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Measurement invariance of information, communication and technology (ICT) engagement and its relationship with student academic literacy: Evidence from PISA 2018

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ABSTRACT

The present study aimed to examine the measurement invariance of the information, communication and technology (ICT) engagement questionnaire in the Programme for International Student Assessment (PISA) across countries, and further to explore the effects of ICT engagement on student literacy. The sample included 98,758 15-year-old students from 16 countries in PISA 2018. The multi-group confirmatory factor analyses results indicated that the ICT engagement questionnaire was invariant at the residual level so that meaningful cross-country comparisons can be made at the observed level. Furthermore, the multi-level model results indicated that perceived ICT autonomy was a positive predictor, while use of social media was a negative predictor of student literacy across the countries. However, the relations of interest in ICT and perceived ICT competence to student literacy were inconsistent, with some countries showing positive and linear relationships, while others negative and linear relationships.

1. Introduction

The Programme for International Student Assessment (PISA), coordinated by Organization for Economic Co-operation and Development (OECD), is an international large-scale assessment that measures 15-year-old students' literacy in mathematics, science and reading every three years. PISA has become the world's benchmark for comparing education quality and equity across different countries, and a powerful force in shaping education policies and reforms (OECD, 2019a).

In 2015, PISA introduced a new information, communication and technology (ICT) engagement questionnaire in the main study, and the questionnaire continued to be used in PISA 2018. The construct of ICT engagement was developed based on the self-determination theory (SDT, Deci & Ryan, 1985). SDT holds that both intrinsic and extrinsic motivation are decisive factors of individuals' behaviors, and both drive individuals to meet three basic needs: competence, autonomy and relatedness. Accordingly, ICT engagement is characterized in terms of four factors: (1) interest in ICT, an individual's intrinsic motivation to engage in ICT-related tasks or activities; (2) perceived ICT competence, an individual's notion about his/her own ICT-related knowledge and skills; (3) perceived ICT autonomy, an individual's perceived control and independence in using ICT; and (4) use of social media, the extent to which an individual communicates and interacts with others using ICT (Zylka, Christoph, Kroehne, Hartig, & Goldhammer, 2015).

Developed in 2015, the PISA ICT engagement questionnaire is indeed a relatively new assessment tool. A key concern when a (new) construct or questionnaire is used for making comparisons across different groups, which is a primary goal of the PISA assessment, is measurement invariance (MI). MI is the property that an instrument measures the same construct to the same extent across groups. More formally, MI can be defined as the absence of group-based bias: Given an individual's true score, the group membership should not affect the probability of obtaining a specific observed score (Wu, Li, & Zumbo, 2007). Hence, the psychometric properties (e.g., factor loadings, item intercepts) relating the observed variables to the latent factor(s) should be similar across groups. Otherwise, meaningful and valid comparisons across groups may be severely hampered (Bluemke, Jong, Grevenstein, Mikloušić, & Halberstadt, 2016). MI testing is an important validity issue in comparative studies (Tracey & Xu, 2017), yet the MI of the newly introduced ICT engagement questionnaire in PISA has not been fully examined. To our knowledge, only one study by Meng, Qiu, and Boyd-Wilson (2019) exists that has established the equivalence of the ICT

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engagement questionnaire between China and Germany at the scalar level based on the PISA 2015 data. It is therefore necessary to further validate the questionnaire before applying it to make robust national and international comparisons. Thus, the first purpose of the present study was to investigate whether the MI of the ICT engagement questionnaire is supported at an acceptable level across different countries using the PISA 2018 data.

If the MI of the ICT engagement questionnaire holds at an acceptable level, then our second research goal was to explore whether and how particular ICT engagement factors may relate with students' mathematical, scientific and reading literacy across countries. Over the past decades, ICT has been fundamentally transforming the way we interact with each other and making significant impacts on educational practices. A growing body of literature has been conducted to examine the associations between ICT-related constructs and student learning outcomes (e.g., Gumus & Atalmis, 2011; Juhaňák, Zounek, Záleská, Bárta, & Vlčková, 2019). Nonetheless, several issues or challenges arise in evaluating and interpreting these prior results. First, many researchers have explored how ICT usage and availability of ICT resources may influence student achievements. However, empirical studies that examined the influences of ICT from a motivational perspective are limited (Senkbeil & Ihme, 2017). For instance, Gumus and Atalmis (2011) explored the relationship between Turkish students' reading performance and their use of computers for educational and entertainment purposes based on the PISA 2006 data. Results indicated that the use of computers for entertainment purposes had positive effects on students' reading performance, but the use of computers for educational purposes had negative impacts. Murillo and Roman (2011) found that availability of computers in school, basic infrastructure and services, didactic facilities and the number of books in the library significantly influenced the achievements of primary school students in 15 countries of Latin America.

Second, there is a variety of motivational factors related to ICT (e.g., self-efficacy, interest, and enjoyment in ICT). However, the existing studies involving motivational aspects of ICT have only focused on one or two of these factors. For example, Rohatgi, Scherer, and Hatlevik (2016) examined the role of ICT self-efficacy in ICT use and ICT literacy among Norwegian students. Results showed that (1) self-efficacy in basic ICT skills was positively related to ICT literacy, whereas self-efficacy in advanced ICT skills was negatively related to ICT literacy; (2) ICT self-efficacy was positively associated with some of the ICT use purposes; and (3) ICT use affected ICT literacy through ICT self-efficacy. Juhaňák et al. (2019) found that children who started using a computer at a later age (after the age of seven) demonstrated significantly lower ICT competence and autonomy at the age of fifteen.

Furthermore, the effects of ICT-related constructs on learning outcomes might be country- or culture-specific (Meng et al., 2019), but many prior ICT-related studies were conducted using data from a single country. For example, Kim, Kil, and Shin (2014) examined individual- and school-level factors predicting the ICT literacy level of Korean primary school students. Results indicated that individual-level factors including gender, completion of computer courses, computer use time and satisfaction level of ICT use in classes, and school-level factors including school location, achievement level and the number of computers per student were all significant predictors of student ICT literacy. Srijamdee and Pholphirul (2020) investigated the effect of ICT familiarity on educational outcomes using the Thailand data in PISA 2015. Results showed that using ICT for educational purposes helped improve Thai students' PISA performance, yet using ICT for non-educational purposes had no significant relationship with educational outcomes.

For those reasons, it might be interesting and important to draw on the PISA 2018 data to comprehensively identify how the four factors of ICT engagement (i.e., interest in ICT, perceived ICT competence, perceived ICT autonomy, and use of social media) may influence student literacy across different countries (regions). We hypothesized that interest in ICT might positively associate with student three domain literacy across countries, as prior studies have shown a positive relationship between intrinsic motivation and achievement in general (Zhu, Yang, MacLeod, Yu, & Wu, 2019). Consistent with Lee and Wu (2012), we hypothesized that the relations of perceived ICT competence to student three domain literacy might vary across countries/culture, with students in Western countries demonstrating a positive relationship, whereas a negative relationship for Eastern students. For perceived ICT autonomy, we hypothesized that it might positively associate with student three domain literacy because students with higher autonomy in using ICT may be better at planning and monitoring their learning processes, and thus achieve better academic outcomes (Vansteenkiste, Zhou, Lens, & Soenens, 2005). For use of social media, we hypothesized that it might negatively associate with student three domain literacy because frequent use of social media may distract students from effective learning (Englander, Terregrossa, & Wang, 2010).

In this study, we selected 16 countries (regions) for investigation, namely Korea, Japan, Hong Kong-China, the United States, Germany, France, Italy, Croatia, Finland, Switzerland, Turkey, Australia, New Zealand, Brazil, Chile and Hungary because first they represent different areas in the world (e.g., Asia, Europe, North America, South America, Australia). Second, they reflect different cultures. The Eastern (Asian) countries (e.g., Korea, Japan) represent a collectivist culture, while the Western countries (e.g., USA, Germany) represent an individualist culture. By comparing those countries (regions) together, this study may provide deeper insights into how ICT engagement, as well as its relationship with student literacy, may differ across countries with similar or distinct cultures. Third, they have different education systems. For example, the Korean education system is highly competitive where students work very hard to achieve better academic achievements. In Finland, equity is a central feature of the education system. Educators avoid comparing students against one another and there is no homework and no standardized testing until students reach high school (Halinen & Jarvinen, 2008). Germany has a dual system of education in which students can choose to enter general education or vocational education (Furstenau, Pilz, & Gonon, 2014). Moreover, those countries have different PISA performances. For instance, Hong Kong-China ranked among the top league of the PISA assessments, the USA fell into the middle rank, while Brazil the low rank (OECD, 2019c), which can be used to explore the relationships between ICT engagement factors and achievements.

2. Literature review

ICT engagement is a relatively new construct proposed by Zylka et al. (2015). So far, however, this construct has not been fully investigated although some relevant concepts (e.g., computer self-concept, attitudes toward computers) have been studied in the literature. To better understand ICT engagement, a review of the literature on the role of ICT in education, ICT literacy, the theoretical framework of ICT engagement and its relations to academic achievements will be presented. This is followed by a brief review on measurement invariance.

2.1. The role of ICT in education

ICT has significantly changed the ways people live and work around the world, and it has also played a central role in the educational field. The past two decades have witnessed a rapid development of the integration of ICT into educational practices, pushing the schools to renovate their pedagogical approaches, and to avail and exploit new technological resources (Benini, 2014). There are high expectations on ICT, as it has the potential to promote economic growth, facilitate social development, and advance education reform (McGarr, 2009). Many education initiatives and research have been directed towards ICT integration in schools. One example is in Italy, where the integration of ICT in schools was marked by the launch of the Action Plan for the Information Technology Society (2001-2003). Research has indicated that the use of ICT in education can increase students' motivation, promote deep and cooperative learning, offer easy access to information and resources, enable adaptive and individualized instruction, and facilitate lifelong learning (Benini, 2014). Furthermore, students in technology-rich environments tend to perform better in academic subjects and ICT integration would promote deep and interactive learning in a context where schools may respond more effectively to the changing needs of the students in today's world (Lau & Sim, 2008).

2.2. ICT literacy

As ICT permeates and transforms almost all aspects of people's life in recent decades, individual competence to deal with ICT, often referred to as ICT literacy in education, has become increasingly important for both career success and everyday life (Zylka et al., 2015). According to Lennon, Kirsch, Von Davier, Wagner, and Yamamoto (2003), ICT literacy is defined as "the interest, attitude and ability of individuals to appropriately use digital technology and communication tools to access, manage, integrate, and evaluate information, construct new knowledge, and communicate with others in order to participate effectively in society." (p.8).

In the literature, ICT literacy has often been reflected by student self-reported frequency and diversity of ICT use in school and at home (Kunina-Habenicht & Goldhammer, 2020). Results from previous studies indicated that students use ICT more often at home than in school (Zhong, 2011). Students use ICT for various purposes, ranging from seeking information, playing computer games to social networking (Fraillon, Ainley, Schulz, Friedman, & Gebhardt, 2014). Furthermore, many researchers have investigated the relations of ICT use to student achievements. For example, Liem, Martin, Anderson, Gibson, and Sudmalis (2014) used the data from 25 countries in PISA 2003 to investigate the role of arts-related ICT use in predicting students' problem-solving skills and science and mathematics achievements. They found that the quality of arts-related ICT use was a positive predictor of problem-solving skills, whereas the quantity of arts-related ICT use was a negative predictor of problem-solving skills. Moreover, the effects of arts-related ICT use on achievements were mediated by problem-solving skills. Agasisti, Gil-Izquierdo, and Han (2020) utilized the data from 15 European countries in PISA 2012 to examine the effects of ICT use at home on student achievements using propensity score matching. Results showed that in most countries using computers intensely for homework was negatively associated with test scores across all domains, and such negative impacts held for both low- and high-performing students.

As demonstrated above, many prior studies have investigated ICT literacy from a behavioral perspective (i.e., ICT use). However, some researchers have emphasized the need to incorporate motivational and social-cognitive aspects into ICT literacy (De Wit, Heerwegh, & Verhoeven, 2012). For example, based on Bandura's (1986) social cognitive theory, LaRose and Eastin (2004) extended the uses and gratifications approach/ model of media attendance (MMA). They found that active consideration of internet use and gratifications, habitual behavior and deficient self-regulation were powerful indicators of media attendance and computer use.

Senkbeil and Ihme (2017) adapted the MMA model and proposed an ICT motivation inventory model. In their model, five motivational factors were specified for ICT literacy: instrumental motive (information seeking, learn and work), hedonic motive (entertainment, escapism), social interaction motive (social exchange, self-presentation), ICT-related self-efficacy, and ICT-related self-regulation. Further, they empirically tested the model with German students and found that instrumental motive, ICT-related self-efficacy and ICT-related self-regulation were significantly related with ICT literacy, but hedonic and social interaction motive had no significant relations to ICT literacy. Besides, the five motivational factors were associated with individual characteristics such as social background and need for cognition.

Venkatesh, Morris, Davis, and Davis (2003) synthesized eight important ICT acceptance models (e.g., the technology acceptance mode or TAM) in the literature into the Unified Theory of Acceptance and Use of Technology (UTAUT) model. In the UTAUT model, four factors were identified as core determinants of intention to use information technology and usage behavior: (1) performance expectancy, the extent to which an individual believes that using the technology would help him/her improve job performance; (2) effort expectancy, the level of easiness in using the technology; (3) social influence, the degree to which an individual perceives that important others, such as relatives, peers and subordinates, believe that he/she should use the technology; and (4) facilitating conditions, the degree to which an individual perceives that organizational and technical infrastructure exist to support the use of the technology. Moreover, they found four factors that might moderate those relationships: gender, age, experience and voluntariness of technology use.

Janneck, Vincent-Höper, and Ehrhardt (2013) introduced a computer-related self-concept (CSC) model to study the emotions, attitudes and behaviors related to computers. The CSC model includes three components: (1) conative component, i.e., concrete actions, behaviors or specific experiences with computers; (2) motivational component, i.e., positive or negative emotions, attitudes and individual reasons for using computers; and (3) cognitive component, i.e., perceived competence and self-efficacy regarding computer use, and personal strategies for handling new information technology. Further, they investigated gender differences in CSC and its relationship to technology-related career development. They found that compared with women, men showed more positive CSC and were slightly advantaged in career motivation.

2.3. Theoretical framework of ICT engagement and its relations to academic achievements

ICT engagement, a more comprehensive cognitive-motivational aspect of ICT literacy, was proposed by Zylka et al. (2015). Originally, Zylka et al. (2015) identified five dimensions of ICT engagement: interest in computers, interest in mobile devices, positive self-concept in using ICT, negative self-concept in using ICT, and social exposure to ICT. Later, this ICT engagement construct was theoretically extended by the aspect of "perceived ICT autonomy" and it was adopted in the main study of PISA 2015 and PISA 2018.

The new ICT engagement construct involves four factors: interest in ICT, perceived ICT competence, perceived ICT autonomy and use of social media. Specifically, interest in ICT describes an individual's intrinsic motivation to deal with ICT-related tasks or activities, which is supposed to initiate ICT-related behaviors and produce positive emotions, learning and performance outcomes (Goldhammer, Gniewosz, & Zylka, 2017). Perceived ICT competence refers to an individual's beliefs about his/her own ICT-related knowledge and skills, which is assumed to maintain ICT-related activities and foster ICT skills (Goldhammer et al., 2017). Perceived ICT autonomy reflects an individual's perceived control and independence while undertaking ICT-related activities, which is supposed to foster positive self-concept and increase the likelihood of showing self-regulated ICT-related behaviors in future (Goldhammer et al., 2017). Use of social media addresses the extent to which individuals make ICT a subject of interpersonal communication and interaction, and thus represents the connectedness or belongingness to others when dealing with ICT (Goldhammer et al., 2017). This new construct (questionnaire) in PISA is significant in several ways. First, it has comprehensively integrated cognitive, motivational and social factors. Second, it may receive more empirical support because PISA collects data on a large scale (Meng et al., 2019). Third, it may contribute to the development of educational interventions to improve ICT engagement by identifying relevant factors and by implication, engagement change techniques. Thus, this four-factor ICT engagement questionnaire was adopted in the present study.

ICT engagement has been investigated as a multidimensional construct in terms of its relationship with student achievements. When researchers focused on some of the four dimensions (or a similar construct), they obtained mixed results (Hu, Gong, Lai, & Leung, 2018; Luu & Freeman, 2011). For example, based on the PISA 2009 data, Lee and Wu (2012) reported that student reading literacy improved if they had more positive attitudes and higher confidence toward computers. Hu et al. (2018) found that students with higher enjoyment in ICT social interaction had lower academic performance. Cheema and Zhang (2013) found that the relations of perceived ICT autonomy to achievements might be moderated by task features: perceived ICT autonomy was a positive predictor of ordinary and familiar task performance, while a negative predictor for complicated and unfamiliar task performance.

2.4. Measurement invariance

Measurement invariance (MI) addresses the key question of whether a construct is measured and understood in the same way across groups or across time (Putnick & Bornstein, 2016). MI is a necessary prerequisite for valid comparative research (e.g., cross-cultural studies, Hoffman, 2015) because it ensures that group differences in the latent/observed scores are not attributable to the measurement instrument, but their true differences in the underlying construct one is attempting to measure (Hoffman, 2015). MI has been studied using certain statistical approaches such as Structural Equation Modeling (SEM, Meade & Lautenschlager, 2004) and Item Response Theory (IRT, Masters, 1982; Muraki, 1992). For example, Senese, Bornstein, Haynes, Rossi, and Venuti (2012) established the MI of the Parental Style Questionnaire (PSQ) across Italian and USA mothers using hierarchical multi-group confirmatory factor analyses. Behrend, Foster Thompson, Meade, Newton, and Grayson (2008) applied IRT methods to examine the MI (or differential item functioning, DIF) of a self-report survey on the importance of providing patient care across gender. In the present study, we adopted the SEM approach (i.e., multi-group confirmatory factor analysis, MG-CFA).

According to Widaman and Reise (1997), four typical sequential phases of MI testing within the MG-CFA framework are as follows: (1) Configural invariance (pattern invariance). When assessing MI, the first step is to test configural invariance, i.e., whether or not the same items measure the constructs across groups. Invariance at the configural level indicates that the overall factor structure of the constructs fits well across groups. Ascertaining configural invariance does not allow for group comparisons or full group analyses at the latent or observed level (Li, Gooden, & Toland, 2016). The configural invariance model serves as a baseline model for further MI tests.

(2) Metric invariance (weak invariance). If configural invariance is supported, then the next step is to examine metric invariance, i.e., whether or not the factor loadings of the items are equivalent across groups. Factor loadings reflect the extent to which differences among individuals' responses to items arise from differences among their levels of the underlying construct that is assessed by the items (Bialosiewicz, Murphy, & Berry, 2013). Ascertaining metric invariance allows for substantiating multi-group comparisons of variances, covariances and correlations at the latent level (Li et al., 2016).

(3) Scalar invariance (strong invariance). If metric invariance is supported, then the next step is to examine scalar invariance, i.e., whether or not the intercepts/thresholds of the items are equivalent across groups. Item intercepts are considered as the origin or starting values of the scale that the latent factors are based on (Bialosiewicz et al., 2013). Ascertaining scalar invariance allows for substantiating multi-group comparisons of means, variances, covariances and correlations at the latent level (e.g., t-test and ANOVA for latent variable means, linear regression for the relations among latent variables; Li et al., 2016).

(4) Residual invariance (strict invariance). If scalar invariance is supported, then the next step is to examine residual invariance, i.e., whether or not the residuals of the items are equivalent across groups. Residual invariance means that the sum of specific variance (variance of the item that is not shared with the factor) and error variance (measurement error) is similar across groups (Bialosiewicz et al., 2013). Ascertaining residual invariance allows for substantiating multi-group comparisons of means, variances, covariances and correlations at the observed level (e.g., t-test and ANOVA for observed variable means, linear regression for the relations among observed variables; Li et al., 2016). Although a required component for full factorial invariance (Meredith, 1993), testing residual invariance is of debatable necessity and importance (Putnick & Bornstein, 2016). Often the decision is made by researchers whether or not to examine residual invariance based on their needs (Meade & Lautenschlager, 2004).

Notably, these four levels of invariance definitions are developed for continuous variables. As such, all observed variables have an inherent scale and can be described as having means, variances and covariances with other variables (Wu & Estabrook, 2016). However, categorical and ordinal data (e.g., Likert-type ICT engagement questionnaire used in this study) lack these features. Thus, constraints are needed to properly define their scales so that relevant parameters can be uniquely identified and estimated (Wu & Estabrook, 2016). One option is to set the intercept of each latent factor to zero and its variances to one ("delta-parameterization"). Another option is to set the variances of residuals to one ("theta-parameterization"). This study utilized the latter option to examine the four invariance levels of the ICT engagement questionnaire because residual invariance for categorical/ordinal variables can only be examined using the theta-parameterization.

3. The present study

The purpose of the present study was to examine the MI of the new ICT engagement questionnaire across countries (regions) using the PISA 2018 data, and further to explore the effects of ICT engagement on student mathematical, scientific and reading literacy.

3.1. Methods

3.1.1. Data source

Data from the 16 countries (regions), namely Korea (KOR), Japan (JAP), Hong Kong-China (HKG), the United States (USA), Germany (GER), France (FRA), Italy (ITA), Croatia (COA), Finland (FIN), Switzerland (SWZ), Turkey (TUR), Australia (AUS), New Zealand (NZL), Brazil (BRA), Chile (CHI) and Hungary (HUN) were retrieved from the PISA 2018 official website (http://www.oecd.org/pisa/data/2018database/).

The sample size for each country (region) was as follows: Korea (N = 6,512 students from 188 schools), Japan (N = 5,996 students from 183 schools), Hong Kong-China (N = 5,546 students from 152 schools), the United States (N = 4,467 students from 162 schools), Germany (N = 4,507 students from 208 schools), France (5,432 students from 251 schools), Italy (N = 9,426 students from 530 schools), Croatia (N = 6,609 students from 183 schools), Finland (N = 4,899 students from 205 schools), Switzerland (N = 5,182 students from 228 schools), Turkey (N = 6,508 students from 186 schools), Australia (N = 10,675 students from 714 schools), New Zealand (N = 5,308 students from 192 schools), Brazil (N = 6,866 students from 572 schools), Chile (N = 5,693 students from 246 schools) and Hungary (N = 5,132 students from 236 schools). All the above countries (regions) administered the ICT engagement questionnaire and domain assessments on computers rather than using paper-and-pencil tests so that their responses are comparable. Student, school and country characteristics are summarized in Table 1, by country (region).

3.1.2. Measures

3.1.2.1. ICT engagement.

The ICT engagement questionnaire from PISA

Table 1
Descriptive statistics of student, school and country characteristics, by country (region).

	Mean (SD)/Percentage							
Variables	KOR	JAP	HKG	USA	GER	FRA	ITA	COA
Student characteristics								
Gender (% of female)	48.4%	51.1%	50.2%	49.1%	47.3%	49.4%	48.4%	51.0%
Age	15.73 (0.29)	15.78 (0.29)	15.74 (0.29)	15.85 (0.29)	15.83 (0.29)	15.87 (0.29)	15.78 (0.29)	15.74 (0.29)
ESCS	0.09 (0.77)	−0.10 (0.72)	−0.52 (1.01)	0.09 (1.00)	−0.55 (1.02)	−0.06 (0.94)	−0.19 (0.88)	−0.23 (0.77)
ICT resources	−0.35 (0.79)	−0.52 (0.82)	−0.31 (0.89)	0.17 (1.12)	0.05 (0.87)	−0.18 (0.91)	−0.18 (0.80)	−0.41 (0.70)
ICT use during lessons	0.07 (1.12)	−0.62 (0.75)	−0.41 (0.94)	0.40 (0.87)	−0.25 (0.86)	−0.20 (0.83)	−0.06 (0.91)	−0.33 (0.89)
ICT use outside of lessons	−0.44 (0.97)	−0.87 (0.66)	−0.37 (1.10)	0.30 (1.01)	−0.02 (0.84)	−0.11 (0.97)	0.08 (0.98)	−0.19 (0.98)
Interest in ICT	−0.12 (0.97)	−0.30 (1.07)	0.04 (0.93)	0.09 (0.97)	0.28 (0.95)	0.32 (1.16)	−0.12 (0.94)	0.08 (1.05)
Perceived ICT competence	−0.32 (0.97)	−0.83 (1.00)	−0.07 (0.81)	0.12 (0.93)	0.08 (1.08)	0.19 (1.08)	−0.07 (0.93)	0.22 (1.03)
Perceived ICT autonomy	−0.21 (0.95)	−0.17 (1.07)	0.28 (0.90)	−0.05 (0.99)	0.37 (1.04)	0.25 (0.99)	−0.14 (0.94)	0.06 (1.00)
Use of social media	−0.21 (1.07)	−0.44 (1.05)	0.10 (0.90)	0.04 (0.99)	−0.17 (0.98)	0.15 (1.08)	0.05 (0.89)	0.13 (1.09)
Mathematical literacy	529.36 (91.95)	528.08 (79.78)	557.04 (83.99)	477.70 (85.53)	512.16 (88.03)	495.41 (89.20)	501.57 (83.04)	467.04 (77.77)
Scientific literacy	521.96 (91.12)	530.68 (86.76)	521.98 (77.79)	502.52 (93.24)	515.79 (99.95)	494.99 (91.61)	482.20 (81.59)	475.28 (81.98)
Reading literacy	517.72 (96.43)	505.17 (93.11)	531.88 (91.37)	506.71 (103.12)	511.79 (99.95)	494.91 (98.55)	488.65 (88.59)	482.78 (83.61)
School characteristics								
School type (% of public schools)	61.0%	69.4%	10.6%	95.0%	96.6%	82.4%	91.0%	97.2%
School location	4.17 (0.96)	3.90 (0.80)	4.16 (0.89)	3.22 (1.13)	3.06 (0.96)	2.91 (0.93)	2.97 (0.88)	3.21 (0.88)
Education material shortage	0.42 (0.94)	0.74 (0.91)	−0.21 (0.87)	−0.44 (0.95)	0.25 (0.98)	−0.25 (0.95)	0.27 (0.93)	0.79 (0.94)
Education staff shortage	0.16 (0.86)	0.94 (0.74)	0.10 (1.03)	−0.16 (1.03)	0.37 (0.80)	0.04 (0.85)	0.45 (0.91)	0.04 (0.93)
Country characteristics								
GDP per capita (US$)	31761.98	40246.88	48755.84	65118.36	46258.88	40493.93	33189.57	14853.24

	Mean (SD)/Percentage							
Variables	FIN	SWZ	TUR	AUS	NZL	BRA	CHI	HUN
Student characteristics								
Gender (% of female)	50.2%	48.3%	49.5%	49.7%	51.8%	51.2%	48.8%	50.8%
Age	15.72 (0.29)	15.81 (0.28)	15.82 (0.29)	15.79 (0.29)	15.78 (0.29)	15.91 (0.28)	15.81 (0.28)	15.78 (0.29)
ESCS	0.32 (0.77)	0.03 (0.92)	−1.14 (1.17)	0.34 (0.89)	0.19 (0.96)	−0.96 (1.19)	−0.25 (1.09)	−0.06 (0.92)
ICT resources	0.15 (0.70)	0.19 (0.89)	−1.05 (0.95)	0.62 (0.93)	0.36 (0.97)	−1.11 (0.90)	−0.44 (0.97)	−0.20 (0.83)
ICT use during lessons	0.09 (0.77)	−0.28 (0.84)	0.23 (1.03)	0.74 (0.89)	0.62 (0.79)	−0.61 (0.90)	−0.10 (0.92)	−0.32 (0.85)
ICT use outside of lessons	−0.19 (0.85)	−0.27 (0.88)	−0.02 (1.00)	0.48 (1.03)	0.33 (0.95)	0.08 (1.21)	0.20 (1.07)	−0.12 (0.92)
Interest in ICT	−0.09 (0.88)	0.01 (0.97)	−0.16 (1.17)	0.16 (0.95)	0.19 (0.94)	0.15 (1.15)	0.09 (1.01)	−0.20 (0.91)
Perceived ICT competence	−0.02 (0.96)	0.00 (1.03)	−0.21 (1.07)	0.18 (0.95)	0.18 (0.93)	−0.01 (0.96)	0.11 (0.99)	0.07 (0.99)
Perceived ICT autonomy	0.16 (0.92)	0.09 (0.99)	−0.12 (1.05)	0.15 (0.95)	0.09 (0.98)	−0.02 (1.01)	−0.02 (1.01)	−0.04 (0.98)
Use of social media	0.09 (0.94)	−0.14 (1.06)	0.21 (1.00)	0.04 (0.94)	−0.05 (0.92)	0.23 (0.94)	0.11 (1.00)	0.02 (0.98)
Mathematical literacy	513.03 (73.18)	521.02 (85.78)	455.58 (80.28)	497.10 (85.15)	500.27 (84.75)	400.57 (80.52)	439.61 (81.24)	488.11 (84.18)
Scientific literacy	529.20 (87.27)	499.94 (89.51)	470.90 (76.83)	509.88 (95.31)	516.73 (93.73)	422.28 (84.41)	463.87 (81.72)	487.49 (88.59)
Reading literacy	528.92 (91.52)	490.39 (96.02)	468.57 (82.66)	511.68 (103.70)	515.26 (99.44)	435.07 (94.84)	475.47 (89.36)	482.91 (93.85)
School characteristics								
School type (% public schools)	95.6%	90.8%	87.1%	63.7%	93.2%	88.2%	32.3%	75.8%
School location	2.92 (0.95)	2.51 (0.87)	3.92 (1.02)	3.79 (1.22)	3.44 (1.16)	3.39 (1.10)	3.73 (1.03)	3.12 (1.25)

(continued on next page)

Table 1 (*continued*)

Variables	Mean (SD)/Percentage FIN	SWZ	TUR	AUS	NZL	BRA	CHI	HUN
Education material shortage	0.10 (0.82)	−0.46 (0.84)	−0.52 (0.92)	−0.47 (0.91)	−0.26 (0.85)	0.05 (1.10)	−0.28 (0.89)	0.35 (0.96)
Education staff shortage	0.07 (0.84)	−0.51 (0.80)	0.13 (1.11)	−0.31 (0.96)	−0.05 (0.87)	−0.13 (1.08)	−0.26 (1.00)	0.02 (0.72)
Country characteristics								
GDP per capita (US$)	48685.85	81993.73	9042.49	54097.10	42084.35	8717.19	14896.45	16475.74

Notes: SD = standard deviation; Pairwise comparison test results for selected variables at 0.05 significance level using Bonferroni correction were as follows: Interest in ICT between countries were all significant except that for AUS with BRA, CHI, COA and NZL, BRA with CHI, NZL and USA, CHI with COA, HKG and USA, COA with HGK and USA, FIN with ITA, KOR and TUR, FRA with GER, HKG with SWZ and USA, HUN with TUR, ITA with KOR and TUR, KOR with TUR.
Perceived ICT competence between countries were all significant except that for AUS with COA, FRA and NZL, BRA with FIN, HKG and SWZ, CHI with GER, HUN, and NZL, COA with FIN and NZL, FIN with HKG, ITA and SWZ, FRA with NZL, GER with HUN and USA, HKG with ITA and TUR, HUN with SWZ and USA, ITA with TUR, NZL with USA.
Perceived ICT autonomy between countries were all significant except that for AUS with FIN, NZL and SWZ, BRA with CHI, HUN and USA, CHI with HUN and USA, COA with NZL and SWZ, FRA with HKG, HUN with USA, ITA with JAP, JAP with KOR and TUR, KOR with TUR, NZL with SWZ.
Use of social media between countries were all significant except that for AUS with FIN, HUN, ITA and USA, BRA with TUR, CHI with COA, FIN, FRA, HKG, ITA and USA, COA with FIN, FRA, and HKG, FIN with FRA, HKG, ITA and USA, FRA with HKG and TUR, GER with KOR and SWZ, HKG with ITA and USA, HUN with ITA, NZL and USA, ITA with USA.
Mathematical literacy between countries were all significant except that for AUS with FRA and HUN, FIN with GER, FRA with HUN, ITA with NZL, JAP with KOR.
Scientific literacy between countries were all significant except that for AUS with GER, COA with ITA and TUR, FIN with HKG and KOR, FRA with HUN, GER with NZL, HKG with KOR, SWZ with USA;
Reading literacy between countries were all significant except that for AUS with GER, JAP and USA, CHI with TUR, COA with HUN and ITA, FIN with KOR, FRA with HUN, ITA and SWZ, GER with JAP and USA, HUN with ITA and SWZ, ITA with SWZ, JAP with USA.

2018 includes four scales: interest in ICT, perceived ICT competence, perceived ICT autonomy and use of social media (OECD, 2019a). A four-point Likert rating scale was utilized for all of the four scales (1 = “strongly disagree”, 2 = “disagree”, 3 = “agree”, 4 = “strongly agree”). Higher values indicate better ICT engagement.

3.1.2.1.1. Interest in ICT. Interest in ICT refers to an individual’s enduring preference for dealing with ICT-related tasks or activities. Six items were included in this scale. Some example items were: “I forget about time when I am using digital devices.” and “I really feel bad if no internet connection is possible”. PISA also constructed an overall index of interest in ICT based on the six items, of which the average is zero and the standard deviation is one across OECD countries.

3.1.2.1.2. Perceived ICT competence. Perceived ICT competence reflects an individual’s perception of his/her own ICT-related knowledge and skills, which was operationalized by five items. Some example items were “I feel comfortable using digital devices that I am less familiar with.” and “When I come across problems with digital devices, I think I can solve them”. PISA also constructed an overall index of perceived ICT competence based on the five items, of which the average is zero and the standard deviation is one across OECD countries.

3.1.2.1.3. Perceived ICT autonomy. Perceived ICT autonomy measures an individual’s control and independence in dealing with ICT-related activities. This scale included five items. Some example items were “If I need new software, I install it by myself.” and “If I need a new application, I choose it by myself”. PISA also constructed an overall index of perceived ICT autonomy based on the five items, of which the average is zero and the standard deviation is one across OECD countries.

3.1.2.1.4. Use of social media. Use of social media refers to the extent to which an individual communicates and interacts with others using ICT, which was assessed through five items. Some example items were “I like to meet friends and play computer and video games with them.” and “I like to share information about digital devices with my friends”. PISA also constructed an overall index of use of social media based on the five items, of which the average is zero and the standard deviation is one across OECD countries.

The McDonald’s ω reliability coefficients of the four ICT engagement scales for each of the selected countries (regions) ranged from 0.880 to 0.952, which are presented in Table 2.

Table 2
McDonald’s ω reliability coefficients of the four ICT engagement scales, by country (region).

Countries (regions)	Interest in ICT	Perceived ICT competence	Perceived ICT autonomy	Use of social media
Overall sample	.931	.931	.908	.901
Korea	.922	.914	.905	.906
Japan	.912	.920	.916	.903
Hong Kong	.938	.932	.936	.912
USA	.952	.936	.912	.907
Germany	.944	.929	.902	.880
France	.916	.919	.891	.889
Italy	.928	.907	.891	.889
Croatia	.933	.923	.912	.910
Finland	.942	.933	.907	.910
Switzerland	.922	.926	.890	.886
Turkey	.918	.931	.916	.908
Australia	.944	.928	.911	.908
New Zealand	.947	.939	.909	.907
Brazil	.931	.922	.917	.908
Chile	.930	.929	.919	.913
Hungary	.933	.913	.900	.905

3.1.2.2. Literacy in mathematics, science and reading. PISA measures students’ literacy in mathematics, science and reading. The literacy construct focuses on “the mastery of processes, the understanding of concepts, and the application of knowledge and functioning in various situations” (OECD, 2019a, p. 12).

3.1.2.2.1. Mathematical literacy. Mathematics is a minor domain in PISA 2018. As one of the two minor domains, about one quarter of the assessment was devoted to mathematics items designed to measure students’ capabilities to “formulate situations mathematically; employ mathematical concepts, facts, procedures and reasoning; and interpret, apply and evaluate mathematical outcomes” (OECD, 2019a, p. 75). “Formulate situations mathematically” accounted for 25% of the total test items; “employ mathematical concepts, facts, procedures and reasoning” accounted for 50% of the total test items; and “interpret, apply and evaluate mathematical outcomes” accounted for 25% of the total test items.

3.1.2.2.2. Scientific literacy. Science is a minor domain in PISA 2018. As one of the two minor domains, about one quarter of the assessment was devoted to science items designed to measure students' capabilities to "explain phenomena scientifically; evaluate and design scientific enquiry; and interpret data and evidence scientifically" (OECD, 2019a, p. 100). All of these competences require knowledge. Scientific knowledge includes (1) content knowledge, the knowledge of the content of science, which accounted for 54% - 66% of the total test items; (2) procedural knowledge, the knowledge of the procedures that scientists use to establish scientific knowledge, which accounted for 19% - 31% of the total test items; and (3) epistemic knowledge, an understanding of the rationale for the common practices of scientific inquiry, the status of the claims that are generated, and the meaning of foundational terms such as theory, hypothesis and data. Epistemic knowledge accounted for 10% - 22% of the total test items (OECD, 2019a).

3.1.2.2.3. Reading literacy. Reading was the major domain in PISA 2018. As the major domain, about half of the assessment was devoted to reading items designed to measure students' capabilities to "access and retrieve information, understand, use, evaluate, reflect on and engage with one or more texts" (OECD, 2019a, p. 33). The percentages of the test items for each reading process were as follows: "access and retrieve" represented 25% of the total test items; "integrate and interpret" represented 50% of the total test items; and "reflect and evaluate" represented 25% of the total test items.

For each of the above three domain assessments, each participating student received ten plausible values (PVs). Similar to many prior PISA studies (e.g., Von Davier, Gonzalez, & Mislevy, 2009), we used the average of the ten PVs for each domain to represent student mathematical/scientific/reading literacy.

3.1.2.3. Student-, school- and country-level control variables

3.1.2.3.1. Gender. Gender was dichotomously recorded, with 1 = female and 2 = male.

3.1.2.3.2. Economic, social and cultural status (ESCS). The PISA index of ESCS represents student socioeconomic status (SES), which was derived from three family background variables: "parents' highest occupational status", "parents' highest level of education", and "home possessions" (OECD, 2019b). The average of the index is zero and the standard deviation is one across OECD countries. Higher scores indicate better SES.

3.1.2.3.3. Age. The age of a student was calculated as the difference between the year and month of the testing and the year and month of a student's birth (OECD, 2019b).

3.1.2.3.4. ICT resources. In PISA, students were asked about their availability of ICT-related items at home, including "educational software", "a link to the Internet", "cell phones with Internet access (e.g., smartphones)", "computers (desktop computer, portable laptop, or notebook)", "Tablet computers (e.g., iPad, BlackBerry, Playbook)" and "E-book readers (e.g., KindleTM, Kobo, Booken)". The average of the index is zero and the standard deviation is one across OECD countries. Higher scores indicate more access to ICT resources.

3.1.2.3.5. Subject-related ICT use during lessons. This index reflects the amount of time students use digital devices during classroom lessons. The average of the index is zero and the standard deviation is one across OECD countries. Higher values indicate more frequent subject-related use of ICT during lessons.

3.1.2.3.6. Subject-related ICT use outside of lessons. This index reflects the amount of time students use digital devices outside of classroom lessons regardless whether at home or in school. The average of the index is zero and the standard deviation is one across OECD countries. Higher values indicate more frequent subject-related use of ICT outside of classroom lessons.

3.1.2.3.7. School type. School type was dichotomously recorded, with 1 = private school and 2 = public school.

3.1.2.3.8. School location. This variable was recorded in PISA 2018 using the following categories: 1 = A village, hamlet or rural area (fewer than 3000 people), 2 = A small town (3000 to about 15000 people), 3 = A town (15000 to about 100000 people), 4 = A city (100000 to about 1000000 people), and 5 = A large city (with over 1000000 people). School location was treated as a continuous variable in the data analysis, with higher values indicating that the school was located in a larger populated community.

3.1.2.3.9. Shortage of educational material. This PISA index was constructed based on school principals' responses about their perceptions about educational resources in the schools. They were asked to report whether their school's capacity to provide instruction was hindered by a shortage of educational materials (e.g., textbooks, IT equipment, library or laboratory material) and physical infrastructure (e.g., building, grounds, heating/cooling, lighting and acoustic systems). The average of the index is zero and the standard deviation is one across OECD countries. Positive values reflect principals' perceptions that a shortage of educational resources hinders the capacity to provide instruction to a greater extent than the OECD average, whereas negative values indicate that school principals believe a shortage hinders the capacity to provide instruction to a lesser extent.

3.1.2.3.10. Shortage of educational staff. This PISA index was constructed based on school principals' responses about their perceptions about human resources in the schools. They were asked to report whether their school's capacity to provide instruction was hindered by a shortage of teaching and assisting staff. The average of the index is zero and the standard deviation is one across OECD countries. Positive values reflect principals' perceptions that a shortage of education staff hinders the capacity to provide instruction to a greater extent than the OECD average, whereas negative values indicate that school principals believe a shortage hinders the capacity to provide instruction to a lesser extent.

3.1.2.3.11. Gross Domestic Product per capita (GDP per capita). GDP per capita is an important indicator of economic performance and a useful unit to make cross-country comparisons of average living standards and economic wellbeing, which is released by the World Bank every year (see https://data.worldbank.org/indicator/NY.GDP.PCAP.CD for more details). In this study we utilized the 2019 GDP per capita for each sampling country in the analysis.

3.1.3. Data analysis

First, before testing the MI of ICT engagement, a conceptually consistent and cross-country applicable ICT engagement measurement model needs to be determined (Buerger, Kroehne, & Goldhammer, 2016). Thus, single-group confirmatory factor analyses using robust weighted least squares mean and variance (WLSMV, Muthen & Muthen, 1998-2019; Muthen and Muthen, 1998) were conducted in Mplus 8.5 to examine the factor structure of the ICT engagement questionnaire for each of the selected countries (regions), and for the overall sample. This WLSMV method is recommended for analyzing measurement models with categorical/ordinal data such as Likert-scale data (Kline, 2016). The model fit indices include Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Residual (SRMR). Conventional model fit criteria for continuous indicators using the maximum likelihood (ML) estimator are as follows: CFI and TLI (larger value indicates better model fit; acceptable fit $\geq$.90, good fit $\geq$.95), and RMSEA and SRMR (smaller value indicates better model fit; acceptable fit $\leq$.10, good fit $\leq$.05, Hu & Bentler, 1999). As for the WLSMV estimator, however, the criteria/cutoff values of CFI, TLI, RMSEA and SRMR have received limited attention and no clear cutoff scores have been provided in the literature (DiStefano & Morgan, 2014). According to a simulation study by Beauducel and Herzberg (2006), when indicators are categorical and have more categories, (1) no significant differences in CFI were found between ML and WLSMV; (2) TLI based on WLSMV was smaller than that based on ML; and (3) RMSEA and SRMR based on WLSMV was (slightly) larger than that based on ML. Moreover, they found that increasing number of latent factors (with five indicators per factor) were associated with a decrease of CFI and TLI, and an increase of RMSEA and

SRMR. From the above simulation results, it seems that less stringent cutoff values can be utilized for WLSMV given that our model included four latent factors with each factor involving five or six indicators and each indicator involving four categories. To be consistent with prior studies (e.g., Lu et al., 2018; Elhai, Tiamiyu, & Weeks, 2018), we used the conventional criteria to evaluate the model fit in this study. That is, CFI and TLI (acceptable fit ≥ .90, good fit ≥ .95), and RMSEA and SRMR (acceptable fit ≤ .10, good fit ≤ .05, Hu & Bentler, 1999). Local fit of the single-group CFA models was also assessed by examining the residual correlation matrix for the overall sample and for each of the selected countries (regions). The residual correlation matrix represents the difference between observed correlation matrix and predicted correlation matrix. Large residual correlations indicate poor item fit within the model. However, recommendations for cut-offs have not been established with WLSMV (Hooker, Dow, Morgan, Schatschneider, & Wetherby, 2019).

Second, multi-group confirmatory factor analyses (MG-CFA) were performed in Mplus 8.5 using the WLSMV estimator (ESTIMATOR = WLSMV) and theta parameterization (PARAMETERIZATION = THETA) to examine the MI of ICT engagement across the countries (regions) at the configural, metric, scalar and residual invariance levels. Given that our study included four latent factors with each factor involving five or six categorical indicators and 16 countries comparison, we considered the following model fit criteria as evidence of reasonable MI: Δ RMSEA ≤ 0.01, Δ SRMR ≤ 0.01, Δ CFI ≥ - 0.002, and Δ TLI ≥ - 0.002 (Chen, 2007; Svetina & Rutkowski, 2017; Svetina, Rutkowski, & Rutkowski, 2019). χ^2 statistic was not appropriate for likelihood-ratio tests when WLSMV estimator was utilized (Muthen & Muthen, 1998-2019; Muthen and Muthen, 1998), but the DIFFTEST function that rescales the χ^2 values was implemented to compare different MG-CFA models.

PISA 2018 utilized a two-stage stratified complex design where schools were sampled within countries, and students within schools (OECD, 2019b). Thus, “sampling weight” (W_FSTUWT) and “cluster” (SCHOOLID) were considered in the single-group and multi-group CFA models. All the missing data were coded as “99”. The percentage of missing data is 2.973% (< 5%, Schafer, 1999), thus pairwise deletion was utilized to deal with the missing values (TYPE = MISSING, Muthen & Muthen, 1998–2019Muthen and Muthen, 1998Muthen & Muthen, 1998–2019).

In order to examine the effects of ICT engagement on student literacy, three-level models (students at level-1, schools at level-2, and countries at level-3) were built in Mplus 8.5 for each of the three academic subjects. We considered multi-level analysis because students were nested within schools, and schools were nested within countries. The intra-class correlations (ICCs) among mathematics/science/reading performance for students within the same school and the same country is 0.497, 0.440 and 0.394 respectively. The intra-class correlations among mathematics/science/reading performance for students for different schools within the same country is 0.176, 0.141 and 0.099 respectively.

In the three-level models, student domain literacy was entered as the dependent variable, with the four factors of ICT engagement (i.e., interest in ICT, perceived ICT competence, perceived ICT autonomy, and use of social media) and student characteristics (i.e., gender, age, ESCS, ICT resources, subject-related ICT use during lessons, subject-related ICT use outside of lessons) as the level-1 variables, with school characteristics (i.e., school type, school location, education material shortage and education staff shortage) as the level-2 variables, and with the country dummy variables (i.e., 15 dummies for 16 countries) and GDP per capita as the level-3 variables. The multi-level model equations were as follows:

Level-1 Model (student level):

$$\begin{aligned} Domain\ Literacy_{ijk} = {} & \pi_{0jk} + \pi_{1jk} * gender_{ijk} + \pi_{2jk} * age_{ijk} + \pi_{3jk} * ESCS_{ijk} \\ & + \pi_{4jk} * ICT\ reources_{ijk} + \pi_{5jk} * ICT\ interest_{ijk} + \pi_{6jk} \\ & * perceived\ ICT\ competence_{ijk} + \pi_{7jk} \\ & * perceived\ ICTautonomy_{ijk} + \pi_{8jk} \\ & * use\ of\ social\ media_{ijk} + \pi_{9jk} \\ & * ICT\ use\ during\ lessons_{ijk} + \pi_{10jk} \\ & * ICT\ use\ outside\ of\ lessons_{ijk} + \varepsilon_{ijk} \end{aligned}$$

Level-2 Model (school level):

$$\begin{aligned} \pi_{0jk} = {} & \beta_{00k} + \beta_{01k} * school\ location_j + \beta_{02k} * school\ type_j + \beta_{03k} \\ & * education\ material\ shortage_j + \beta_{04k} * education\ staff\ shortage_j + r_{0jk} \end{aligned}$$

$$\begin{aligned} \pi_{1jk} = {} & \beta_{10k},\ \pi_{2jk} = \beta_{20k},\ \pi_{3jk} = \beta_{30k},\ \pi_{4jk} = \beta_{40k},\ \pi_{5jk} = \beta_{50k} + \gamma_{5jk},\ \pi_{6jk} \\ & = \beta_{60k} + \gamma_{6jk},\ \pi_{7jk} = \beta_{70k} + \gamma_{7jk},\ \pi_{8jk} = \beta_{80k} + \gamma_{8jk},\ \pi_{9jk} = \beta_{90k},\ \pi_{10jk} \\ & = \beta_{100k} \end{aligned}$$

Level-3 Model (country level):

$$\beta_{00k} = \gamma_{000} + \gamma_{001}(GDP\ per\ capita) + \mu_{00k}$$
$$\beta_{01k} = r_{010}, \beta_{02k} = r_{020},\ \beta_{03k} = r_{030},\ \beta_{04k} = r_{040},\ \beta_{10k} = r_{100},\ \beta_{20k} = r_{200},\ \beta_{30k} = r_{300},\ \beta_{40k} = r_{400},\ \beta_{90k} = r_{900},\ \beta_{100k} = r_{1000},\ \beta_{50k}$$
$$= r_{500} + r_{501}(Brazil) + \ldots + r_{5015}(Croatia),\ \beta_{60k} = r_{600} + r_{601}(Brazil) + \ldots + r_{6015}(Croatia),\ \ \beta_{70k} = r_{700} + r_{701}(Brazil) + \ldots + r_{7015}(Croatia),\ \ \beta_{80k}$$
$$= r_{800} + r_{801}(Brazil) + \ldots + r_{8015}(Croatia),\ \ \beta_{90k} = r_{900},\ \beta_{100k} = r_{1000}$$

Furthermore, student sampling weights were considered in the multi-level analysis. We employed the variance inflation factor (VIF) to check the multicollinearity of the predictors (Park & Weng, 2020), and no VIFs exceeded 10 (ranged from 1.003 to 1.983). Thus, multicollinearity was not a concern in this study. The assumptions of

Table 3
Model fit indices for the single-group confirmatory factor analysis, by country (region).

Countries (regions)	CFI	TLI	RMSEA (90% C.I.)	SRMR
Overall sample	.93	.92	.041 (.041, .042)	.043
Korea	.91	.90	.109 (.108, .111)	.066
Japan	.90	.88	.103 (.102, .105)	.055
Hong Kong	.93	.92	.081 (.079, .082)	.050
United States	.95	.94	.075 (.074, .077)	.047
Germany	.94	.93	.071 (.070, .073)	.054
France	.93	.92	.075 (.074, .077)	.049
Italy	.93	.92	.049 (.048, .051)	.047
Croatia	.93	.92	.101 (.099, .102)	.055
Finland	.91	.90	.097 (.095, .099)	.057
Switzerland	.94	.93	.063 (.062, .065)	.056
Turkey	.94	.93	.066 (.065, .068)	.033
Australia	.93	.91	.090 (.089, .091)	.057
New Zealand	.92	.91	.085 (.084, .087)	.058
Brazil	.95	.94	.071 (.069, .072)	.039
Chile	.91	.90	.074 (.072, .076)	.048
Hungary	.93	.92	.085 (.083, .087)	.051

multi-level models, including normality and homogeneity of variance for level-1, level-2 and level-3 residuals were visually inspected using Q-Q plots, histograms and scatterplots (see Supplemental Material B). In general, no severe violations of the assumptions were found. Also, we checked the skewness and kurtosis of the level-1, level-2 and level-3 residuals, and found that all of the values were within the range from -3 to 3 (except the level-2 residual kurtosis, which was 3.829, 4.229 and 3.845 for mathematics, science and reading respectively). Thus, we assume that normality and homogeneity of variances were generally met. We did not report and use significance tests (e.g., Shapiro-Wilk test for normality and chi-square test for homogeneity of variance) to check those assumptions because the tests are highly sensitive to large sample size (Siddiqui, 2013).

3.2. Results

3.2.1. Single-group confirmatory factor analysis

Table 3 presents the model fit indices of the single-group confirmatory factor analyses for the overall sample and for each of the selected countries (regions). As shown in Table 3, the four-factor measurement model of ICT engagement showed an acceptable model fit across the countries (regions): all the CFI and TLI values were equal to or greater than 0.90 (except Japan with TLI = 0.88), and all the RMSEA and SRMR values were smaller than 0.10 (except Korea, Japan and Croatia, with RMSEA = 0.109, 0.103 and 0.101 respectively).

To further evaluate the local fit of the measurement model, we examined the residual correlation matrix for the overall sample (Table 4) and for each of the 16 countries (see Supplemental Material A; Kline, 2016). It can be seen from Table 4 that the absolute values of the residual correlations for the overall sample ranged from 0.000 to 0.159, with 3.8% of the values greater than 0.10. The absolute values of the residual correlations across the 16 countries (see Supplemental Material A) ranged from 0.000 to 0.245, with 9.6% of the values greater than 0.10, and 0.3% greater than 0.20. In general, we believe there were small differences between the observed and predicted correlation matrices. Thus, the ICT engagement measurement model was assumed to demonstrate an acceptable local fit.

The standardized item loadings of the measurement model for the overall sample are presented in Table 5. As seen in Table 5, the loadings ranged from 0.567 to 0.882, which were all much greater than 0.30 (Nunnally, 1978). This suggested that all the items were valid indicators for the specific ICT engagement scales.

Furthermore, the correlations among the four engagement factors are presented in Table 6. It can be seen from Table 6 that the correlations ranged from 0.483 to 0.722, indicating that these four scales assessed distinct aspects of ICT engagement.

3.2.2. Multi-group confirmatory factor analysis (MG-CFA)

The MG-CFA results are shown in Table 7. As seen in Table 7, the configural model showed an acceptable model fit: CFI = .927 > .90, TLI = .916 > .90, RMSEA = .081 < .10, and SRMR = .052 < .10. The metric model demonstrated an acceptable model fit: CFI = .937 > .90, TLI = .933 > .90, RMSEA = .072 < .10, and SRMR = .057 < .10. Although the χ^2difference test between the configural and the metric model was significant (χ^2diff. = 10669.122, df = 255, p < .000), ΔCFI = .010 > −.002, ΔTLI = .017 > −.002, $\Delta RMSEA$ = -.009 < .01, and $\Delta SRMR$ = .005 ≤ .01, indicating that the more constrained metric model did not have a poorer fit than the less constrained configural model. Thus, metric invariance was established.

Furthermore, the scalar model showed an acceptable fit: CFI = .918 > .90, TLI = .933 > .90, RMSEA = .073 < .10, and SRMR = .062 < .10. Although the χ^2 difference test between the metric and the scalar model was significant (χ^2diff. = 47265.790, df = 885, p < .000) and ΔCFI = -.019 < -.002, ΔTLI = .000 > − .002, $\Delta RMSEA$ = .001 < .01, and $\Delta SRMR$ = .005 < .01, indicating that the more constrained scalar model

Table 4
Measurement model residual correlation matrix for the overall sample.

Items	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-																			
2	.048	-																		
3	.019	.092	-																	
4	-.044	-.056	-.001	-																
5	.121	-.086	.011	.008	-															
6	.009	-.008	-.004	-.073	.055	-														
7	.029	-.001	-.013	.035	-.013	.004	-													
8	-.026	-.017	-.036	.046	-.025	-.002	.045	-												
9	.075	.143	.078	.049	.062	.159	-.013	-.045	-											
10	-.085	-.051	-.092	-.002	-.077	-.047	-.064	-.035	-.036	-										
11	-.103	-.079	-.109	-.005	-.079	-.062	-.060	.004	-.087	.068	-									
12	-.018	-.020	-.049	-.039	-.059	-.041	.028	-.001	-.067	-.037	-.039	-								
13	-.060	-.019	-.061	.003	-.072	-.060	.004	.004	-.085	-.015	-.016	.082	-							
14	.064	.103	.091	.009	.027	.116	.015	-.025	.090	-.046	-.073	-.030	-.051	-						
15	-.046	-.007	-.048	-.008	-.059	-.025	.011	.018	-.011	.092	.063	-.035	-.022	-.018	-					
16	.015	.030	.028	.000	-.013	.027	.010	-.012	.001	-.039	-.049	.034	-.044	.046	.000	-				
17	.027	-.009	-.020	.090	.010	.002	.047	.047	-.038	-.024	.001	.030	.065	-.034	-.012	-.024	-			
18	-.028	-.096	-.063	.070	.015	-.073	.018	.024	-.110	-.015	.015	.002	.077	-.087	-.010	-.055	.039	-		
19	.016	-.033	-.013	.084	.042	.029	.053	.021	-.024	-.008	-.003	.064	.052	.018	.029	.039	-.071	-.040	-	
20	-.022	-.083	-.056	.087	.011	-.037	.013	.025	-.091	-.014	.009	-.001	.057	-.060	-.004	-.026	-.028	-.002	.002	-
21	-.027	-.068	-.046	.090	.023	-.040	.000	.024	-.074	-.013	.029	-.030	.037	-.094	-.025	-.037	-.022	.009	-.021	.041

Table 5
Standardized item loadings for the overall sample.

Items	Standardized item loadings
Interest in ICT	
1 I forget about time when I'm using digital devices.	.567
2 The Internet is a great resource for obtaining information I am interested in (e.g., news, sports, dictionary).	.758
3 It is very useful to have social networks on the Internet.	.741
4 I am really excited discovering new digital devices or applications.	.819
5 I really feel bad if no Internet connection is possible.	.595
6 I like using digital devices.	.857
Perceived ICT competence	
7 I feel comfortable using digital devices that I am less familiar with.	.696
8 If my friends and relatives want to buy new devices or applications, I can give them advice.	.841
9 I feel comfortable using my digital devices at home.	.800
10 When I come across problems with digital devices, I think I can solve them.	.882
11 If my friends and relatives have a problem with digital devices, I can help them.	.878
Perceived ICT autonomy	
12 If I need new software, I install it by myself.	.790
13 I read information about digital devices to be independent.	.783
14 I use digital devices as I want to use them.	.797
15 If I have a problem with digital devices, I start to solve it on my own.	.868
16 If I need a new application, I choose it by myself.	.807
Use of social media	
17 To learn something new about digital devices, I like to talk about them with my friends.	.841
18 I like to exchange solutions to problems with digital devices with others on the Internet.	.818
19 I like to meet friends and play computer and video games with them.	.709
20 I like to share information about digital devices with my friends.	.867
21 I learn a lot about digital media by discussing with my friends and relatives.	.808

Table 6
Factor correlations for the overall sample.

Factors	(1)	(2)	(3)	(4)
(1) Interest in ICT	1			
(2) Perceived ICT competence	.683***	1		
(3) Perceived ICT autonomy	.595***	.722***	1	
(4) Use of social media	.483***	.596***	.593***	1

Notes: ***p < .001.

did not have a poorer fit than the less constrained metric model. Thus, a scalar level of invariance was established.

The last step for testing measurement invariance, "residual invariance", proceeds backward by comparing the less constrained non-invariance residual model (residual variances were freely estimated) with the more constrained scalar invariance model (residual variances were fixed to one; Hoffman, 2015; Li et al., 2016). As shown in Table 7, although the χ^2 difference test between the non-invariance residual model and the scalar model was significant (χ^2 diff. = 23394.170, df = 315, p < .000) and ΔCFI = -.005 < -.002, ΔTLI = .002 > −.002, $\Delta RMSEA$ = .000 < .01, and $\Delta SRMR$ = .007 < .01, indicating that the more constrained model with all residual variances fixed to one did not have a poorer fit than the model with all residuals freely estimated. Thus, a residual level of invariance was established.

3.2.3. Multi-level analysis

Because the ICT engagement questionnaire was tested to be invariant at the residual (strict) level across the countries (regions), students' observed scores on the ICT engagement questionnaire can be used to make meaningful and valid comparisons. The associations between ICT engagement and domain literacy were then examined using multi-level analyses, with student three domain literacy as the dependent variable respectively, with the four factors of ICT engagement (i.e., interest in ICT, perceived ICT competence, perceived ICT autonomy, and use of social media) and student characteristics (i.e., gender, ESCS, age, ICT resources, subject-related ICT use during lessons, subject-related ICT use outside of lessons) as the level-1 variables, with school characteristics (i.e., school type, school location, education material shortage, and education staff shortage) as the level-2 variables, and with the country dummy variables and GDP per capita as the level-3 variables. The results are summarized in Table 8.

As seen in Table 8, the total $R^2$for the three domain literacy were 0.17, 0.12 and 0.18 respectively, which were considered as minimal to moderate effect sizes according to Ferguson (2016).

Using Australia as the reference country, the estimates of the relationships between the four ICT engagement factors and academic literacy for the other fifteen countries (regions) in Table 8 provided a measure of the difference between the specific country and Australia. Taking mathematics literacy and interest in ICT as an example, the estimate for Brazil was -0.49. This suggested that after accounting for student-, school- and country-level variables, the actual regression coefficient of interest in ICT for mathematics literacy for Brazil was 0.49 lower than that of Australia, which was 5.17-0.49 = 4.68, indicating a positive relationship between ICT interest and mathematics literacy. Comparing the actual regression coefficients among the countries (regions), similar patterns on the relations of perceived ICT autonomy and use of social media to academic literacy were found across the countries (regions). Specifically, perceived ICT autonomy tended to have positive relationships with domain literacy across the countries (except Turkey on mathematics), while use of social media tended to have negative relationships. Nonetheless, the relationships of interest in ICT and perceived ICT competence showed different patterns across the countries (regions). Specifically, controlling for student-, school-, and country-level variables, (1) Interest in ICT tended to show positive relationships with mathematical literacy in some countries (e.g., Korea, Japan, USA, Australia, New Zealand, Brazil, Chile, Finland, Hong Kong-China, Italy, Tukey, Hungary), while negative in other countries (e.g., France, Croatia, Germany, Switzerland); (2) Interest in ICT tended to show positive relationships with scientific literacy in some countries (e.g., Korea, Japan, USA, Turkey, Australia, New Zealand, Brazil, Chile, Finland, Hong Kong- China, Italy, Switzerland), while negative in other countries (e.g., France, Germany, Croatia, Hungary); (3) Interest in ICT

Table 7
Model fit indices for the multi-group confirmatory factor analysis.

Invariance Level	DIFFTEST	CFI	TLI	RMSEA (90% C.I.)	SRMR	ΔCFI	ΔTLI	ΔRMSEA	ΔSRMR
Configural	-	.927	.916	.081 (.081, .082)	.052	-	-	-	-
Metric	10669.122***	.937	.933	.072 (.072, .073)	.057	.010	.017	-.009	.005
Scalar	47265.790***	.918	.933	.073 (.072, .073)	.062	-.019	.000	.001	.005
Residual	23394.170***	.923	.931	.073 (.073, .074)	.055	-.005	.002	.000	.007

Notes: ***p < .001.

Table 8
Results for the multi-level analysis on student academic literacy.

Variables	Estimates (SE)		
	Mathematics	Science	Reading
Fixed effect			
Intercept	473.48*** (11.54)	487.15*** (8.29)	487.70*** (5.31)
ICT interest			
Australia (reference country)	5.17***(1.05)	6.80***(1.13)	11.03*** (1.25)
Brazil	−0.49(1.54)	−0.13(1.66)	−1.14(1.84)
Chile	−4.69**(1.71)	−4.47*(1.84)	−7.69*** (2.04)
Finland	−2.83(1.78)	−0.99(1.92)	−1.40(2.13)
France	−7.71*** (1.58)	−10.07*** (1.70)	−12.27*** (1.88)
Germany	−5.87*** (1.83)	−8.48*** (1.97)	−9.41*** (2.19)
Hong Kong	−3.24(1.77)	−5.37** (1.90)	−7.50*** (2.10)
Italy	−4.89**(1.83)	−3.99*(1.97)	−7.69*** (2.19)
Japan	4.23**(1.52)	5.70***(1.64)	2.86(1.82)
Korea	0.66(1.52)	−0.93(1.63)	−1.46(1.80)
New Zealand	−1.47(1.67)	0.22(1.80)	1.35(1.99)
Switzerland	−5.36**(1.76)	−5.12** (1.90)	−7.26*** (2.10)
Turkey	−4.09**(1.46)	−5.44*** (1.56)	−8.22*** (1.73)
USA	−0.03(1.85)	−0.30(1.99)	−0.19(2.21)
Hungary	−4.63**(1.76)	−10.10*** (1.90)	−11.88*** (2.11)
Croatia	−8.12*** (1.51)	−10.09*** (1.63)	−11.16*** (1.80)
Perceived ICT competence			
Australia (reference country)	0.52(1.19)	1.03(1.32)	2.30(1.45)
Brazil	−1.48(1.93)	−1.89(2.13)	−2.46(2.35)
Chile	1.86(1.94)	1.57(2.16)	3.25(2.37)
Finland	2.77(1.89)	2.38(2.11)	−0.75(2.32)
France	−2.26(1.81)	−3.07(2.02)	−2.97(2.22)
Germany	−1.42(2.02)	−2.21(2.24)	−3.05(2.46)
Hong Kong	−2.15(2.12)	−2.63(2.36)	−2.57(2.60)
Italy	5.81**(2.03)	4.49*(2.25)	3.73(2.47)
Japan	−5.49**(1.76)	−6.39*** (1.96)	−5.06*(2.16)
Korea	−7.46*** (1.76)	−10.41*** (1.96)	−10.98*** (2.15)
New Zealand	−1.48(1.92)	2.73(2.14)	1.12(2.35)
Switzerland	1.79(1.89)	2.05(2.10)	0.09(2.31)
Turkey	4.56**(1.69)	5.40**(1.89)	4.47*(2.08)
USA	2.40(2.11)	4.21(2.35)	3.33(2.58)
Hungary	1.77(1.90)	0.55(2.11)	3.33(2.32)
Croatia	−0.57(1.72)	3.64(1.91)	−0.40(2.10)
Perceived ICT autonomy			
Australia (reference country)	14.04*** (1.19)	18.53*** (1.31)	16.64*** (1.47)
Brazil	−7.48*** (1.87)	−8.78*** (2.06)	−8.79*** (2.31)
Chile	−8.68*** (1.84)	−10.60*** (2.03)	−10.70*** (2.30)
Finland	−2.02(1.88)	−5.58** (2.07)	−4.35(2.34)
France	−4.05*(1.90)	−7.61*** (2.09)	−3.79(2.36)
Germany	−6.22*** (1.91)	−6.27** (2.10)	−8.65*** (2.37)
Hong Kong	−1.73(1.90)	−3.64(2.10)	2.25(2.39)
Italy	−8.10*** (2.00)	−10.21*** (2.20)	−9.78*** (2.48)
Japan	−9.65*** (1.63)	−14.46*** (1.79)	−12.33*** (2.04)
Korea	5.22**(1.74)	3.71(1.92)	5.17*(2.17)
New Zealand	0.03(1.84)	−2.16(2.02)	−2.98(2.29)
Switzerland	−5.63**(1.93)		−5.09*(2.41)

Table 8 (*continued*)

Variables	Estimates (SE)		
	Mathematics	Science	Reading
		−7.30*** (2.13)	
Turkey	−14.05*** (1.65)	−17.74*** (1.82)	−14.75*** (2.07)
USA	−1.08(2.01)	−7.48**** (2.21)	−5.01*(2.50)
Hungary	−6.84*** (1.94)	−7.83*** (2.13)	−8.08*** (2.41)
Croatia	−3.32(1.79)	−7.49*** (1.97)	−4.83*(2.22)
Use of social media			
Australia (reference country)	−13.59*** (1.02)	−17.52*** (1.11)	−22.37*** (1.24)
Brazil	6.57***(1.72)	7.74***(1.87)	11.87*** (2.09)
Chile	6.35***(1.67)	8.58***(1.81)	11.33*** (2.04)
Finland	4.92**(1.67)	7.74***(1.81)	7.69***(2.04)
France	4.27**(1.56)	7.55***(1.69)	9.58***(1.91)
Germany	10.22*** (1.76)	8.76***(1.91)	14.29*** (2.14)
Hong Kong	−0.63(1.74)	3.64(1.89)	3.58(2.13)
Italy	4.18*(1.85)	7.85***(2.01)	10.63*** (2.25)
Japan	8.10***(1.50)	10.96*** (1.62)	11.99*** (1.83)
Korea	1.32(1.48)	7.40***(1.60)	9.53***(1.81)
New Zealand	−1.77(1.63)	−3.37(1.77)	−2.67(1.99)
Switzerland	5.08**(1.63)	5.17**(1.76)	7.91***(1.99)
Turkey	8.34***(1.54)	10.86*** (1.66)	16.93*** (1.88)
USA	−1.86(1.73)	−1.24(1.87)	0.37(2.11)
Hungary	8.83***(1.71)	11.82*** (1.85)	14.15*** (2.08)
Croatia	8.19***(1.49)	10.36*** (1.61)	13.44*** (1.82)
Gender	16.86*** (1.01)	10.22*** (1.10)	−12.30*** (1.22)
ESCS	15.25*** (0.64)	15.64*** (0.70)	15.77*** (0.77)
Age	11.94*** (1.63)	8.90***(1.78)	11.06*** (1.97)
ICT resources	−0.99(0.65)	−3.11*** (0.71)	−2.78*** (0.79)
ICT use outside lessons	0.70(0.50)	1.31*(0.55)	1.64**(0.61)
ICT use during lessons	0.72(0.55)	1.00(0.61)	−0.25(0.67)
School type	−23.86*** (5.73)	−19.80*** (5.73)	−23.34*** (6.05)
School location	8.78***(1.61)	8.57***(1.62)	10.40*** (1.72)
School educational material shortage	−7.42*** (1.89)	−8.64*** (1.90)	−8.31*** (2.02)
School educational staff shortage	−5.18*(2.07)	−4.65*(2.11)	−4.46*(2.19)
GDP per capita ($US)	0.001(0.001)	0.001** (0.0004)	0.001*** (0.002)
Random effect			
Interest in ICT slope	30.05*** (5.48)	25.77*(5.08)	32.92(5.74)
Perceived ICT competence slope	21.63*(4.65)	41.95*** (6.48)	43.27*** (6.58)
ICT autonomy slope	14.45*** (3.80)	23.68*** (4.87)	51.89*** (7.20)
Use of social media slope	14.30(3.78)	11.20(3.35)	28.33*(5.32)
Variance within schools	3776.38 (61.45)	4510.05 (67.16)	5513.61 (74.25)
Variance across schools	2419.17*** (49.19)	2404.37*** (49.03)	2677.01*** (51.74)
Variance across countries	812.20*** (28.50)	409.41*** (20.23)	154.31*** (12.42)
Total unexplained variance (full model)	7007.75	7323.83	8344.93

(*continued on next page*)

Table 8 (*continued*)

Variables	Estimates (SE)		
	Mathematics	Science	Reading
Total variance (null model without any predictors)	8438.12	8321.12	10118.04
Total R^2	0.17	0.12	0.18

Notes: SE = robust standard error; *p < .05, **p < .01, ***p < .001; Total $R^2 = 1$ – unexplained variance (full model) / total variance (null model without any predictors).

tended to show positive relationships for reading literacy in some countries (e.g., Korea, Japan, Hong Kong-China, USA, Finland, Turkey, Australia, New Zealand, Brazil, Chile, Germany, Italy, Switzerland), while negative in other countries (e.g., France, Hungary, Croatia).

Furthermore, controlling for student-, school- and country-level variables, (1) Perceived ICT competence tended to have positive relationships with mathematical literacy in some countries (e.g., Australia, Italy, Finland, Turkey, Chile, Hungary, Switzerland, USA), while negative in other countries (e.g., Korea, Japan, Hong Kong-China, Brazil, France, Germany, New Zealand, Croatia); (2) Perceived ICT competence tended to have positive relationships with scientific literacy in some countries (e.g., Australia, Chile, Finland, Italy, New Zealand, Switzerland, Turkey, USA, Hungary, Croatia), while negative in other countries (e.g., Brazil, France, Germany, Hong Kong-China, Japan, Korea); (3) Perceived ICT competence tended to have positive relationships with reading literacy in some countries (e.g., Australia, Chile, Finland, Italy, New Zealand, Switzerland, Turkey, USA, Hungary, Croatia), while negative in other countries (e.g., Brazil, France, Germany, Hong Kong-China, Japan, Korea).

4. Discussion

The purpose of this study was to investigate the measurement invariance of the PISA ICT engagement questionnaire across countries (regions), and further to explore the effects of ICT engagement on student literacy in mathematics, science and reading using the PISA 2018 data.

4.1. Measurement invariance of ICT engagement

The results of the single-group confirmatory factor analyses suggested that the four-factor ICT engagement measurement model fit well across the 16 countries (Tables 3 and 4). All the items were valid indicators of the specific ICT engagement factors (Table 5) and the questionnaire was reliable in terms of measuring student ICT engagement levels (Table 2). Furthermore, the results of the multi-group confirmatory factor analyses showed that a residual (strict) level of measurement invariance was established across the countries (Table 7), indicating that the construct of ICT engagement had the same meaning across the countries, and students' observed scores on the ICT engagement questionnaire can be meaningfully and validly compared. In fact, measurement invariance of the ICT engagement questionnaire has not been fully investigated since its first use in PISA 2015. Only one study by Meng et al. (2019) has attempted to establish the equivalence of the questionnaire across countries based on the Chinese and German data from PISA 2015. The current study, using the data from 16 countries (regions) in PISA 2018, provides an important generalization of the prior findings and confirmed that the PISA ICT engagement questionnaire can be used for making robust and meaningful comparisons across countries at the observed level.

4.2. The relations of ICT engagement to student literacy

The results of the multi-level analyses demonstrated that controlling for student, school and country characteristics, similar patterns on the relations of perceived ICT autonomy and use of social media to three domain literacy were observed across the countries (regions). Specifically, perceived ICT autonomy tended to have positive relationships with academic literacy across the countries (regions), while use of social media tended to show negative relationships. However, the relations of interest in ICT and perceived ICT competence to academic literacy tended to show different patterns across the countries (regions), and for some countries those relationships differed across domains.

4.2.1. Interest in ICT

The relationships of interest in ICT to literacy performance were inconsistent across the countries (regions). For Asian (Eastern) countries (e.g., Korea, Japan), interest in ICT tended to have positive relationships with student literacy. For Western countries, however, the relationships tended to be positive in some countries (e.g., USA, Australia, New Zealand, Brazil, Finland, Chile, Italy), while negative in other countries (e.g., France, Croatia).

In fact, the distinct patterns on the relationship between ICT interest and academic literacy across the countries (regions) might be explained by their differences in the culture and educational system. Specifically, the education systems in Asian countries (e.g., Korea, Japan) are featured as being highly competitive and stressful. In those countries, academic achievement is of paramount social importance and strongly linked with social mobility, income levels and positions of power (Mani & Trines, 2018). Students who want to go to university and succeed in the future must take a national high-stake test and do very well on the test (e.g., "College Scholastic Ability Test" in Korea, "National Center Test for University Admissions" in Japan). To prepare for this test, a high proportion of students in those countries take prep classes outside of school, including classes at afterschool/weekend tutoring programs (e.g., "Juku" in Japan, "Hagwons" in Korea) or by private tutoring providers. Moreover, parents have high expectations on children in terms of academic success, and those expectations tend to be considered seriously by children themselves when setting goals because they do not want to let their parents down, particularly in a collectivist cultural environment where values such as social harmony, interdependence and conformity are emphasized (Hofstede, 1980). For those reasons, it is conceivable that students develop ICT interests to serve exam-oriented purposes, and thus positive relationships between interest in ICT and literacy performance were observed (Meng et al., 2019).

In contrast, Western countries stress an individualist culture that advocates for independence and autonomy (Markus & Kitayama, 1991). The learning goals and behaviors of Western students may rely more on their own will rather than on external factors (e.g., expectations, praise, competition, rewards). Furthermore, students in the Western countries do not have to face high-stake examinations as their Eastern peers do. For example, in Chile "All students are assessed in an ongoing manner throughout the school year in each curriculum area or subject. Assessment criteria and methods are defined by each school, and no externally-based national final examinations exist at any level" (Santiago, Benavides, Danielson, Goe, & Nusche, 2013, p. 66). In Germany, students are cultivated in a dual system of education (Furstenau et al., 2014), in which they either enter general education to pursue a higher degree or vocational education to develop job-related expertise, and thus not all students in Germany aim to achieve academic success. Therefore, Western students tend to have more self-directed freedom and independence while using ICT, which may influence their academic literacy either positively (as shown for countries such as USA, Australia, New Zealand, Finland,) or negatively (as shown for countries such as France and Croatia).

The different patterns on the relations of ICT interest to literacy across the countries (regions) might also reflect the countries' different perceptions about the role of ICT. According to Kozma (2008), educators in Asian countries tend to focus on the educational role of ICT and consider ICT as a way to facilitate curriculum reform, renovate pedagogical approaches and foster students' higher-order skills. In this case, students may be affected to use ICT more for learning purposes and thus achieve better academic outcomes. In contrast, Western countries, particularly the European countries, tend to emphasize the social impact of ICT, and use ICT to expand digital literacy and reduce inequality of ICT-related resources (Kozma, 2008). This may influence students to have broader ICT interests rather than academic-focused, and thus exert inconsistent impacts on their academic literacy.

Furthermore, slight differences were observed in terms of the relations of ICT interest to different domain literacy. For most sampled countries, it seemed that ICT interest was more positively related with reading literacy than the other two domains. This might occur because students encounter, read and comprehend "texts" most often while using ICT for either learning or entertainment purposes (e.g., check e-mails, read news and play computer games). Therefore, their reading skills such as retrieving useful information and speed reading may be better facilitated compared to mathematical and scientific skills (Gumus & Atalmis, 2011).

4.2.2. Perceived ICT competence

As hypothesized, we found that the relations of perceived ICT competence to student literacy were mixed across the countries (regions). For Asian (Eastern) countries (e.g., Korea, Japan, Hong Kong-China), perceived ICT competence tended to have negative relationships with student literacy. For Western countries, however, either positive or negative relationships were found across the countries (regions).

The different associations between perceived ICT competence and student literacy across the countries (regions) may be explained by their cultural differences (Meng et al., 2019). Specifically, Eastern (Asian) culture emphasizes being modest and exploring knowledge in depth. Students in Eastern (Asian) countries often work hard to achieve better academic outcomes, yet they may not wish to be seen as overconfident in their responses on perceived competence. In fact, many prior studies (e.g., Liu & Meng, 2010; Shen & Pedulla, 2000) have empirically supported this argument by showing that students in the Eastern countries, despite having a modest perceived competence, have better academic performance than students in the Western countries. The results of Korea, Japan and Hong Kong-China were consistent with those studies: the lower perceived ICT competence, the better their academic literacy.

In contrast, Western culture supports a confident and unique self in comparison with others (Yoshino, 2012). Students in the Western countries tend to exhibit higher confidence in their own competences, which may motivate them to invest more effort, develop deeper understanding of challenging topics, and apply more effective strategies when solving problems (Bandura, 2006; Pintrich & Schunk, 2002). Thus, positive relationships between perceived ICT competence and academic literacy were found in most of the sampled Western countries (e.g., Australia, USA, Italy, Finland, Turkey, Chile, Hungary, Switzerland). However, the literacy performance of students in some other Western countries (e.g., France, Brazil, Germany) were negatively related to their perceived ICT competence. These inconsistent results may reflect the free will and independence that individualist cultures espouse (Meng et al., 2019).

4.2.3. Perceived ICT autonomy

As hypothesized, positive relationships between perceived ICT autonomy and student three domain literacy performance were found across the countries (regions), suggesting that there might be some universality of perceived ICT autonomy that is not dependent on country or cultural contexts. This result is consistent with many prior studies (e.g., Diseth & Samdal, 2014; Marshik, Ashton, & Algina, 2017; Vasquez, Patall, Fong, Corrigan, & Pine, 2016). For instance, using data from 42 PISA 2015 participating countries, Areepattamannil and Santos (2019) found that perceived autonomy in using ICT was significantly positively related to enjoyment of science, interest in broad science topics, science self-efficacy and epistemological beliefs about science. It is likely that students with higher levels of autonomy are more capable to concentrate while learning, plan and monitor learning processes, develop higher-order cognitive and meta-cognitive skills, and thus achieve better academic outcomes (Vansteenkiste et al., 2005).

Given the positive relations of perceived ICT autonomy to student literacy, we suggest that teachers should provide support to satisfy students' autonomy needs. According to Reeve (2009), autonomy-supportive instruction includes such instructional behaviors as "nurture inner motivational resources, provide explanatory rationales, rely on non-controlling and informational language, display patience to allow time for self-paced learning, and acknowledge and accept expressions of negative affect" (p. 160). From the perspective of ICT education, teachers could organize various activities (e.g., group competition) to motivate students to learn and utilize ICT, give students the responsibility of planning a task using ICT and coach them by asking questions at intervals, and discussing with students the different software available to help them select the appropriate ICT tools and resources for the solution. Teachers could also encourage students to reflect on their ICT learning process, become aware of their achievements and identify the areas that need for improvement. Moreover, parents should provide their children with autonomy support, for instance, emphasize the importance of ICT, allow children to arrange their assignment time, and encourage children when they encounter difficulties.

4.2.4. Use of social media

As hypothesized, negative relations of use of social media to student three domain literacy were found across the countries (regions), indicating that there might be some universality of use of social media that does not rely on specific cultural contexts. This result is in line with some prior studies in the literature. For instance, Paul, Baker, and Cochran (2012) found that more time spent on online social networks were associated with lower academic performance. Similarly, Huang (2018) found in his meta-analysis study a negative correlation between the use of social networks and student achievements. However, our results are contradictory with some other findings in the literature. For example, Hoffman (2009) found that the use of social network increased students' enjoyment, sense of involvement and learning performance. Junco, Heiberger, and Loken (2011) conducted an experimental study on the effect of Twitter on college student engagement and achievements. They discovered that groups that were taught using Twitter had not only a significantly greater increase in engagement, but also higher scores than those not. In general, researchers supporting the positive relationship claimed that use of social media may facilitate student knowledge sharing, communication and collaboration with others.

In the present study, we found a negative relationship between use of social media and student literacy across the countries (regions), which might be partly due to the fact that the use of social media scale included items related to playing computer and video games. More importantly, the negative relationship might occur because first students who spend too much time on social media may not devote sufficient time to learning (Englander et al., 2010). Also, students who frequently use social media while learning may easily be distracted by internet activities such as accessing emails, chatting or collaborative gaming. Furthermore, the use of social media may cause sleep disturbance (Levenson, Shensa, Sidani, Colditz, & Primack, 2016) and excessive pressure (Fox & Moreland, 2015; Pillai, Roth, Mullins, & Drake, 2014), which may negatively affect students' academic performance. From the results, we may suggest that teachers and parents should encourage students to take advantage of the ICT, and meanwhile prevent them from being addicted to online entertainments such as playing computer games.

4.3. Limitations and future research

This study has several limitations. First, the present study has established a residual (strict) level of MI for the PISA ICT engagement questionnaire across different countries (regions). Future studies could further explore its invariance property across different PISA cycles (e.g., between PISA 2015 and PISA 2018) to examine whether or not the meaning of the ICT engagement construct changes across time. Second, PISA utilized a self-report questionnaire to indirectly measure student ICT engagement, thus the data may arguably be unreliable and suffer from self-reported bias such as acquiescence, i.e., the tendency to endorse items positively regardless of content, and social desirability, i.e., the tendency to endorse items in accord with the social desirability of the response. To limit the possibility of such bias, it might be better to include attention checks or collect both student themselves' and peer-/teacher-reported data to double-check. Also, future studies could design and utilize some objective measures to better capture student actual ICT engagement levels (e.g., student computer logs; objective ICT-related task performance). Third, causal relationships cannot be established from this study because the PISA data was cross-sectional. For instance, it remains unclear whether better academic performance improved students' perceived ICT autonomy, or higher autonomy in using ICT increased students' achievements. Thus, future studies using longitudinal or experimental designs are needed. Fourth, this study tested the MI of the PISA ICT engagement questionnaire using the multiple-group confirmatory factor analysis (MG-CFA) approach. MI or DIF can also be examined using other parametric (e.g., IRT, logistic regression) and nonparametric methods (e.g., Mantel-Haenszel). It would be interesting to compare the results from those different methods. Finally, this study utilized MG-CFA to examine the MI of ICT engagement questionnaire across 16 countries (regions). Other alternative approaches to testing MI across many groups have been developed in the literature such as multilevel confirmatory factor analysis (ML CFA), multilevel factor mixture modeling (ML FMM), Bayesian approximate MI testing, and alignment optimization (see Kim, Cao, Wang, & Nguyen, 2017 for more details). Future studies could further explore and compare those different methods.

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Declaration of Competing Interest

The authors report no declarations of interest.

Appendix A. Supplementary data

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