This problem-solving skill requires engagement with two aspects: (1) accessing information through communication and information technologies (ICT skills), and, (2) solving everyday problems that exist due to the presence of ICT itself, or that can be solved through them (OECD, 2013). Harris (2015) also considers that PS-TRE encompasses the whole spectrum of different digital literacies. The author defends that digital literacy in the 21st Century is not enough in itself, but that it must be applied to everyday problem-solving. Following Vanek (2017), this use of technological competence in everyday tasks requires three fundamental elements: a statement of the problem or the task to be performed; familiarity with the use of digital devices (ICT skills); and the cognitive dimensions needed to solve a problem (figure 1), all indicating that PS-TRE is a complex and multidimensional construct (Csapó & Funke 2017).



Source: OECD (2009, p. 11)

Figure 1. Three core dimensions of problem solving in technology-rich environments

To further underline its relevance, Wing (2010 p. 3), Care, Griffin and Wilson (2018), Griffin, McGaw and Care (2012) and Vanek (2017) claimed that PS-TRE is one of the new main literacies, being considered, as mentioned before, as one of the core 21st Century skills (P21-Partnership for 21st Century Learning 2017). This set of competences has been developed with input from teachers, education experts and business leaders to define and illustrate the skills and knowledge that people need to succeed in work and life more generally (OECD 2012). Given the need for the current working population to engage with 21st Century skills, it is increasingly important for the adult education sector to engage with these skills as well (Holford and Mohorcic-Spolar 2012; Iñiguez-Berrozpe & Marcaletti 2017; Iñiguez-Berrozpe, Valero-Errazu, Elboj-Saso 2018).

Adults' PS-TRE Skills for an Inclusive Information Society

The development of ICT as an unprecedented technical and cultural revolution has reformulated both public and private life spheres. This has led to the existence of an Information Society (Castells, 2002), a society in which ICT permeates all production processes, impossible to be disconnected from the social, economic and cultural bases of today's world. In this sense, the currently required skills to survive in today's society have also been transformed. These requirements range from the high-level skills demanded by employers (OECD 2012) to the personal aptitudes needed to function effectively in any social field. All these domains increasingly demand the use of technological skills (Van Greunen & Steyn 2015). These include not only the use and management of ICT, but also the ability to select, process and use information, and the cognitive skills necessary to use technology to solve real-world problems (Vanek 2017; OECD 2013; Rampey et al. 2016; Reder 2015).

However, despite the focus on the need for further development of PS-TRE skills among the population, current economic production continues to represent a capitalist model, distributing technological and informational resources unequally among people (Castells 2002). This provokes a twofold effect: there is a large part of the population without access to ICT resources, but there are also social groups with the opportunity of accessing them, but who have difficulties in developing the necessary skills for an effective relationship with ICT. This inequality is translated into a 'Social Darwinism' (Compaine 2001) fostered by the transformation of capitalist society into the Information Society (Habermas 1987; Compaine,2001), in which only those who have the necessary resources and skills can "survive" both in the labor market and the broader sociocultural environment. This negative effect is especially pre-eminent among the most vulnerable adults in society, like older people, immigrants, people who live in rural areas, or lower educated adults (Van Greunen & Steyn 2015).

On the other hand, as stated by several authors, skills development has a strong relationship with socioeconomic status (see for example Cunha, Heckman & Schennach 2010; Cunha & Heckman 2007; Bowles, Gintis & Osborne 2001; Hanushek 2015). However, for the adult population, the level of skills in technology-rich environments and the use of ICT is, in general, much lower than in the younger population (OECD 2016). This finding represents the so-called 'generational digital gap' (Compaine 2001), which, according to Ballestero (2002), contributes to a greater risk of socioeconomic exclusion of the adult population. Currently, the current European workplace is challenging adults' expertise (Tynjälä et al. 2014). This is because workers are at risk of being replaced by technologies, their jobs descriptions change rapidly, and, even so, they run the risk of being excluded from their workplaces because they do not have the required skills to perform their jobs. This risk is especially pronounced among low-educated adults, due to the *Matthew Effect* (Boeren 2009, 2016), which leads them to be even more reluctant to participate in training activities in the present, although further participation in education and training has been evidenced as a fundamental element to help to break this digital divide (Iñiguez-Berrozpe & Marcaletti 2017).

Although the aforementioned risks for adults are evident across competences (for example reading, writing, numeracy), we will focus specially on PS-TRE, as it has been considered as one of the main 21st Century Skills needed to be applied to many areas of life (Care, Griffin & Wilson 2018). This is especially the case at work, where adults are increasingly expected to accomplish non-routine tasks (Goos 2013; Tynjälä 2013). Activities to change people's way of thinking to a more holistic one, combining analytic, creative, critical and pragmatic thinking, joint to the use of technological tools to solve every day problems, are therefore needed to be introduced into adult education practices (Vanek, 2017; Harteis & Billett 2013). According to Vanek (2017), Newman, Rosbash and Sarkisian (2015) and Jacobson (2012), although 21st Century Skills are being effectively introduced into Primary and Secondary school curricula, adult education is failing to take the opportunity of developing PS-TRE training in order to “truly prepare learners to succeed outside the classroom” (Vanek 2017 p. 34).

The inner resilience that this kind of training should give learners the opportunities to cope with fast changes at home, at work, and in cultural and social life, is the path for getting a sustainable and inclusive Information Society for all, not leaving adults behind.

Variables that are Related to the Acquisition of PS-TRE: Hypothetical Model

The main objective of this paper is to analyse the presence of PS-TRE skills in adults between 25 and 65 years old in Europe. Specifically, it explores the factors that are related to higher PS-TRE proficiency score. Given the absence of available models that analyse this issue, we started from research published by Scandurra and Calero (2017), in which the authors propose a structural equation model (SEM). Their work uses data from OECD’s PIAAC to analyze socio-personal and educational variables that could influence adults' literacy level (Figure 2). Their sample included all OECD countries except Australia, Cyprus and Russia because of the unavailability of data. The construction of their model was based on research by Desjardins (2003) on literacy proficiency. In Scandurra and Calero’s model, educational level of the father (*Family background*) influences the respondent’s educational level (*Education*). Due to the intergenerational transmission of education, both play an important role in the configuration of adult skills and skill practices. Also, the uses of skills at home and in the workplace were found to have a relevant effect on literacy scores. The authors also controlled for covariates such as *Age*, *Gender* and being born in the country (*Native*). These had an effect on the educational level (negative in the case of age), on the use of skills, and on literacy.

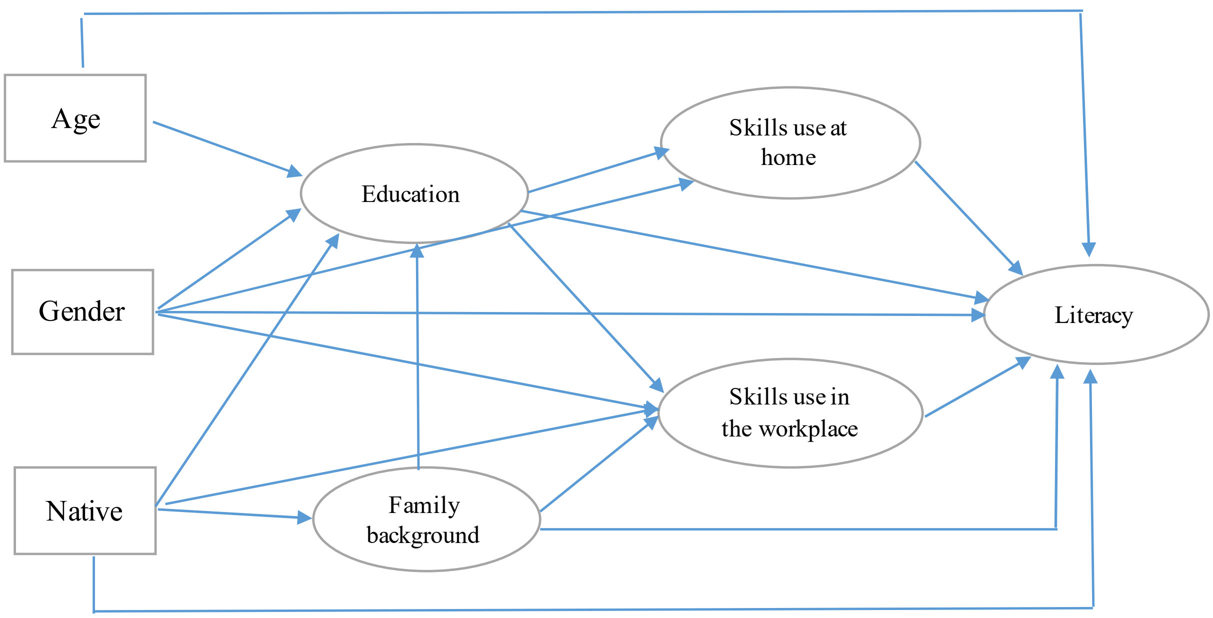


Figure 2. Path diagram, visual representation of Scandurra & Calero (2017) model

Source: Own elaboration from Scandurra & Calero (2017)

*Observed variables are represented as squares and latent variables as ellipses

In our own analyses, we use a modified version of this model. Regarding the choice of variables, first, the literature shows that *Age* is related inversely proportional to the levels of the three skills measured in the PIAAC survey (literacy, numeracy and PS-TRE) (Desjardins & Warnke 2012; Calero et al. 2016), and, specially, on PS-TRE (Hämäläinen et al. 2015). This is due to biological reasons, such as aging and cognitive decline, and because of older adults' restricted access to education when they were young (Scandurra & Calero 2017). In relation to *Gender*, although in the PIAAC survey, men obtained higher scores in the three direct skills measurements (literacy, numeracy and PS-TRE, OECD, 2016), evidences have indicated that, after controlling for age and other social characteristics, the gender gap has a weakened influence on skills attainment (Scandurra & Calero 2017; Christl & Köppl-Turyna 2017). However, given the traditionally unequal access to education by adult women, especially in the workplace, the gender variable is commonly used to test its influence on educational level, and the level of foundational skills, such as literacy, numeracy or PS-TRE, being critical for training and workplace success (Christl & Köppl-Turyna 2017). Continuing with the personal characteristics, being *Native* or migrant is also highlighted as an important variable within the literature. Differences in the educational systems of the country of origin and the country of destination, and the fact that the immigrant population often starts from a socioeconomic situation generally more precarious than that of natives, might put them in an unfavourable position (Isphording 2014; Marks 2006).

In relation to the educational variables, the *Educational Level* or highest level of qualification obtained in the past (measured by ISCED levels) has been used in this model as one of the variables that, hypothetically, contributes most to the skill indices (at home and in the workplace) and the level PS-TRE proficiency. Both in relation to the generic development of skills (Kerckhoff 2001, Carbonaro 2007) and improved socio-economic destinations (Hanushek et al., 2013), but also in relation to the specific development of PS-TRE skills (Hämäläinen, De Wever, Nissinen & Cincinnato 2017; Iñiguez-Berrozpe & Marcaletti 2017), educational attainment is usually considered as a fundamental explanatory variable. *Family Background*, measured through the "Father's highest level of education" strongly influences this factor. According to Bukodi and Goldthorpe (2012), this variable helps explain a wider set of relevant aspects, such as educational level, socioeconomic background, social and cultural capital, etc. As such, it is relevant to be used in PIAAC analyses, as the dataset does not include alternative measures such as the International Socio-Economic Index, ISEI. Family capital and the intergenerational transmission of education have been traditionally discussed as one of the main factors for explaining educational success, both because of the better access to resources, and because of schooling decisions taken by the family (Jerrim & Macmillan 2015; Breen & Karlson 2014).

Finally, the *Skills in Use* indices, both at home and in the workplace, have been considered in our models, both as predictors of PS-TRE, but also as dependent variables of the previous individual and educational factors. The constructs *Skills used at home* and *Skills used in the workplace* were already computed and defined in the PIAAC survey, integrating data from the variables *use of writing skills*, *use of reading skills*, *use of numeracy skills* and *use of ICT skills* respectively. The index on skills used in the workplace also included the *use of task discretion at work*. Information on these variables was presented through the use of ordinal scales ranging from 1-5, where 1 represents the "lowest to 20%", 2 the "20-40%", 3 the "40-60%", 4 the "60-80%" and 5 the "80-100%". According to Collins and Evans (2007) or Flyvberg (2001), individuals tend to practice their skills on daily basis. This practice, or its absence, leads them to improve their levels of competences, being the best way to gain further proficiency. A variable that often appears in analytical models of skills attainment is employment. In this study, it has not been considered, because it did not feature as a significant contributor to previous models (Hämäläinen, De Wever, Nissinen & Cincinnato 2017, Iñiguez-Berrozpe & Marcaletti 2017, Scandurra & Calero 2017) and being in employment is in fact covered by the variable *Skills in the workplace*. We did run a separate model that included employment, but a significant effect has not been found.

However, in our hypothetical model we have taken into account a variable that did not appear in the study by Scandurra and Calero (2017), which is participation in non-formal education activities (*AET - Adult Education Training*). The introduction of this variable in the model is based on the observation that participation in adult education seems to be a determinant in the acquisition of PS-TRE. Several authors came to this conclusion based on analyses conducted using PIAAC data (Hämäläinen, De Wever, Nissinen & Cincinnato 2017; Hämäläinen, De Wever, Malin, &

Cincinnato 2015). This relationship was also found in previous work by one of the authors of this paper (Iñiguez-Berrozpe & Marcaletti 2017; Iñiguez-Berrozpe, Valero-Errazu, Elboj-Saso 2018).

Considering all these factors, our hypothesized model is described graphically in Figure 3. In this model, *Family background*, *Education* and *AET* have been considered as observed or endogenous variables (variables directly measured in the PIAAC survey and represented in the figure as squares) for avoiding redundancies of using more than one indicator. On the other hand, the same relationships between variables proposed by Scandurra and Calero (2017) have been hypothesized, but with adding in the potential relationship between *Age* and the use of *Skills at home* as stated by Ballestero (2002). When testing this assumption[1], *Age* did not show a clear relationship with the use of *Skills at work*. We therefore decided to eliminate this causal relationship with the aim to arrive at a stronger model. As it has been aforementioned, the *AET* variable has been included using the PIAAC variable *Participation in non-formal education activities in the last 12 months*, known to be largely predicted by educational level, and predicting skills use and PS-TRE proficiency levels. The observed variable *Participation in formal education activities in the last 12 months* was not included because the percentage of adults in the sample that answered yes to this question was very low, and when it was included in the model, it was not found to be significant.

As in Scandurra and Calero's model (2017) *Skills use at home*, *Skills use in the workplace* and *PS-TRE* were defined as endogenous or latent variables, composed by the observed variables specified in Table 1 and represented as ellipses in the graphical model (Figure 3).

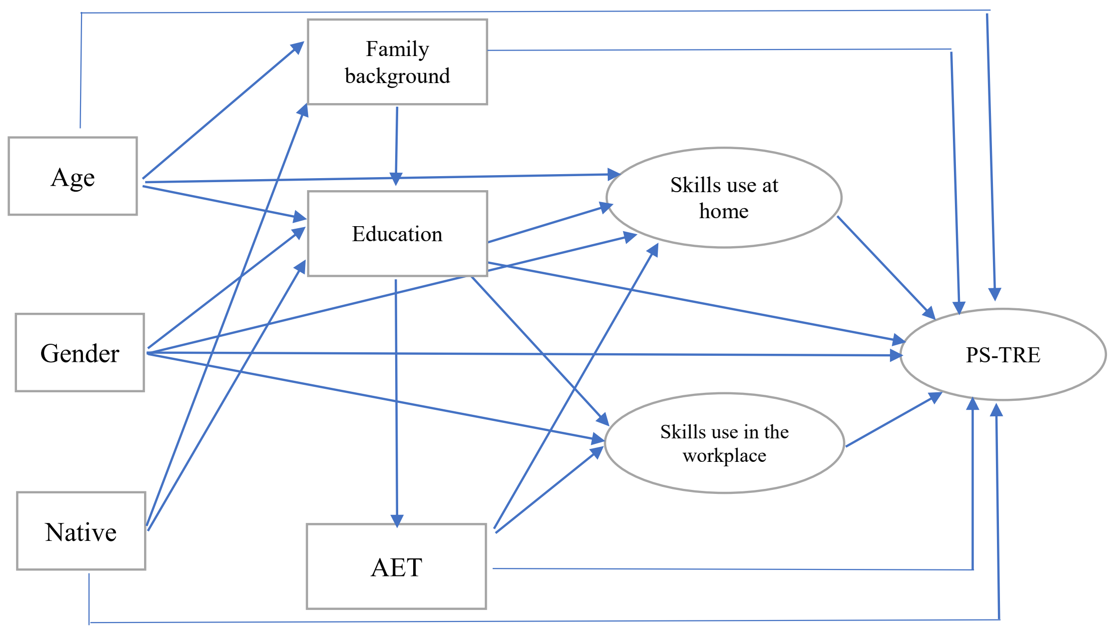


Figure 3. Path diagram, visual representation of our PS-TRE model.

Source: Own processing

*Observed variables are represented as squares and latent variables as ellipses

[1] To avoid an excessively long and complex paper, the different models tested from the initial model by Scadurra & Calero have not been included. The criteria for defining the final model have been based only on significant relations among the variables (p<0.001), with the aim to get a stronger and more optimal model.

Method

Instrument

Our analysis is based on data from the first (2013) and the second (2016) rounds of the PIAAC's Survey of Adult Skills which measures adults' proficiency in key information-processing skills, and how these adults use these skills in different environments such as at home or in the workplace (OECD, 2016). The third round has not been taken into account as data have not been released yet. So far, the survey has been conducted in 40 countries. Respondents were between 16 and 65 years old. According to the OECD, cognitive skills are necessary to enable individuals to participate successfully in society and to contribute to a productive economy. Apart from literacy and numeracy skills, PS-TRE skills were evaluated through adults' performances on different tasks. Ten plausible values (PV) were calculated as a result. These PV are a statistical means to replicate a probable score distribution that summarizes how well each respondent answered a small subset of the assessment items; and, how well other respondents from a similar background performed on the rest of the assessment item pool. Each individual case in the PIAAC dataset has a set of ten PVs for each proficiency domain (literacy, numeracy, problem solving in technology-rich environments), and all ten PVs must be used together to estimate proficiency (OECD, 2012). This then leads to a more reliable and unbiased estimate of respondents' skills proficiency. The final PS-TRE scores range from 0 to 500. Level <1 comprises values of score 240 or below; level 1 from 241-290; level 2, 291-340; and level 3, 341-500.

The PIAAC questionnaire also includes questions about socio-demographic and socio-economic variables such as age, sex, country of origin, educational level, or employment and salary situation, among others, that allow the characterization of the sample. In addition to other relevant issues informing our further understanding of adult skills, for example social and linguistic history, the use of different skills both at home and in the workplace, and the participation in educational activities, were also included as variables in PIAAC.

Sample

In the two first rounds of the PIAAC survey, around 250,000 adults have been evaluated, representing the total population between 16 and 65 years of OECD member countries (OECD 2016). For the present analysis, we decided to work with European countries only. However, those countries that either had not collected some of the core variables of interest (such as PS-TRE), or that measured concepts differently, were excluded from the analysis. Finally, the countries included in our sample are Belgium, Czech Republic, Denmark, Finland, Ireland, Netherlands, Norway, Poland, Slovak Republic, Sweden and United Kingdom. Among the countries that composed the sample, we selected individuals aged 25-65, in accordance to the European way of describing this group as the working age population. Finally, cases with missing data on the model variables were excluded to make the sample more robust for the modelling process.

The final sample has been n = 20,034 (see APPENDIX for sample features), distributed equitably in terms of country of residence, age group (mean age 42.6, with a standard deviation of 10.8), and gender. In terms of educational level, there is an overrepresentation of people with higher education (54.6 of individuals with ISCED 5 level). This is due to the fact that we are using a selective sample, excluding respondents with missing values on the skills measured. However, we used the same criteria for inclusion and thus obtained a similar sample bias as our model of reference (Scandurra & Calero 2017). Not including missing data with the aim to get a stronger model led to the focus on individuals in employment at the time of data collection, as those with missing data on "Skills used in the workplace" were excluded. Similar to our model of reference, Scandurra and Calero (2017), we did not apply sampling weights and thus conducted analyses based on the unweighted number of respondents. The distribution between natives (92.8) and non-natives (7.2) is representative of European population distribution (6.9% according to Eurostat, 2017). Regarding family background, low-level educated father represents more than a third of the sample (36.6), but with the largest group consists of respondents with medium-level of paternal education (40.7). Two thirds of the participants in our analyses have undertaken non-formal education activities in the last year. Information on the use of skills at home and in the workplace, derived from original variables in the PIAAC dataset, was presented in quintiles (lower than 20% of use, 20-40%, 40-60%, 60%-80% and over 80%). More than the 50% of the sample uses falls into the two highest levels (60%-80% and over 80%), indicating a stronger than average use of skills among the selected sample compared to all respondents in the dataset. More detailed results are shown in APPENDIX (Table 5). Finally, the mean of all the plausible values for PS-TRE in our sample is 293.29 (level 2).

Selection of Variables

From the 1,329 variables included in the PIAAC survey, we have selected a number of observed and latent variables shown in Table 1, in order to test our hypothetical model presented above. The types of the variables (dichotomous, ordinal and continuous) have been selected following our model of reference.

Table 1. Variables used in the model

Latent variables		Observed variables		Type
Description	Label	Description	Label	
		Gender (male/female)	Gender	Dychotomus
		Age	Age	Ordinal
		Born in country	Native	Dychotomus
		Highest level of education	Education	Ordinal
		Father's highest level of education	Family	Ordinal
		Participation in non-formal educational activities in the last 12 months	AET	Dychotomus
Use of Skills at Home	Skills Home	Use of writing skills at home	WRITH	Ordinal
		Use of reading skills at home	READH	Ordinal
		Use of numeracy skills at home	NUMH	Ordinal
		Use of ICT skills at home	ICTH	Ordinal
Use of Skills in the workplace	Skills Work	Use of writing skills at work	WRITW	Ordinal
		Use of reading skills at work	READW	Ordinal
		Use of numeracy skills at work	NUMW	Ordinal
		Use of ICT skills at work	ICTW	Ordinal
		Use of task discretion at work	TASKW	Ordinal
PS-TRE proficiency	PS-TRE	Plausible value PS-TRE 1	PV1	Continuous
		Plausible value PS-TRE 2	PV2	Continuous
		Plausible value PS-TRE 3	PV3	Continuous
		Plausible value PS-TRE 4	PV4	Continuous
		Plausible value PS-TRE 5	PV5	Continuous
		Plausible value PS-TRE 6	PV6	Continuous
		Plausible value PS-TRE 7	PV7	Continuous
		Plausible value PS-TRE 8	PV8	Continuous
		Plausible value PS-TRE 9	PV9	Continuous
		Plausible value PS-TRE 10	PV10	Continuous

Source: OECD, 2016, Own processing

For its selection we have revised the existing literature (explained above in *Variables that are Related to the Acquisition of PS-TRE. Hypothetical Model* epigraph) proposing 5 components of skills acquisition, using the following observed variables: education (Highest level of education), family background (Father's highest level of education), AET (participation in non-formal educational activities in the last Twelve months); and the latent variables: Use of Skills at Home (using the four items: reading, writing, numeracy and ICT), and Use of Skills in the workplace (using the five items reading, writing, numeracy, ICT and task discretion – as explained above, we added this variable taking into account its relevance for PS-TRE score). The level of skills use was used based on the skill use scales computed by the OECD, as explained above. Finally, the latent construct of PS-TRE comprises the 10 plausible values of PS-TRE. Similar to the original model by Scandurra and Calero (2017), we controlled for the following observed variables: age, gender and being native-born (or not).

Analysis

To test the proposed hypothetical model, resulting from the theoretical review on the factors that are potentially related to the acquisition of PS-TRE skills, an analysis through SEM has been conducted. The choice to use this technique, and following Byrne (2010), was taken for a number of reasons: first, because of the lack of research that applies SEM to the field of adult education which limits the field's understanding of complex relationships between variables; second, due to the advantages that SEM has over conventional linear regressions. In this sense, SEM allows to use several dependent variables in a same model, to construct latent variables (more reliable than the observed ones, by including measurement errors, allowing the combination of almost all kinds of items). SEM also produces multiple goodness-of-fit measures that allow checking if our model fits the data.

To carry out this analysis, we used the IBM-SPSS extension AMOS (version 22). A two-step modelling has been performed to, on the one hand, describe the contribution of each observed variable to its corresponding latent variable (see results section, Table 3), and then to analyse the proposed structural model, including both observed variables and latent variables (see results section, Figure 4, and Table 4). This full structural equation model is used to test hypothetical patterns of a causal structure linking several variables onto the construct (Byrne 2010). This technique has a confirmatory nature to test a model derived from theoretical revision, such as the one proposed in this paper. As explained above, the inclusion of variables defining the final model has been based on a previous model predicting literacy proficiency by Scandurra and Calero (2017). In order to get a stronger and more optimal model, only those relations among variables that were found to be significant ($p<0.001$) were included in the final model.

The selected estimator was a Maximum Likelihood Estimator (MLE). This type of estimator is recommended when the analysis incorporates variables measured in different ways (Byrne, 2010), such as dichotomous, ordinal and scale level variables in our case. It has specifically been recommended within the literature on applying SEM using AMOS (Pérez, Medrano & Sánchez Rosas 2013; Byrne 2010).

Below, we will report our results. First, the goodness-of-fit of our model is tested using RMSEA; CFI; TLI; NFI and GFI as indicators, as recommended by Schlermelleh-Engel et al. (2003), Vandenberg (2006) and Byrne (2010) (see table 2). These authors suggest not using chi square/d.f. indicator for large samples. In reporting the coefficients of our final model (see tables 3 and 4), we have included both unstandardized and standardized regression weights as produced by AMOS. Although the literature recommends using standardized coefficients to facilitate the interpretation and comparison of results, unstandardized regression weights within AMOS outputs provide additional information about standard errors, critical residues, and the significance of each variable. We have also calculated the indirect effects on endogenous variables to check the mediating effects of the variables on PS-TRE level, as recommended by Pérez, Medrano and Sánchez Rosas (2013). Within the results section below (table 4), and as discussed above, we will only focus on significant relationships. The aim of this paper has not been to make comparisons between the different European countries within the sample. Their participant features were more or less equivalent after the depuration of the cases. However, we have replicated our analysis for each individual country, obtaining similar results, which further validates our model.

Results

Regarding the evaluation of the goodness-of-fit of our model, the analyzed indicators (RMSEA, CFI, TLI, NFI, GFI; similarly used in our model of reference by Scandurra and Calero 2017), demonstrate that the matrix derived from the data and those from the conceptual model (Figure 3) do not have significant differences. As such, it can be considered as an optimal model.

Table 2. Goodness-of-fit indicators for the proposed model

Index	Value	Limit criteria	Interpretation
RMSEA	.05	< .80	Fits
CFI	.96	> .93	Fits
TLI	.96	> .90	Fits
NFI	.96	>.90	Fits
GFI	.95	>.90	Fits

Own processing

In our measurement model (the first step in the modelling process), all observed variables were significant in their loads onto the latent variables ($p<0.001$; critical residues, Est./S.E.>1.96). Both for skills used at home and skills used at work, the strongest contribution was made by the variable ICT use (.761 and .676 respectively in their standardized regression weights).

Table 3. Measurement model

	Estimate	S.E.	Est/S.E.	P
Regression weights				
WRITW<-Skills_Work	1.000			
READW<-Skills_Work	1.044	.021	49.164	***
NUMW<-Skills_Work	1.298	.027	48.260	***
ICTW<-Skills_Work	1.754	.033	53.473	***
TASKW<-Skills_Work	.563	.020	27.703	***
WRITH<-Skills_Home	1.000			
READH<-Skills_Home	.950	.016	59.918	***
NUMH<-Skills_Home	1.084	.019	57.642	***
ICTH<-Skills_Home	1.147	.019	61.290	***
PVPSL1<-PSTRE	1.000			
PVPSL2<-PSTRE	1.005	.005	215.868	***
PVPSL3<-PSTRE	1.005	.005	216.356	***
PVPSL4<-PSTRE	.990	.005	214.561	***
PVPSL5<-PSTRE	.994	.005	214.878	***
PVPSL6<-PSTRE	1.012	.005	216.931	***
PVPSL7<-PSTRE	1.003	.005	214.813	***
PVPSL8<-PSTRE	.990	.005	212.738	***
PVPSL9<-PSTRE	1.003	.005	215.397	***
PVPSL10<-PSTRE	1.003	.005	215.287	***
Standardized regression weights				
WRITW<-Skills_Work	.481			
READW<-Skills_Work	.552			
NUMW<-Skills_Work	.533			
ICTW<-Skills_Work	.761			
TASKW<-Skills_Work	.246			
WRITH<-Skills_Home	.580			
READH<-Skills_Home	.639			
NUMH<-Skills_Home	.593			
ICTH<-Skills_Home	.676			
PVPSL1<-PSTRE	.909			
PVPSL2<-PSTRE	.910			
PVPSL3<-PSTRE	.911			
PVPSL4<-PSTRE	.908			
PVPSL5<-PSTRE	.909			
PVPSL6<-PSTRE	.912			
PVPSL7<-PSTRE	.908			
PVPSL8<-PSTRE	.905			
PVPSL9<-PSTRE	.909			
PVPSL10<-PSTRE	.909			

Source: OECD, 2016. Own processing

The second step of our analyses is being represented in the structural model shown in Figure 4, together with its values specified in Table 4. Turning first to the standardized estimates for the structural parameter paths, it is clear that all of these estimates are significant ($p < 0.001$; critical residuals, Est/SE>1.96). For facilitating comparisons across different types of variables (dichotomous, ordinal and continuous measured in different ways), we have used standardized parameters both in Table 4 and in Figure 4, which should be interpreted as percentage change in the standard deviation of the endogamous variable (dependent factor) for every one single point change in the standard deviation of the exogenous variable (independent factor).

Results demonstrate that age is the strongest factor affecting the PS-TRE score, (standardized coefficient -.326), therefore, the older adults are, the lower their PS-TRE score. Factors such as educational level (.170), the use of skills at work (.164) and at home (.148) (especially, as we have explained above, the use of ICT skills), as well as the family background (.080), seem to be decisive when it comes to obtaining higher scores in PS-TRE. Origin and gender seem to be characteristics that can affect PS-TRE score. Both being not native and female indicators are related with a lower coefficient in this skill. Finally, introducing the AET variable is also relevant, assuming a standardized coefficient of .057.

It is also interesting to check the influence of these socio-personal and educational variables on the indices of use of skills at home and at work. In this case, as an explanatory variable, educational level is the strongest predictor (coefficient of .293 for skills at work and .283 for skills at home), followed by gender, where being a woman again means a lower score on both indices. However, age does not seem to be as relevant as having participated in non-formal educational activities during the last 12 months in relation to skills used at home. While age has a coefficient of -.052 in its weight to skills used at home, AET coefficients are .141 in relation to predicting of the use of skills at work and .091 for the use of skills at home.

We have also verified the relevance of the intergenerational transmission of education. We can see from the model that the coefficient of family background on educational level is .237, higher than other aspects such as age, gender or being immigrant. On the other hand, as expected, being older is also related to having a father with a lower educational level (-.216). Finally, the aforementioned Matthew Effect is also noted, given that one's educational level is a strong predictor of participation in educational activities (standardized coefficient of .163).

Finally, we have calculated the indirect effects to check whether the intermediation of the used variables was relevant for the PS-TRE score. Analysing the standardized coefficients of this mediating effect, we can appreciate that the variables that are more relevant in this sense are the skills used at home and at work, attenuating the effects of gender (-.030 and -.036 respectively) and age (-.008 on skills at home) on the PS-TRE score (see Table 4 Indirect effects on PS-TRE). This relevant role of intermediation of the use of skills on the PS-TRE score is also clearly shown in the case of respondents' educational level (.042 skills at home; .048 skills at work), and their participation in AET (.013 skills at home; .026 skills at work). Another variable that seems to mediate is educational level. For example, the positive relation with family background increases the PS-TRE score (.040), reduces the relevance of age in this skill (-.005), but also serves as an important mediator for women to score better in PS-TRE (.012, versus -.049 without the mediating effect of the educational level). Finally, participation in non-formal education activities has a certain mediating role, both between the effect of the educational level in the PS-TRE (.009), as well as in relation to gender and educational level (.001).

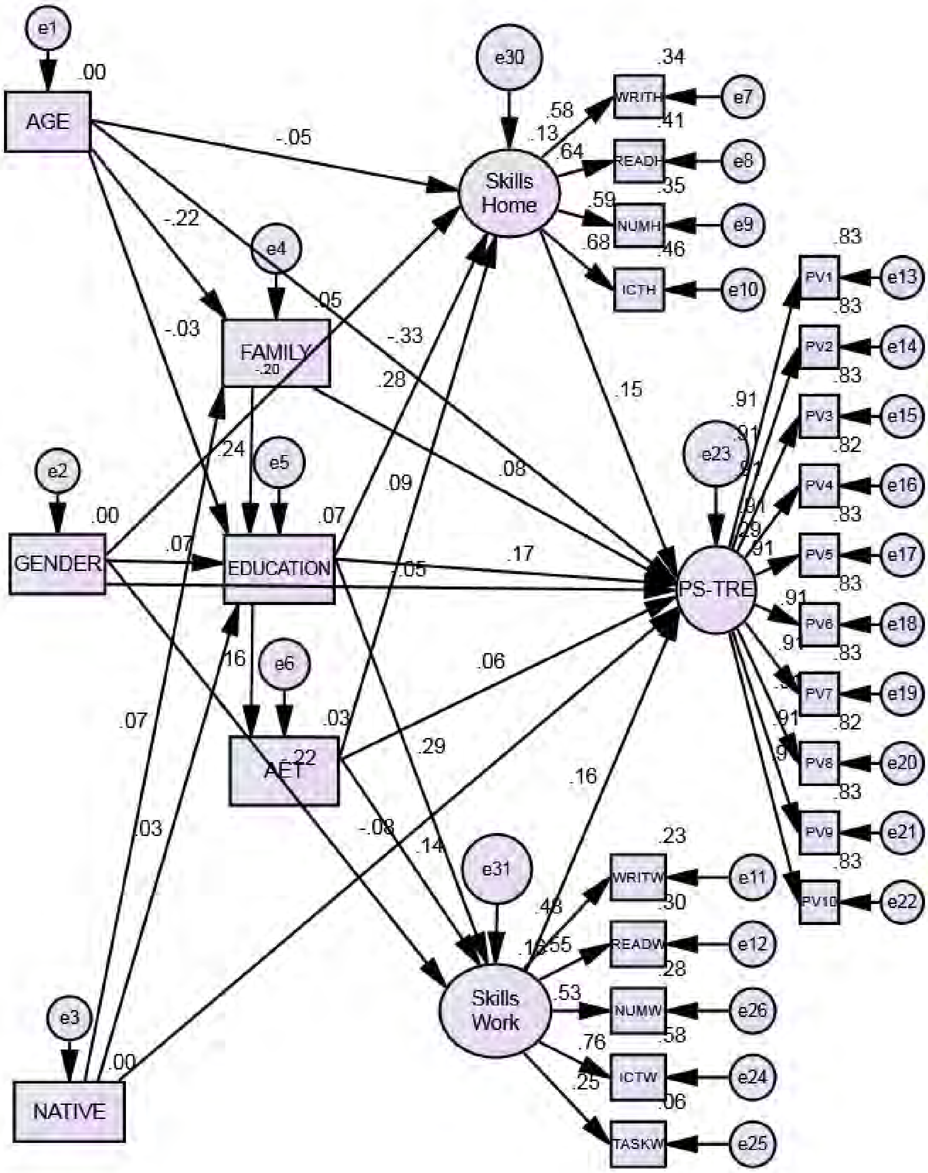


Figure 4. Visual representation of the model. Standardized estimates and estimates of error variance parameters (e)[2]

Source: OECD, 2016. Own processing

[2] error (e) is an unobserved variable. Whereas traditional multivariate procedures are incapable of either assessing or correcting for measurement error, SEM provides explicit estimates of these error variance parameters, avoiding inaccuracies of other traditional methods (Byrne, 2010, p. 24)

Table 4. PS-TRE model results

	Estimate	S.E.	Est/S.E.	P
Regression weights				
FATHERED<-AGE	-.015	.000	-31.413	***
FATHERED<-BORN	.219	.020	10.860	***
EDUCATION<-FAMILY	1.058	.031	33.839	***
EDUCATION<-AGE	-.010	.002	-4.466	***
EDUCATION<-GENDER	.478	.046	10.370	***
EDUCATION<-BORN	.437	.089	4.885	***
NFE<-EDUCATION	.021	.001	23.310	***
Skills_Home<-GENDER	-.286	.012	-24.223	***
Skills_Work<-GENDER	-.243	.009	-25.658	***
Skills_Home<-AET	.147	.013	11.226	***
Skills_Work<-AET	.177	.010	17.165	***
Skills_Home<-EDUCATION	.060	.002	32.626	***
Skills_Work<-EDUCATION	.048	.001	32.167	***
Skills_Home<-AGE	-.003	.001	-6.593	***
PSTRE<-Skills_Work	10.360	.530	19.538	***
PSTRE<-Skills_Home	7.240	.395	18.338	***
PSTRE<-AGE	-1.061	.021	-51.461	***
PSTRE<-GENDER	-3.424	.459	-7.453	***
PSTRE<-BORN	-11.114	.826	-13.453	***
PSTRE<-FAMILY	3.711	.297	12.503	***
PSTRE<-EDUCATION	1.757	.075	23.565	***
PSTRE<-AET	4.470	.501	8.922	***
Standardized regression weights				
FATHERED<-AGE	-.216			
FATHERED<-BORN	.075			
EDUCATION<-FATHERED	.237			
EDUCATION<-AGE	-.031			
EDUCATION<-GENDER	.071			
EDUCATION<-BORN	.033			
AET<-EDUCATION	.163			
Skills_Home<-GENDER	-.200			
Skills_Work<-GENDER	-.219			
Skills_Home<-AET	.091			
Skills_Work<-AET	.141			
Skills_Home<-EDUCATION	.283			
Skills_Work<-EDUCATION	.293			
Skills_Home<-AGE	-.052			
PSTRE<-Skills_Work	.164			
PSTRE<-Skills_Home	.148			
PSTRE<-AGE	-.326			
PSTRE<-GENDER	-.049			
PSTRE<-BORN	-.082			
PSTRE<-FATHERED	.080			
PSTRE<-EDUCATION	.170			
PSTRE<-AET	.057			
Indirect effects on PS-TRE				
PSTRE<-BORN	.020			
PSTRE<-AGE	-.048			
PSTRE<-FATHERED	.065			

	Estimate	S.E.	Est/S.E.	P
PSTRE<-GENDER	-.046			
PSTRE<-EDUCATION	.105			
PSTRE<-NFE	.037			
PSETRE<-SKILLSH<-AGE	-.008			
PSE-TRE<-FATHERED<-AGE	-.017			
PSTRE<-ED<-AGE	-.005			
PSTRE<-ED<-FATHERED<-AGE	-.009			
PSTRE<-SKILLSH<-GENDER	-.030			
PSTRE<-SKILLSW<-GENDER	-.036			
PSTRE<-ED<-GENDER	.012			
PSTRE<-AET<-ED<-GENDER	.001			
PSTRE<-SKILLSH<-ED<-GENDER	-.002			
PSTRE<-SKILLSW<-ED<-GENDER	.003			
PSTRE<-FATHERED<-BORN	.006			
PSTRE<-ED<-BORN	.006			
PSTRE<-SKILLSH<-ED<-BORN	.001			
PSTRE<-SKILLSW<-ED<-BORN	.002			
PSTRE<-ED<-FATHERED	.040			
PSTRE<-SKILLSH<-ED<-FATHERED	.005			
PSTRE<-SKILLSW<-ED<-FATHERED	.011			
PSTRE<-AET<-ED	.009			
PSTRE<-SKILLSH<-ED	.042			
PSTRE<-SKILLSW<-ED	.048			
PSTRE<-SKILLSH<-AET<-ED	.002			
PSTRE<-SKILLSW<-AET<-ED	.004			
PSTRE<-SKILLSH<-AET	.013			
PSTRE<-SKILLSW<-AET	.023			

Source: OECD, 2016. Own processing

Reference category of gender (male), for born (native) and AET (no)

Discussion

The rapidly changing labour markets and social environments of recent years have made it necessary for people to develop high levels of skills, especially the so-called 21st Century skills (P21-Partnership for 21st Century Learning 2017; Care, Griffin & Wilson 2018, Griffin, McGaw & Care 2012). Among these skills, PS-TRE is highly relevant, especially since ICT has permeated all kinds of activities (Vanek 2017; Harteis & Billett 2013). However, as discussed in the earlier parts of our paper, factors such as age, gender, belonging to immigrant or ethnic minorities, as well as having low levels of education can negatively influence decreased opportunities for skills development, favouring Social Darwinism in the new Information Society. This inevitably leads to consequent risks of social exclusion and marginalization of certain social groups (Compaine 2001, Van Greunen & Steyn 2015). Previous research has already demonstrated that the development of skills strongly relates to people socio-economic status (Cunha, Heckman & Schennach 2010; Cunha & Heckman 2007; Bowles, Gintis & Osborne 2001; Hanushek 2015). That is why social research, still in an embryonic status on this topic of PS-TRE (Hämäläinen et al. 2017), must analyse what factors promote or hinder the development of these skills, with the aim of achieving a more inclusive society in which there is access to these 21st Century skills for all.

In the study presented in this paper, we have analysed the factors that are related to the achievement of a higher PS-TRE proficiency score, with the aim of acting as a knowledge base to further strengthen the debate in relation to the development of the PS-TRE for all. The use of SEM allowed us to simulate a predictive model exploring the complex relationships between variables, instead of only testing them as separate independent variables in a multiple linear regression analysis. This has given us the chance to look into direct as well as indirect relationships between PS-TRE proficiency and the other variables. For example, while participation in AET was found to be a relevant predictor of a higher PS-TRE score, participation in itself could also be predicted by adults' educational attainment, hence adding an indirect effect on top of the direct one we found between educational level and PS-TRE score.

In order to assist our research procedures, the previous literature has been taken as a starting point, specifically the model proposed by Scandurra and Calero (2017) who analysed Literacy and Numeracy competencies using data from PIAAC, inspired by Desjardins' (2003) work on literacy achievement. Given the relevance of participation in adult education in previous research on problem-solving (Hämäläinen, et al. 2017; 2015; Iñiguez-Berrozpe & Marcaletti 2017; Iñiguez-Berrozpe, Valero-Errazu, Elboj-Saso 2018), we decided to include this variables into our model (measured in this case as non-formal education activities in the last 12 months), at the same level as the respondents' educational level and their family background.

The results of our model on PS-TRE corroborate some of the issues highlighted by Scandurra and Calero (2017) in relation to Literacy and Numeracy. This includes similar effects of educational level on the skills measured (.188 in the previous model, and .170 in our model). This effect was also found in other previous studies such as those by Kerckhoff (2001), Carbonaro (2007) or Hämäläinen, et al. (2017). As hypothesized in the previous model on literacy, we also found a prediction from adults' family background onto their own educational level. The importance of educational level is, as in the study by Scandurra and Calero (2017), even more relevant in relation to the use of skills at home and at work, with a standardized coefficient of .283 and .293 respectively. Thus, both variables in relation to the use of skills have a decisive relation to the PS-TRE score, especially the use of ICT skills. These variables were found to be stronger predictors of PS-TRE proficiency levels than other variables such as family background or being an immigrant. Evidence on the effects of the use of skills in relation to generic competencies scores were also found by Collins and Evans (2007) or Flyvberg (2001).

However, in our study, age was found to be a stronger predictor of PS-TRE scores, (-.326), compared to similar analyses based on PIAAC data in previous research. Scandurra and Calero did not focus on PS-TRE but on Literacy (-.032) and Numeracy (-.011). As such, our finding in relation to age corroborates the previous literature warning about the risk of exclusion of older people in a technological world (Desjardins & Warnke 2012; Calero et al. 2016, Hämäläinen et al. 2015). However, negative predictors such as "age" (being older) or gender ("female"), can be mediated through the development of skills at home and at work, educational level and participation in AET. These findings were also discussed in previous similar studies (Scandurra & Calero 2017; Christl & Köppl-Turyna 2017). These findings further underline the importance of education, either theoretical/academic (educational level, AET), or practical (AET, skills in use). This line of thought has been confirmed in the literature (Holford and Mohorcic-Spolar 2012; Iñiguez-Berrozpe & Marcaletti 2017; Vanek 2017; Harteis & Billett 2013) and further highlights the value of education as a fundamental strategy to achieve equitable access to the development of the different competences.

Conclusion

In spite of the relevance given by different national and supranational organizations, such as the OECD, to the development of high level skills in a knowledge-based economy, the truth is that the so-called "new literacies" (or the 21st Century skills, including PS-TRE) have received attention within compulsory levels of schooling, but are not typically referred to in relation to the adult population. This causes a lack of alignment for adults with the current demands of the labour market, or economic, cultural and social environments. This is especially true for the most vulnerable groups in society.

Levels of initial educational, use of skills at home and in the workplace and participation in AET predicted, both directly and through intermediation, respondents' levels of PS-TRE proficiency. Therefore, translating the main findings of this study into a set of recommendations for policy and practice, it is clear that providing everyone with equal access to education should be a core priority. Adults who did not receive the opportunity to achieve high levels of education could profit from participation in adult education. So do migrants whose foreign qualifications might not have been validated in the context of the host country. Widening access to adult education among older adults might also further guarantee their skills are being updated on a regular basis. More incentives for women to participate in work-related training and obtain a more satisfying work-life balance could also help the development of their skills. As family background remains a relevant predictor of adults' educational attainment, it is also important to keep on investing in the education and development of children growing up in the most deprived families in Europe. This will hopefully help to reduce the attainment gap between the richest and the poorest teenagers, as, for example, visible in PISA data.

To finalise, recommendations for future research are being discussed as well. The limitations of the study are found in the absence of a reflection on the structural characteristics of both Europe in general, and of the countries that make up the sample in particular. Having started from the seminal proposal by Desjardins (2003) and its subsequent assumption as a model by Scandurra and Calero (2017), both core underpinnings of our study, justify this absence. Additionally, the chosen sample can be considered slightly biased after its depuration. However, our approach and results have been aligned with previous studies. Due to these limitations, future research could be carried out taking into account national samples and their structural characteristics. Additionally, data from subsequent OECD PIAAC rounds could be included too.

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APPENDIX

Table 5. PIAAC Sample features

		Frecuency	Percentage
Country	Belgium	1603	8.0
	Czech Republic	1579	7.9
	Denmark	3049	15.2
	Finland	2450	12.2
	Ireland	1470	7.3
	Netherlands	1997	10
	Norway	2289	11.4
	Poland	1151	5.7
	Slovak Republic	1115	5.6
	Sweden	1969	9.8
	United Kingdom	1362	6.8
Gender	Male	10299	51.4
	Female	9735	48.6
Education	No formal qualification or below ISCED 1	54	0.3
	ISCED 1	73	0.4
	ISCED 2	671	3.3
	ISCED 3	1163	39.2
	ISCED 4	1039	5.2
	ISCED 5	10955	54.6
	ISCED 6	430	2.1
Born in country	Yes	18591	92.8
	No	1443	7.2
Father Education	ISCED 1-2	7336	36.6
	ISCED 3- 4	8152	40.7
	ISCED 5-6	4546	22.7
Non formal education	Did not participate	5341	26.7
	Participated	14693	73.3
Use of ICT skills at home	Lowest to 20%	1370	6,8
	More than 20% to 40%	3434	17,1
	More than 40% to 60%	5036	25,1
	More than 60% to 80%	5473	27,3
	More than 80%	4721	23,6
Use of ICT skills at work	Lowest to 20%	1962	9,8
	More than 20% to 40%	3889	19,4
	More than 40% to 60%	4829	24,1
	More than 60% to 80%	4866	24,3
	More than 80%	4488	22,4
Use of numeracy skills at home	Lowest to 20%	2549	12,7

	More than 20% to 40%	3659	18,3
	More than 40% to 60%	4577	22,8
	More than 60% to 80%	5212	26
	More than 80%	4037	20,2
Use of numeracy skills at work	Lowest to 20%	2633	13,1
	More than 20% to 40%	3268	16,3
	More than 40% to 60%	4447	22,2
	More than 60% to 80%	4689	23,4
	More than 80%	4997	24,9
Use of reading skills at home	Lowest to 20%	423	2,1
	More than 20% to 40%	2528	12,6
	More than 40% to 60%	5313	26,5
	More than 60% to 80%	6374	31,8
	More than 80%	5396	26,9
Use of reading skils at work	Lowest to 20%	302	1,5
	More than 20% to 40%	2199	11
	More than 40% to 60%	4659	23,3
	More than 60% to 80%	6421	32,1
	More than 80%	6453	32,2
Use of task discretion at work	Lowest to 20%	1536	7,7
	More than 20% to 40%	3058	15,3
	More than 40% to 60%	4188	20,9
	More than 60% to 80%	5273	26,3
	More than 80%	5979	29,8
Use of writing skills at home	Lowest to 20%	1967	9,8
	More than 20% to 40%	2996	15
	More than 40% to 60%	6165	30,8
	More than 60% to 80%	4732	23,6
	More than 80%	4174	20,8
Use of writing skills at work	Lowest to 20%	971	4,8
	More than 20% to 40%	3135	15,6
	More than 40% to 60%	5724	28,6
	More than 60% to 80%	5454	27,2
	More than 80%	4750	23,7

Base n.= 20,034

Source: OECD, 2016, Own processing