Pre Registration

A Review of Digital Self-Efficacy Measurement around International Large-Scale Assessments

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1. What is the hypothesis that will be investigated?

Digital self-efficacy (hereinafter DSE), defined as *expectations about one's capabilities to learn and accomplish tasks in digital technologies and digital environments*, is one of the principal components to promote the formation of digital competences (Ulfert-Blank & Schmidt, 2022). DSE is a construct frequently measured in international large-scale assessments (ILSAs), as substantial evidence indicates its critical role as an explanatory variable in the development of digital competences within educational settings (Scherer & Siddiq, 2019; Hatlevik et al., 2018; Claro et al., 2018). Studies consistently demonstrate that DSE not only influences individuals' engagement with digital technologies but also predicts their ability to acquire and apply digital skills effectively (Rohatgi et al., 2016; Siddiq et al., 2017). Consequently, ILSAs such as ICILS (International Computer and Information Literacy Study) and PISA (Programme for International Student Assessment) often incorporate DSE metrics to assess their relationship with digital literacy outcomes (Fraillon et al., 2020; OECD, 2021).

The conceptualization and operationalization of DSE vary notably across the literature. Some studies treat DSE as a unidimensional construct, measuring individuals' overall confidence in using digital technologies without distinguishing between types of tools and/or levels of complexity (e.g., Hatlevik et al., 2015; Rohatgi et al., 2016). Such unidimensional approach facilitates modeling and broader comparisons, but may obscure important differences in how users perceive their abilities in specific digital contexts. In contrast, other studies adopt a multidimensional approach, distinguishing between general and specialized self-efficacy to

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account for the nature and complexity of digital tasks (Scherer et al., 2017). For example, general DSE encompasses confidence in everyday tasks such as internet navigation or word processing, whereas specialized DSE involves more advanced activities such as programming or data analysis.

Both the unidimensional and the multidimensional approaches not only influence measurement instruments but also lead to different research findings: unidimensional models could underestimate the predictive power of DSE for complex digital problem-solving, while multidimensional models offer greater explanatory precision but can introduce challenges such as construct overlap or reduced generalizability across contexts, limiting findings across educational systems and cultural contexts (Scherer & Siddiq, 2019; Scherer et al., 2021). Thus, the choice between unidimensional and multidimensional models of DSE is not merely theoretical, as it has significant implications for the validity, reliability, and utility of research on digital competence development.

Between the two most relevant ILSAs in the Digital Competence agenda (ICILS and PISA), a critical inconsistency persists in their conceptualization and measurement of DSE. PISA operationalizes DSE as a unidimensional construct, aggregating all digital task-related confidence into a single generalized measure (OECD, 2021). In contrast, ICILS adopts a bidimensional framework, distinguishing between general DSE (basic digital tasks, such as information navigation and communication) and specialized DSE (advanced tasks, such as data analysis or programming) (Fraillon et al., 2020; Scherer & Siddiq, 2019). This discrepancy raises essential questions about construct validity and cross-assessment comparability, particularly given that the choice of model (unidimensional vs. multidimensional) may influence policy interpretations and pedagogical interventions in different educational contexts (Rohatgi et al., 2016).

At the same time, understanding the proper use of the dimensions of DSE is necessary to refine the scientific use of this construct to understand different populations' expectations with technologies. This bidimensional differentiation emerged, in part, from observed gender disparities in self-efficacy patterns: some studies show that while gender gaps in general DSE are minimal or non-existent, women tend to report significantly lower confidence in specialized DSE domains—particularly those involving STEM-related digital tasks (Hargittai & Shafer, 2006; Cai et al., 2017; OECD, 2021). Without a two-dimensional approach, these gender gaps might become invisible.

Aiming to contribute to this research area, the present study's objective is to *evaluate the measurement of a two-dimensional model of DSE and its comparability across countries and by gender in different large-scale assessments.* Our contribution is twofold: (i) To test the bi-dimensional approach to DSE (as in ICILS) to PISA data (which assumes unidimensionality), and (ii) To test the comparability of these two dimensions by gender and country in ICILS and PISA.

To address these research goals, we will employ **confirmatory factor analysis (CFA)** and **measurement invariance testing** as core methodological strategies (Brown, 2015; Kline, 2016). CFA is particularly well-suited for testing theoretical models where specific latent structures are hypothesized a priori—such as the proposed distinction between general and specialized dimensions of digital self-efficacy. This approach allows for the rigorous evaluation of model fit and the validation of factor structures based on observed indicators from large-scale assessments. Accordingly, the first hypothesis refers to:

> **H**$_{1:}$ It is possible to identify two latent dimensions of digital self-efficacy (general and specialized) based on related batteries and indicators included in large-scale assessments such as PISA and ICILS (bi-dimensional hypothesis)

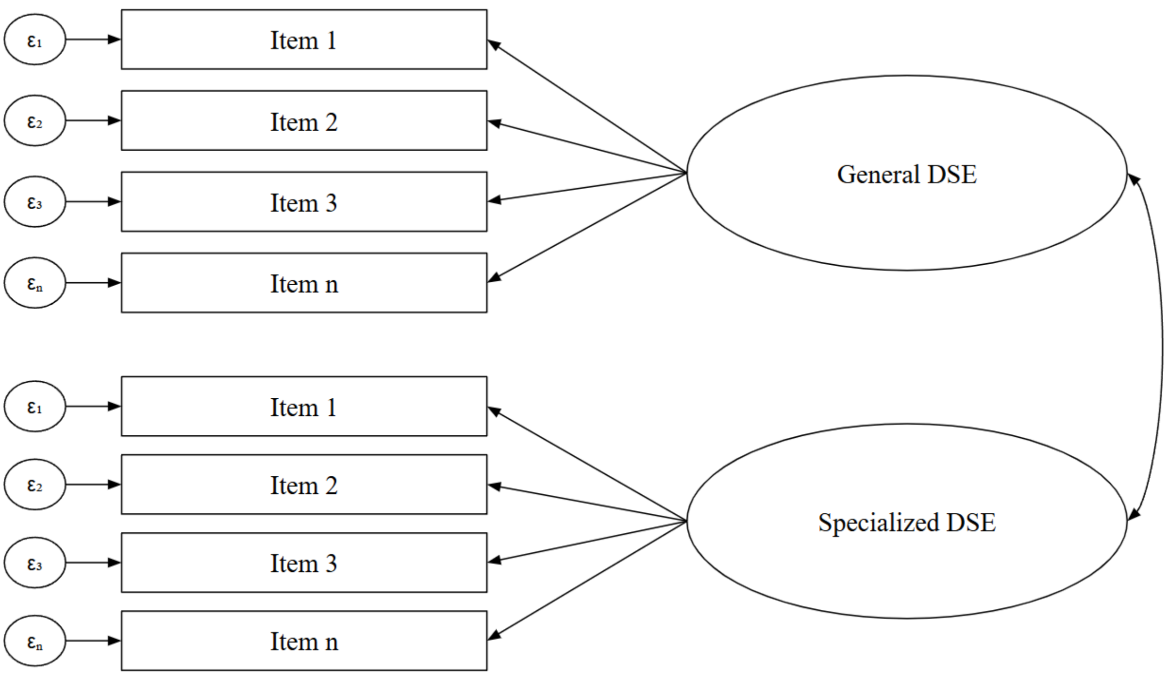
Furthermore, testing for **measurement invariance** across gender and countries is essential to ensure that the latent constructs are interpreted in a comparable manner across groups (Leitgöb et al., 2023; Meuleman et al., 2023). Without such invariance, any observed differences in self-efficacy levels may reflect measurement artifacts rather than substantive differences. From this perspective, the second and third hypotheses are

> **H**$_{2:}$ The bi-dimensional measurement model of digital self-efficacy is equivalent between girls and boys

> **H**$_{3:}$ The bi-dimensional measurement model of digital self-efficacy is equivalent across countries

Figure 1

Confirmatory measurement model



2. What is the source of the data included in the analyses?

We have two main data sources. The first one is ICILS, developed by the International Association for the Evaluation of Educational Achievement (IEA), assesses students' digital literacy across three cycles (2013, 2018, 2023). The 2023 cycle expanded to 35 education systems, testing 67,682 Grade 8 students on computer and information literacy (CIL) and computational thinking. The study evaluates students' ability to use digital tools responsibly, solve problems, and collaborate online. Data is collected through performance tests and contextual questionnaires for students, teachers, and schools. A key feature of ICILS is its bidimensional measurement of digital self-efficacy (DSE), distinguishing between general and specialized digital confidence. For the analysis we will use the students' database, including all countries.

The second data source is PISA, organized by the OECD, has assessed 15-year-olds' skills in mathematics, science, and reading across multiple cycles (the last three ones 2015, 2018, 2022). The study's primary objective remains evaluating education systems' effectiveness in preparing students for future challenges, with a growing emphasis on digital readiness. The 2022 assessment covered 81 countries/economies with a sample exceeding 600,000 students. Digital self-efficacy (DSE) was last measured in 2022 as part of the optional ICT familiarity questionnaire, following its absence in the 2018 cycle. This questionnaire was applied in an optional way in 53 countries, which are included in the analysis (n of students = 279,435).

To see in detail the sample of both studies, see Appendix 1.

3. How will the crucial variables be operationalized?

Table 1 summarizes the measurement batteries for self-efficacy in both studies. These items will be treated as numerical values.

Table 1

ICLS and PISA items comparison

Task Category	ICILS 2023 Items	PISA 2022 Items
Question and Response scale	"How well can you do each of these tasks when using ICT?" Very well (3) Moderately well (2) I have never done this, but I could work how to do this (1) I do not think I could do this (0)	"To what extent are you able to do the following tasks when using <digital resources>?" I can easily do this (3) I can do it with a bit of effort (2) I struggle to do this on my own (1) I cannot do this (0)
Search information	Search for and find relevant information for a school project on the internet	Search for and find relevant information online

Find source of information	Find the original sources of information referred to in an article on the internet, if the URL is not given	
Assess information	Judge whether you can trust information you find on the internet	Assess the quality of information you found online
Create multimedia	Create a multi-media presentation (with sound, pictures, or video)	Create a multi-media presentation (with sound, pictures or video)
Edit documents	Insert an image into a document or message	
	Write or edit text for a school assignment	Write or edit text for a school assignment
Edit images	Edit digital photographs or other graphic images	
Upload/share content	Upload text, images, or video to an online profile	Share practical information with a group of students
		Explain to other students how to share digital content online
Collaborate with classmates		Collaborate with other students on a group assignment
Change settings	Change the settings on a device to suit your needs and preferences	Change the settings of a device or App to protect my data and privacy
Install/select programmes	Install a program or [app]	Select the most efficient programme or App for a specific task
Develop Computer program	Use a text-based programming language to write a simple program	Create a computer program (e.g., Scratch, Python, Java)
	Use visual coding to develop a simple program	
Build a webpage	Build or edit a webpage	Create, update and maintain a webpage or a blog
Identify software errors		Identify the source of an error in a software (partial match)

4. How will this data be obtained?

Specify how the data will be requested or accessed. Clarify whether the data were already available and whether the dataset has been previously explored or analyzed.

Databases are available for open access on their respective web page repositories.

ICILS 2023: https://www.iea.nl/data-tools/repository/icils

PISA 2022: https://www.oecd.org/en/data/datasets/pisa-2022-database.html

5. Are there any exclusion criteria for the data?

Specify whether there were any criteria for the exclusions of certain datasets, observations or time points.

Full Information Maximum Likelihood (FIML) will handle remaining partial missingness during confirmatory analysis.

6. What are the planned statistical analyses?

Specify the statistical model that will be used to analyze the data and describe the data pre-processing steps. Be as specific as possible and avoid ambiguity.

Before we begin modelling the data, two pre-proccessing tasks are considered. The option *"I don´t know what this is"* in PISA battery of DSE will be recoded as missing value. In ICILS missing values are provided by defects in the data. Then, we will explore the distribution of missing values in every item of the battery in both studies by country to check the distribution of missing cases.

To address the hypotheses, in a first step, we will test a two-factor CFAs in PISA and ICILS for each country, considering the first factor for general DSE (basic‑task items) and the second for specialized DSE (advanced‑task items). To evaluate the goodness of fit for the model, we will use the chi-square test. Given the sensitivity of the chi-square test to sample size, we will also use the comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA), as proposed by Brown (2006).

To address the measurement invariance, in a second step, we will use a multigroup-CFA, which allows estimating whether the measurement model is equivalent across groups. This approach evaluates the comparability of the instruments' properties across groups, evaluating incremental levels of invariance. The configural level, used as the reference model, estimates the same measurement model for each group freely. The metric level (or weak) estimates the same model and constraint factor loadings to be the same across groups. The scalar level (or strong) estimate the model constraining the loadings and intercepts to be the same across groups. To evaluate the goodness of fit for each invariance level, we will use the same fit indexes named above (Chi-square, CFI, TLI and RMSEA). Advancing in testing the measurement invariance across groups (country and sex), this approach evaluates the changes in fit indexes between higher level of invariance compared with the lower. Then, differences in Chi-square, CFI, TLI and RMSEA could be interpreted as invariance, if the change is under the statistical criteria, or non-invariance, if the change in fit indexes is above the statistical criteria.

Considering the categorical measures of items, the modelling will assume ascending ordered variables. Additionally, we will use the full information maximum likelihood (FIML) method of estimation that allows handling missing data using the most available cases without imputing (Enders & Bandalos, 2001).

Note. The analyses will be performed with R statistical software and MPlus statistical software. The material, such as databases, scripts, or dynamic documents, shall be publicly available in [this repository.]

7. What are the criteria for confirming and disconfirming the hypotheses?

To evaluate the CFA and overall MG-CFA models, the criteria for “CFI and TLI values in the range of .90 –.95 may be indicative of acceptable model fit” (Brown, 2006, p. 87), and values above .95 are considered good. For the case of RMSEA the criteria should be ≤ .06. To evaluate the levels of invariance, the criteria consider as non-invariant models changes greater than ΔRMSEA ≤ .05 and ΔCFI ≥-.004 for metric, and changes greater than ΔRMSEA ≤ .01 and ΔCFI ≥-.004 for scalar (Rutkoswky & Svetina, 2017).

8. Have the analyses been validated on a subset of the data?

The analyses have not been validated.

9. What is known about the data that could be relevant for the tested hypotheses?

ICILS data has been previously explored, but only in the Chilean 2018 sample. In this case, there were two main findings. The first indicates that digital literacy positively affects general DSE, while the impact on specialized DSE is negative. Regarding the second finding, girls have a positive effect (in reference to boys) on general Digital self-efficacy; on the contrary, girls have a negative effect on specialized Digital self-efficacy.

Also, an exploratory factor analysis was applied with PISA 2022 data, which recognizes the existence of two dimensions of self-efficacy in most countries. In addition, the averages of general and specialized digital self-efficacy by country are known.

10. Please provide a brief timeline for the different steps in the preregistration.

Steps	Tasks		June				July				
	Weeks	4	1	2	3	4	1	2	3	4	
Depuration and exploration of data	Unify data (ICILS)										
	Recodification of variables										
	Drop missing values										
	General descriptives and correlational analysis										

First step. Confirmation of bi-dimensional nature of DSE

	Construction of General model										
Second step. Across countries Invariance Analyses	Metrical invariance										
	Scalar invariance										
Third step. By gender Invariance Analyses	Metrical invariance										

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Appendix

Appendix 1. Preregistration template for the preregistration of analyses of preexisting data

This template is based on the following article:

Mertens, G., & Krypotos, A. M. (2019). Preregistration of analyses of preexisting data. *Psychologica Belgica*, *59*(1), 338-352. http://doi.org/10.5334/pb.493

Table 1. Template questions for the preregistration of analyses of preexisting data.

Question	Description
1. What is the hypothesis that will be investigated?	*Provide a brief description of the relevant theory and formulize the hypothesis as precisely as possible.*
2. How will the crucial variables be operationalized?	*State exactly how the variables specified in the hypothesis will be measured.*
3. What is the source of the data included in the analyses?	*Specify the source of the obtained data. Also provide information about the context of the data source and clarify whether the data has been previously published. In case of simulated data, provide information on how the data was generated.*
4. How will this data be obtained?	*Specify how the data will be requested or accessed. Clarify whether the data were already available and whether the dataset has been previously explored or analyzed.*
5. Are there any exclusion criteria for the data?	*Specify whether there were any criteria for the exclusions of certain datasets, observations or time points.*

6. What are the planned statistical analyses?	*Specify the statistical model that will be used to analyze the data and describe the data pre-processing steps. Be as specific as possible and avoid ambiguity.*
7. What are the criteria for confirming and disconfirming the hypotheses?	*Specify exactly how the hypothesis will be evaluated. Give specific criteria relevant to the used analytical model and framework (e.g., alpha-values, Bayes Factor, RMSEA).*
8. Have the analyses been validated on a subset of the data? If yes, please specify and provide the relevant files.	*Indicate whether the proposed data-analyses have previously been validated on a subset of the data or a simulated dataset. If so, provide the data files and data syntax.*
9. What is known about the data that could be relevant for the tested hypotheses?	*Please describe any prior knowledge that you have about the data set (e.g., the known mean of a variable) that is relevant for your research question.*
10. Please provide a brief timeline for the different steps in the preregistration.	*Provide the (foreseen) dates for the different steps in this preregistration form.*

Appendix 2. Comparison of Sample details in ICILS and PISA

Studies	ICILS		PISA	
Data	Available	N	Available	N
Albania				6129
Argentina				12111
Australia				13437
Austria		3448		13437
Azerbaijan		3634		
Belgium		3365		8286
Brasil				10798
Brunéi				5576
Bosnia and Herzegovina		1877		
Bulgaria				6107
Chile		3216		6488
Chinese Taipei		5112		5857
Costa Rica				6113
Croatia		2911		6135
Cyprus		3182		
Czech Republic		8169		8460
Denmark		3038		6200
Dominican Republic				6868
Estonia				6398
Finland		4249		10239
France		3694		
Georgia				6583
Germany		5065		6116
Greece		3576		6403
Hong Kong (China)				5907
Hungary		3491		6198
Iceland				3360
Ireland				5569
Italy		3376		10552

Japan				5760
Jordan				7799
Kazakhstan		4852		19769
Korea		3723		6454
Kosovo		3345		
Latvia		2705		5373
Lithuania				7257
Luxembourg		4703		
Macao (China)				4384
Malaysia				7069
Malta		3115		3127
Morocco				6867
Netherlands		1288		
Norway		4436		
Oman		6437		
Panama				4544
Poland				6011
Portugal		3650		
Romania		3270		7364
Saudi Arabia				6928
Serbia		3125		
Singapore				6606
Slovak Republic		3034		5824
Slovenia		3318		6705
Spain		11799		30800
Sweeden		3401		6072
Switzerland				6829
Thailand				8495
Türkiye				7250
Ukrainian Regions (18 of 27)				3876
United Kingdom				12972
Uruguay		2933		6618

United States		2352		4552
North Rhine-Westphalia (Germany)		2726		