Getting closer to the digital divide: An analysis of impacts on digital competencies based on the German PIAAC sample

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A B S T R A C T

This paper takes an intersectional perspective to investigate the effect of socio-demographic variables that may constitute to digital divide. The concept of digital divide emerged from a perspective on unequal access to digital technology and relates nowadays primarily the differences in the competencies necessary to handle this technology. To investigate digital divide, the present paper uses the PIAAC framework of digital competencies which is called *problem solving in technology-rich environments* (PS-TRE). It introduces the approach of intersectionality that describes persons impaired by multiple inequalities.

The paper analyzes the impact of these factors on PS-TRE for three subsamples of the German study: (1) employed people who use computers at work and at home, (2) employed people who use computers only at home, and (3) people that are out of the labor force. It analyzes furthermore contributions to digital divide by a comparison of these impacts with literacy and numeracy scores.

While employed people with computer use at work and home only had generation as a factor for constituting digital divide, employed people with computer use only at home had migration background as a further factor. Education and cultural capital showed lower impacts on PS-TRE than on literacy and numeracy.

1. Digital competencies as key qualification

During the COVID-19 pandemic, governments worldwide communicated stay at home policies for the citizens (e.g. Engle et al., 2020). Similarly, several companies supported work from home opportunities for their employees. However, working from home requires job profiles that allow working from home as well as employees that can rely on their respective competencies and on a home infrastructure facilitating this. Besides the persons working in system relevant professions, the pandemic revealed a divide between the persons who were able to move their workplace home—which was mostly supported by digital technologies—and the persons who were not able to do this and who often got laid off during the pandemic. The increasing unemployment rates in the US (as well as in other countries) during the pandemic (Bureau of Labor Statistics, 2020), especially in the low-skill job sector, documents evidence for that.

The COVID-19 example illustrates that the ability to use digital technologies for everyday problem-solving purposes belongs to the key competencies of modern societies. It furthermore emphasizes how far digital competencies as well as job profiles requiring digital competencies make a difference for individuals to succeed. This raises the

issue how far these competencies distinguish for individuals with different socio-economic background variables.

This paper will focus on that issue by analyzing impact factors on digital competencies for three target groups: (a) individuals with computer use at work and at home—a target group that may have high chances for being able to work from home; (b) individuals with computer use only at home. This target group may obviously have higher obstacles for working from home and (c) persons out of the labor force. Although this sub-sample has no need for working from home, its members are affected by stay home policies and may therefore be also dependent on technology use. Thus, the paper will first conceptualize the aspect of digital divide before dealing with the issue of multiple inequalities that may affect an individual's bias for acquiring digital competencies. Then, the paper will introduce its rationale for the study and the PIAAC (Program for the International Assessment of Adult Competencies) data set that provides evidence for its analyses.

2. Conceptualizing digital divide

The term of digital *divide* may raise associations of a clear distinction between digital and not digital people (e.g. digital natives and

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digital immigrants; see Prensky, 2001). However, already van Dijk (2006) argues that this metaphor is ambiguous and elaborates on the difficulties when thinking of digital divide as a clear gap between two static groups which provides absolute inequalities between the persons included and those excluded (p. 222). He instead conceptualizes digital divide as a kind of container concept including inequalities in technological opportunities for e.g. life chances, resources, participation, and capabilities. Analyzing aspects of digital divide, van Dijk (2006) distinguishes four types of access: *material access*, that relates to computer and internet access, *motivational access* as the wish to have a computer and internet access, *skills access* as comprising of the skills necessary for handling a computer and accessing the internet, and *usage access* as usage time, diversity, activity and creativity. In the following work (e.g. van Deursen and van Dijk, 2010) the focus of this access typology developed further by recognizing that "the original divide of physical internet access has evolved into a divide that includes differences in skills to use the internet" (p. 893). This conceptual development acknowledges the falling proportion of persons without computer and internet access and missing computer experience. In the German PIAAC sample, for example, there were only 11.6 % of the population left that either had no computer experience or were failing the basic computer test (OECD average: 14.2 %; OECD 2013a, p. 87).

Summarizing this conceptualization process of digital divide, we can see that the concept developed from the dichotomous category of computer access into a focus on skills necessary in the context of digital technologies and that recent approaches take a perspective on digital skills as key competencies for private and professional contexts. This development from a divide in (hardware) access towards competency differences raises the issue if there are specifics of *digital* divide.

Ample of literature already reported differences in digital competencies with respect to socio-demographic characteristics of persons (e.g. Ertl and Tarnai, 2017; OECD, 2013a; Stöger and Peterbauer, 2014; Van Deursen et al., 2011), However, very few is known about how far digital divide is just impairment in another field similarly to literacy and numeracy or if it constitutes an impairment with specific characteristics and factors. Therefore, one must revisit the factors that may constitute this social origin and deal with the issue of multiple impairments.

3. Dealing with multiple inequalities

The interdependencies of multiple impairments could easily be exemplified by the categories of generation, gender, and education. The access to higher education for females in Germany was significantly lower 40 years ago than nowadays: looking at the generation of persons aged 60–65, 30 % of the males but only 22 % of the females had a university access degree. In contrast, looking at the cohort of persons aged 20–25 years, there are 59 % of the females but only 48 % of males with such a degree (see Destatis, 2018). This example shows that the impact of gender is different for—as well as dependent on—the generation in which a person was born. It shows also that this interdependency results in different effects on education, a further dimension of social inequality. Such interdependencies are especially crucial for representative studies investing a broad range of the population and a large span of age cohorts like PIAAC, which focuses on adult persons aged 16–64 (OECD, 2013a).

Recognizing such interdependencies gets more and more into the focus of social science research although it is not yet common in the analyses of international large-scale studies. Research acknowledging these interdependencies applies the term of *intersectionality* and focuses on individuals that are impaired by multiple inequalities (see e.g. Walby et al., 2012). It has its origins in the US social sciences research that was realizing that the experiences of black women "are frequently the product of intersecting patterns of racism and sexism, and […] these patterns tend not to be represented within the discourse of either feminism or racism" (Crenshaw, 1991 p. 1243f.). McCall (2005)

distinguishes three different approaches on intersectionality: an anti-categorial approach questioning the existence of homogenous categories like gender (p. 1776), an intra-categorial approach that focuses on one category but within on neglected points of intersections (p. 1774), and an inter-categorial approach that focuses on inequality among already constituted social groups and takes these groups as center for analysis (p. 1784f.). This approach "focuses the complexity of relationships among multiple social groups within and across analytical categories and not on complexities within single social groups, single categories, or both" (p. 1786). Hancock (2007) emphasizes in this context "the importance of holistic research that examines the potentially cross-cutting role of race, class, and gender in the lives of a particular population" (p. 74). Walby et al. (2012) raise the issue that the categories may not be symmetric, mutually influencing each other but that there may be asymmetries like in the example before: the generation a person was born in has implications for the experiences of gender of an individual; yet, the gender of an individual has no implications on the generation a person was born.

With respect to quantitative studies, Else-Quest and Hyde (2016a) emphasize the need to take an intersectional perspective to "attend to the experience and meaning of belonging to multiple social categories simultaneously" (p. 167) as well as "to consider these categories and their significance as potentially fluid and dynamic" (ibid.). Even if large-scale studies often cannot effectively provide information about how people experience inequality, they may still in fact consider that they belong to different categories simultaneously (Else-Quest and Hyde, 2016b) and that these categories obtain properties of a person during his/her socialization processes. Particularly the latter implies the importance of linking the categories to the individual's socialization processes and treating them accordingly, for example in a hierarchical fashion. This is a difference with respect to traditional regression approaches (in the context of PIAAC e.g. Stöger and Peterbauer, 2014; OECD, 2015) that—although they include different categories in their regressions—treat these categories equally without considering their asymmetric interdependencies. Specifically, for such large-scale studies, Dubrow (2013), introduces the concept of cumulative disadvantage acknowledging that the more disadvantaged demographics a person represents, the more they are disadvantaged with respect to their resources. Ertl and Tarnai, 2017 e.g. followed this approach and were able to distinguish differentiate effects for three subsamples of the Austrian PIAAC. One major result was that that socio-demographic variables could explain nearly the double amount of variance regarding digital competencies for persons out of the labor force (45 %) than for employed person that use the computer at work and at home (24 %). They could furthermore reveal that particularly the impact of generation and gender is three times higher for the persons out of labor force (21.7 %) than for the other group (7.3 %). The third subsample focused employed persons with computer use only at home, which they characterize as individuals in lower status professions. For this subsample, the impact of a migration background was nearly four times higher (7.1 %) than for the other subsample of employed persons (1.8 %). These differences emphasize the importance for intersectional analyses in the context of large-scale studies.

4. Rationale and background for the study

The current study aims at moving forward this approach by not only providing an intersectional analysis how the different factors contribute to digital competencies, but by furthermore contextualizing these results regarding *digital* divide. Therefore, the paper will focus how far the factors on digital competencies distinguish from factors on other key competencies like literacy and numeracy. Differences in the impact may be indications that these factors are specific for digital divide; similarities in these factors, however, may rather indicate that they just serve as background for general inequalities.

This paper will gain its insights with data of the PIAAC study PIAAC

study (Program for the International Assessment of Adult Competencies; OECD, 2013a). The PIAAC study focuses thereby on the competency to apply digital technology as well for private as for professional purposes. It characterizes these competencies as *problem-solving in technology-rich environments* (PS-TRE). More specifically, PIAAC understands PS-TRE competency as a connection between individuals' cognitive and technological skills that allows them to evaluate and work with information when using digital interfaces in order to solve problems related to their work, to their personal or to their social lives (Rouet et al., 2009). It comprises of three dimensions, namely the *content*, the *cognitive* and the *context* dimensions (OECD, 2013a p. 59).

4.1. Content dimension

The content dimension of PS-TRE focuses on the features of a specific activity and includes the respective tasks that have to be solved while applying technology (OECD, 2013a p. 59).

Such problem-solving *tasks* can be characterized by the *explicitness* of the problem as well as by its *intrinsic complexity*. While explicit problems are characterized by clear and obvious affordances resulting in the respective actions, less explicit or even ill-structured problems require first actions to identify the particular problem before considering steps for solving it. The number of steps required to solve a problem can be an indicator for its intrinsic complexity in the way that complex problems usually need more steps to be solved.

The *technology* aspect accounts for different *hardware* devices, *software*, the *functionality* and the *representations* of user interfaces in order to solve problems. This includes e.g. using mp3-players or computers (hardware), working with a room management system (software), knowing about search and filtering mechanisms (functionality) and interpreting text and graphics (representation). This specific focus on the use of different technological features is also reflected in other conceptual frameworks that operationalize "instrumental" or "operational" skills (see van Dijk, 2006v).

4.2. Cognitive dimension

The cognitive dimension understands problem solving as depending on the use of different (meta-)cognitive strategies such as *goal-setting and progress-monitoring, planning, acquiring and evaluating information* as well as *making use of information*. These strategies connect to the content dimension e.g. when specifying the problem or choosing the appropriate technological features. This conceptualization of the cognitive dimension in PIAAC is like the PISA-conceptualization of problem solving (OECD, 2014) and several of its aspects, i.e., searching, selecting and evaluating information, are also considered in other approaches as "information skills" (van Dijk, 2006v) or information-related competences (e.g., Ferrari, 2013).

4.3. Context dimension

The context dimension relates to different situations that require PS-TRE and reflects the approach of PIAAC to include personal, professional, and social aspects in the competency conceptualization (see OECD, 2013a). This aims at grasping "key information-processing skills" necessary for "participating in the labor market, education and training, and social and civic life" (OECD 2013a, p. 26) and distinguishes the PIAAC conceptualization from other approaches, e.g. van Deursen, van Dijk and Peters (2011) that only focus private aspects without communication tasks.

Considering that the PIAAC conceptualization of PS-TRE (see OECD, 2013a) comprises the private and professional use of computers, it seems obvious that persons that don't use the computer at work will have to be analyzed separately as well as persons out of the labor force. This distinction also operationalizes an occupational background.

Summing up, by providing private and professional contexts including communicative tasks, PIAAC has a comprehensive approach on the digital competencies necessary for the individuals succeeding in the 21st century. Being proficient in these competencies allows successful participation in society. However, the PIAAC reports were already able to show differences in this proficiency with respect to different socio-demographic aspects, e.g. age, gender, socio-economic background, occupational background, education, and mother tongue (see e.g. OECD, 2013a). Such differences distinguish persons that can participate well in society and persons that fall back. In the following, we will elaborate on this aspect by borrowing the concept of *digital divide*.

Furthermore, the paper will consider that several factors, e.g. gender, education, and social capital are not independent from one another (see e.g., Friemel, 2016). This implicates taking into account that factors taking place later in the process of socialization, e.g. education, might be dependent on the generation born (age), gender, and migration background and that social capital might be a result of an individual's socialization process. Besides these variables of social origin, the analyses will include a person's efforts in further education and personal computer use as both aspects may have obvious impact on a person's PS-TRE competency.

5. Research questions

This leads to the following research questions:

Research Question 1: To what extent do the three subsamples (employed persons with computer use at work/employed persons without computer use at work/persons out of the labor force) distinguish with respect to problem solving in technology-rich environments?

Regarding this research question, we assume that the results for Germany are similar to the results of the Austrian study (Ertl and Tarnai, 2017), i.e. employed people with computer use at home and at work score the highest and employed people with computer use only at home the lowest.

Research Question 2: To what extent do different demographic backgrounds such as age in the sense of generation, gender and native language impact problem solving in a technology-rich environment in the three subsamples when analyzed hierarchically in the process of socialization?

The second research question considers the hierarchical interdependence of these variables in a way that analyzes the impact of a variable after controlling for variables taking place earlier in the process of socialization, e.g. estimating the effect of education *after* controlling for age, gender, and a migration background. Regarding this research question, we expect effects like those for the Austrian sample (see Ertl and Tarnai, 2017). However, it's also important to consider the differences between both countries, particularly between the educational systems; it should be assumed that the effects cannot be translated directly.

The third research question focuses on the aspect of digital divide and analyzes to what degree effects for problem solving in technology-rich environments distinguish themselves from the effects on literacy and numeracy:

Research Question 3: To what degree can the impacts on PS-TRE be distinguished from the impacts on literacy and numeracy?

Regarding research question 3, we have the clear hypothesis that the digital divide manifests itself in the generation a person was born in. There may be another effect with respect to gender because the literature does in fact report gender differences in digital literacy.

6. Method

The analyses of the study are based on the German version of the PIAAC data set (ZA5845; version 2.2.0; Rammstedt et al., 2016). PIAAC is an international large-scale study implemented by OECD that provides a comprehensive documentation of its measurements and

implementation (see OECD, 2013b; and Zabal et al., 2014 specifically for the German sub-sample). PIAAC assesses a representative sample of adults in the age range of 16–65 (Zabal et al., 2014) with the consequence that persons out of this age range are not part of this sample. Specific weighting procedures during statistical analysis ensure representativity of the results.

The assessment of PS-TRE was computer-based in PIAAC (see Rammstedt, 2013). No PS-TRE value could be assessed for those who did not have at least acceptable computer use skills. This group consisted of (1) people without computer experience (see Table 1), (2) people who failed the basic computer test, and (3) people who refused computer-based assessment (see also Zabal et al., 2013, p.68). This meant that 15.3 % of the German sample had to be excluded due to missing analysis prerequisites. It is important to note that people from these groups scored clearly lower than the other subsamples with respect to literacy and numeracy (see Table 1). One must acknowledge that the PS-TRE assessment excludes very low-skilled people from its analysis. Aspects of intersectionality that lead to these very low skills may therefore be underestimated in the intended analyses.

The sample of the current analyses is comprised of (4) employed people with computer use at work and at home, (5) employed people with computer use only at home, and (6) people that are out of the labor force. Together, these groups built 75.2 % of the German sample, allowing the intended analyses to be quite representative for Germany (keeping in mind the restrictions mentioned above). Some people could not be included in the analyses for different reasons, e.g. because of missing values in predictor variables, belonging to a small subsample of unemployed people, or because of inconsistent values regarding their computer usage. These people are summarized into the category (7) other (9.6 %).

6.1. Variables

The competency measures applied for this study relate to the domains of literacy, numeracy, and PS-TRE as main outcome variables. As mentioned before, the PIAAC study includes personal and professional tasks in the assessment of PS-TRE, e.g. corresponding with respect to room reservations, finding an appropriate job portal, or filling an MP3 player according to specific criteria. For each of these competencies, the PIAAC data set (Rammstedt et al., 2016) provides 10 plausible values as well as 80 weights for each case for allowing estimations for populations.

The socio-demographic variables applied for these analyses comprise the individuals' age in the sense of generation, gender, migration background (operationalized as not having German as a native language), educational background (operationalized by the years in formal education), cultural capital (operationalized by the number of books in the household at the age of 16; see Table 2). Further education is a second aspect of a person's educational background and indicates whether an individual took part in further education within the last 12 months (yes/no). Finally, the study includes individual computer use at home and at work as an aspect of familiarity with the PS-TRE assessment. Computer use at home and at work was split into two scales each: application use (word processing and spreadsheets), and internet use (for email, receiving information, and performing transactions e.g. in the context of shopping or banking). Answers to these questions were recoded as (1) never, (2) less than once a week, (3) once a week, and (4) daily. Summing up the items determined a score and dividing this by the number of items built the respective scales.

Table 2 shows the descriptive statistics for the three subsamples of the study. It's clear that these three groups were quite different with respect to their composition: The group of the employed people was the oldest group, the group of employed people with computer use only at home was about four years younger, and the group of people out of the labor force was about six and a half years younger than the first one. It was the opposite for the standard deviations, with the employed group

showing the lowest and the group of people out of the labor force showing the highest. There were also observable gender differences: employed people with computer use only at home were over-proportionally male while people out of the labor force were over-proportionally female and the regularly employed people consisted of slightly more males than females. Regarding migration background, the subsample of employed people showed only half of the proportion of people with a migrant background than the subsamples of employed people with computer use only at home, while the subsample of people out of the labor force had slightly less than the latter one. For education, the differences were smaller, with employed people showing the longest time in education and people out of the labor force about 2.5 years less. With respect to cultural capital, employed people and people out of the labor force had noticeably higher values than employed people with computer use only at home. Looking at further education, it's seen that employed people show nearly double the participation rate than employed people with computer use only at home, and they themselves also show double the rate than people out of the labor force. The differences were quite small regarding application and internet use at home. Only the group of employed people with computer use only at home scored lower than the other two groups.

To characterize the three groups, the group of employed people (with computer use at work and at home) can be classified as a representative sample of the working population. Regarding this group of persons, only 3% did not participate in computer-based assessment. Employed people with computer use only at home are comparable to younger males with a higher proportion of migrants, i.e. less educated, and indicating lower cultural capital. In this group, almost 15 % did not participate in computer-based assessment. Regarding their literacy and numeracy competencies, they score on average 30 points lower than the first group (see Table 2). Additional analyses have shown that they earned just 58 % of the income of the first sub-sample and thus it is safe to assume that people from this group work in lower-status professions. People out of the labor force are the youngest subsample and over-proportionally female. However, they show a similar percentage of people with high cultural capital than the employed subsample. This group appears to be comprised of a high proportion of students and women on maternal leave. Looking at their literacy and numeracy values, these comprise a 10 % higher standard deviation than the employed people and score intermediate—20 points lower in literacy and 25 points lower in numeracy.

6.2. Analysis

The analyses for the research questions were performed via SPSS using the IDB-Analyzer[1] that provided a macro that was able to analyze the plausible values provided by PIAAC and ensured appropriate weighting of the cases. Because of the before mentioned interdependency of the variables of age (generation), gender and education we decided according to Field, Miles, and Field (2019) for a hierarchical analysis.

7. Results

We now look at the three research questions and answer them based on the PIAAC data set.

7.1. Research question 1: differences in PS-TRE

Looking at research question 1, all three subsamples have their mean at competency level I of III (see Table 2), even if the mean of the employed people was less than a half point away from competency level II that starts at 291 points. Employed people with computer use only at

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[1] http://www.iea.nl/welcome

Table 1

Distribution of the PIAAC sample with respect to the three subsamples analyzed in the study (4, 5, 6), people without a score in PS-TRE, and other people not analyzed in this study. Total numbers, percentages of the whole population, values for literacy (LIT, means, (standard deviations), and (competency levels)), and values for numeracy (NUM, means, (standard deviations), and (competency levels)).

	N	Percent[c]	LIT[b]	NUM[b]
(1) No computer experience	360	6.6 %	227.81 (47.47) (II of V)	213.54 (55.12) (I of V)
(2) Basic computer test failure	178	3.3 %	246.33 (51.12) (II of V)	224.94 (53.93) (I of V)
(3) Computer-based assessment refused	297	5.4%	255.97 (45.61) (II of V)	245.44 (50.02) (II of V)
(4) Employed – computer use at work and at home	2741	50.2 %	285.86 (41.09) (III of V)	293.01 (43.85) (III of V)
(5) Employed – computer use only at home	659	12.1 %	257.24 (43.02) (II of V)	263.88 (43.93) (II of V)
(6) Out of the labor force	707	12.9 %	267.80 (46.42) (II of V)	267.16 (48.38) (II of V)
(7) Other[a]	523	9.6 %	259.02 (46.92) (II of V)	262.54 (47.81) (II of V)
(8) Total	5465	100.0 %	269.92 (47.35) (II of V)	271.87 (52.93) (II of V)

[a] This category comprises several fragmented sub-groups, e.g. unemployed people, people using their computers only at work etc., each of them consisting of less than 130 people.

[b] Competency levels: I: 176–225 points; II: 226–275 points; III: 276–325 points; IV: 326–375 points; V: above 376 points.

[c] Deviations to the percentages reported by Zabal et al. (2013) have their origin in a differing filtering focusing on the three sub-samples of the study and excluding cases with missing variables.

Table 2

Descriptive statistics of the sample factors. Means (SD) for the three subsamples of employed people with computer use at work and at home (Employed), employed people with computer use only at home (Emp.-Home), and people that are out of the labor force (OLF).

	Employed	Emp.-Home	OLF
N	2741	659	707
Proportion of the whole PIAAC data set	50.2 %	12.1 %	12.9 %
Score PS-TRE	290.72[a,b] (40.78)	264.20[a,c] (43.37)	278.17[a,d] (44.00)
Age (Generation)	40.73 (11.70)	36.73 (13.41)	34.32 (17.39)
Gender (f)	45.5 %	41.9 %	59.5 %
Migration (y)	7.6 %	15.4 %	13.4 %
Years of Education	14.49 (2.45)	12.43 (2.18)	12.03 (2.49)
Cultural Capital (#Books > 100)	50.1 %	33.9 %	48.1 %
Further Education (y)	65.9 %	33.1 %	16.7 %
Internet Use at Home (1−4)	2.88 (.63)	2.67 (.68)	2.77 (.63)
Application Use at Home (1−4)	2.04 (.62)	1.78 (.67)	2.04 (.70)
Internet Use at Work (1−4)	2.66 (.85)	n/a	n/a
Application Use at Work (1−4)	2.76 (1.02)	n/a	n/a
Score Literacy	285.86 (41.09)	257.24 (43.02)	267.80 (46.42)
Score Numeracy	293.01 (43.85)	263.88 (43.93)	267.16 (48.38)

[a] Competency levels: I: 241–290 points; II: 291–340 points; III: above 341 points.

[b] 95 %-Confidence interval [288.31; 293.13]; $d_{Cohen(Employed – EMP.-Home)} = .303$; $d_{Cohen(Employed – OLF)} = 0.642$.

[c] 95 %-Confidence interval [259.10; 26.929]; $d_{Cohen(Emp.-Home – OLF)} = 0.320$.

[d] 95 %-Confidence interval [274.72; 281.62].

home scored noticeably lower, with 26.5 points less than the first subsample. People out of the labor force scored almost in the middle of both groups. The differences between the three sub-samples are highly significant with a medium effect size for the difference between employed persons and employed persons with computer use only at home and small effect sizes for the two other differences.

7.2. Research question 2: hierarchical regression of impact factors

Research question 2 is based on the assumption that the impact of each socio-demographic variable is not independent of the others; they instead interact intersectionally. Therefore, research question 2 analyzes the impacts of each variable on the explained variance hierarchically according to their occurrence within the individual's

Table 3

Hierarchical regression with respect to PS-TRE, literacy, and numeracy for employed people with computer use at work and at home. Amounts of additionally explained variance ΔR^2 (total R^2 in brackets)[a]. F-Values showing the significance of the ΔR^2 can be found in Supplement Table 4; the β-weights for the last stage of the hierarchical regression in Supplement Table 1.

Employed	PS-TRE Contribution (Total)	Literacy Contribution (Total)	Numeracy Contribution (Total)
Age (Generation)	+7.0 % (7.0 %)	+1.7 % (1.7 %)	+0.0 % (0.0 %)
+Gender (f)	+0.4 % (7.4 %)	+0.2 % (1.9 %)	+2.8 % (2.8 %)
+Migration (y)	+4.1 % (11.5 %)	+4.1 % (6.0 %)	+3.1 % (5.9 %)
+Years of Education	+12.6 % (24.1 %)	+17.7 % (23.7 %)	+18.3 % (24.2 %)
+Cultural Capital (#Books > 100)	+2.7 % (26.8 %)	+3.5 %% (27.2 %)	+2.5 % (26.7 %)
+Further Education (y)	+0.4 % (27.2 %)	+0.7 % (27.9 %)	+0.3 % (27.0 %)
+Computer Use at Home	+2.8 % (30.0 %)	+1.3 % (29.2 %)	+1.7 % (28.7 %)
+Computer Use at Work	+2.1 % (32.1 %)	+1.4 % (30.6 %)	+0.9 % (29.6 %)

[a] all standard errors (R^2) < .024.

Table 4
Hierarchical regression with respect to PS-TRE, literacy, and numeracy for employed people with computers only at home. Amounts of additionally explained variance ΔR^2 (total R^2 in brackets)[a]. F-Values showing the significance of the ΔR^2 can be found in Supplement Table 5; the β-weights for the last stage of the hierarchical regression in Supplement Table 2.

Emp.-Home	PS-TRE Contribution (Total)	Literacy Contribution (Total)	Numeracy Contribution (Total)
Age (Generation)	+14.3 % (14.3 %)	+7.1 % (7.1 %)	+1.3 % (1.3 %)
+Gender (f)	+0.2 % (14.5 %)	+0.3 % (7.4 %)	+0.6 % (1.7 %)
+Migration (y)	+5.6 % (20.1 %)	+4.4 % (11.8 %)	+3.3 % (5.0 %)
+Years of Education	+2.6 % (22.7 %)	+5.9 % (17.7 %)	+6.0 % (11.0 %)
+ Cultural Capital (#Books > 100)	+1.5 % (24.2 %)	+2.2 % (19.9 %)	+2.0 % (13.0 %)
+Further Education (y)	+0.2 % (24.4 %)	+0.1 % (20.0 %)	+0.1 % (13.1 %)
+Computer Use at Home	+8.5 % (32.9 %)	+6.6 % (26.6 %)	+5.8 % (18.9 %)

[a] all standard errors (R^2) < .042.

socialization process. First, the variable age indicates a belonging to a specific generation. It explains about 7% of the variance for employed people (see Table 3 for this subsample). However, its impact is doubled for employed people with computer use only at home (14.3 %; see Table 4 for this subsample) and nearly tripled for people out of the labor force (19.9 %; see Table 5 for this subsample). Gender in contrast has only a marginal impact of less than 0.5 % except for the subsample of people out of the labor force. However, its impact is rather low for this subsample (1.5 %; see Table 5). The impact of a migration background was much higher, with 4–6 per cent in the three subsamples. The education background explained a large amount of variance (12.5 %/12.6 %) for employed people and people out of the labor force, but only a small amount for employed people with computer use only at home (2.6 %; see Table 4). Cultural capital only has a small impact between 1.4 % for employed people with computer use only at home (see Table 4) and 2.7 % for employed people with computer use at work and at home (see Table 3). The computer use at home had the greatest impact (9.6 %; see Table 4) for employed people with computer use only at home, clearly less for people out of the labor force (3.2 %; see Table 5), and employed people (2.8 %; see Table 3). Computer use at work was assessed for the latter, which provided an additional 2% (see Table 3).

In summary, the highest amount of variance (46.8 %) could be explained for people out of the labor force, with age (generation), education, and migration background as the highest factors, together explaining 38.4 % of the variance (see Table 5). For employed people with computer use at home, only 33.1 % could be explained with age, computer use at home, and a migration background, bringing together 29.5 % of the variance (see Table 4). A similar proportion could be explained for employed people (32.2 %) with the three variables of education, age (generation), and migration background together explaining 23.7 % (see Table 3; Fig. 1 visualizes the top three impacts for each sub-sample for an easier comparison).

7.3. Research question 3: factors constituting digital divide

Research question 3 aims at revealing aspects of digital divide, analyzing to what extent the impacts for PS-TRE are different from the impacts for literacy and numeracy.

Table 3 shows for the subsample of employed people that nearly the same amount of variance could be explained for all three competencies. There is however a major difference for the variables of age and education. Age (generation) explains about 7% of PS-TRE, but far less when it comes to literacy (1.7 %) and numeracy (0.0 %). The variance explained by education (12.6 %) is only about two-thirds compared to its impact for the other two competencies (17.7 % resp. 18.3 %). The impact of gender as a variable of digital divide is marginal; the impact of migration background on PS-TRE (4.1 %) is similar to literacy, but higher than for numeracy. For cultural capital, it's comparable to numeracy and smaller for literacy. With the subsample of employed people, we can see a clear impact of age (a person's generation) as a factor for digital divide that partially reduces the impact of education as a factor for general competency heterogeneities.

A slightly different picture is seen when looking at employed people with computer use only at home (Table 4). Here, age (generation) is still an important factor (14.3 %) that explains 7 percentage points more than for literacy and 13 percent points more than for numeracy. With 5.6 %, the impact of a migration background is substantially higher in this group than for literacy and numeracy. In contrast, the impact of education is less than half than for the other two competency domains. Computer use at home has a major impact (8.5 %) in this subsample. Even if it is hard to interpret its influence on the other two competency domains, it can be safely assumed that individual engagement may reduce heterogeneity, or its lack may increase it. This is also why this subsample shows a digital divide with respect to both age (generation) as well as a migration background.

We could see a further increase in heterogeneity for the last sample of people out of the labor force (see Table 5). For this group, age (generation) explains 19.9 % of the variance, 10.5 percentage points more than for literacy and 17 percent points more than for numeracy. The impact of a migration background is about 2 per cent points higher than for literacy and numeracy, and the impact of education is lower than in the two other domains. Cultural capital has with 2.2 % only half the impact than for the other two competencies, and gender has its

Table 5
Hierarchical regression with respect to PS-TRE, literacy, and numeracy for people that are out of the labor force (OLF). Amounts of additionally explained variance ΔR^2 (total R^2 in brackets)[a]. F-Values showing the significance of the ΔR^2 can be found in Supplement Table 6; the β-weights for the last stage of the hierarchical regression in Supplement Table 3.

OLF	PS-TRE Contribution (Total)	Literacy Contribution (Total)	Numeracy Contribution (Total)
Age (Generation)	+19.9 % (19.9 %)	+9.4 % (9.4 %)	+2.9 % (2.9 %)
+Gender (f)	+1.5 % (21.4 %)	+0.4 % (9.8 %)	+2.8 % (5.7 %)
+Migration (y)	+6.0 % (27.4 %)	+4.2 % (14.0 %)	+4.1 % (9.8 %)
+Years of Education	+12.5 % (39.9 %)	+19.4 % (33.4 %)	+19.4 % (29.2 %)
+ Cultural Capital (#Books > 100)	+2.2 % (42.1 %)	+4.0 % (37.4 %)	+4.7 % (33.9 %)
+Further Education (y)	+1.0 % (43.1 %)	+0.6 % (38.0 %)	+0.2 % (34.1 %)
+Computer Use at Home	+3.2 % (46.2 %)	+1.5 % (39.5 %)	+1.9 % (36.0 %)

[a] all standard errors (R^2) < .034.

	PS-TRE	Literacy	Numeracy
Employed	1. Education (12.6%)	1. Education (17.7%)	1. Education (18.3%)
	2. Generation (7.0%)	2. Migration (4.1%)	2. Migration (3.1%)
	3. Migration (4.1%)	3. Cultural Capital (3.5%)	3. Gender (2.8%)
Emp.-Home	1. Generation (14.3%)	1. Generation (7.1%)	1. Education (6.0%)
	2. Computer use (8.5%)	2. Computer use (6.6%)	2. Computer use (5.8%)
	3. Migration (5.6%)	3. Education (5.9%)	3. Migration (3.3%)
OLF	1. Generation (19.9%)	1. Education (19.4%)	1. Education (19.4%)
	2. Education (12.5%)	2. Generation (9.4%)	2. Cultural Capital (4.7%)
	3. Migration (6.0%)	3. Migration (4.2%)	3. Migration (4.1%)

Fig. 1. Summary of the three main impacts (highest proportions of explained variance) on PS-TRE, literacy and numeracy for the three subsamples of employed people with computer use at work and at home (Employed), employed people with computer use only at home (Emp.-Home), and people that are out of the labor force (OLF). Education and generation (age) are emphasized in dark color to highlight their changing impacts for the different domains and sub-samples. This will be visualized in Fig. 2.

impact with 1.5 % between its contribution to literacy (0.4 %) and numeracy (2.8 %). In contrast to employed people with computer use only at home, the impact of computer use at home is small. Consequently, we have a noticeable digital divide for this sample as well with respect to age (generation) and a migration background, and a small impact of gender. And for this group, the impact of education and cultural capital is reduced compared to the two other competencies.

8. Summary and discussion

The aim of this paper was to obtain better insight into digital divide through social-demographic factors by taking an intersectional perspective. Considering this aim, we ascertain the following interesting aspects. The first relates to the three subsamples of the study that distinguish with respect to different characteristics. The first subsample of employed people with computer use at work and at home is very representative of the German working population. It scores on competency level I, and very close to the next competency level, with the educational background, age (generation), and migration as main impacts on PS-TRE. Compared to the two other competencies, it's seen that mainly age—the generation a person was born in—is the factor for digital divide. When looking at the subsample of employed people with computer use only at home, we can see a younger and more male sample that is less educated, has less cultural capital, and a higher proportion of people with a migration background. People of this sample earn on average just 58 % if the income of persons of the first sample which indicate that they're having lower-status jobs. They furthermore show the lowest competency levels in all three domains. For people in this group, age/generation as well as individual computer use at home and the migration background are the main impacts for PS-TRE. For this subsample, a migration background is a second aspect of digital divide—with a smaller impact than the person's age/generation. The last sample is comprised of even younger people that are over-

proportionally female and out of the labor force e.g. because of doing a university degree, parental leave, etc. This subsample shows an intermediate competency level with age (generation), education, and migration background as main impact factors on PS-TRE. For this sample, age (generation) and a migration background are the main factors for digital divide, with gender also having a minor impact. Applying the intersectional approach for these three subsamples could therefore reveal that the groups distinguish with respect to the competency score reached, to the impacts of some factors as well as with respect to the variances that could be explained. More important, it could reveal that the lower scores of the employed persons with computer use only at home can not only explained by less chances developing competency at the workplace but that the structure and composition of the impact factors is considerably different.

Looking now in greater detail at the factors, it's seen that age—the generation a person was born in—is a main factor for digital divide. Fig. 2 shows how dramatically the impact of age (generation) vanishes from PS-TRE to literacy and even more to numeracy. Even if this phenomenon is widely discussed in literature (Helsper and Eynon, 2010; Tsetsi and Rains, 2017; van Deursen and van Dijk, 2014), only the clear comparison with the two other competency domains of literacy and numeracy can provide evidence that the effect of age (generation) is specifically higher for PS-TRE and much less important for the two other competency domains (numeracy and literacy). Here, Fig. 2 clearly visualizes how the impact of age (generation) shrinks for the other two competencies and reaches even zero for the numeracy of the employed sub-sample with computer use at work and at home. Analyses between the three subsamples show that this effect increases for more heterogeneous subsamples. Relating these results to the ICILS study (Fraillon et al., 2013) that found that even young people do not have a desirable level of ICT competencies, it's clear that this phenomenon is even worse for older generations. Setting this into the context of Prensky (2001), we could assert that the digital natives, although they are far away from desirable competency levels in PS-TRE,
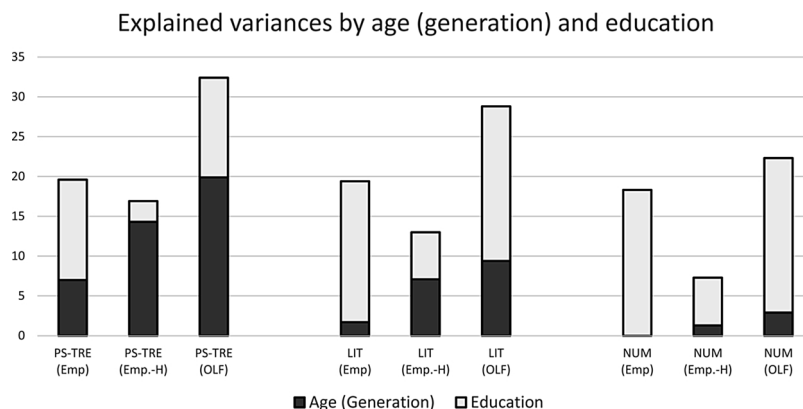

Fig. 2. Contributions of age (generation; dark grey) and education (light grey) on PS-TRE, literacy and numeracy for the three subsamples of employed people with computer use at work and at home (Emp), employed people with computer use only at home (Emp.-H), and people that are out of the labor force (OLF).

they are far ahead the older persons that are seen as digital immigrants (see also Helsper and Eynon, 2010).

Migration background (operationalized by the individual's native language) was an important factor for digital divide for all three of the subsamples. Here, its influence on PS-TRE was either the same or higher than the influence on literacy. This difference between PS-TRE and literacy for the subsamples of employed people with computer use only at home (25 % more than for literacy) and the subsample of people out of the labor force (nearly 50 % more than for literacy) in particular shows that the digital divide of a migration background goes beyond language issues. It may also involve (a lack of) access to facilities and technologies. Dealing with migration background as impact factor is therefore essential when talking about digital divide—especially as other studies (e.g. van Deursen and van Dijk, 2015; Helsper and Eynon, 2010) did not include this aspect in their studies.

In contrast, the effects of gender are fairly marginal, and the only significant effect could be found for people that are out of the labor force. These results appear to differ from some previous outcomes (Ponocny-Seliger and Ponocny, 2014; van Deursen and van Dijk, 2015). On the one hand, this may come from the conceptualization of the PIAAC measurement as assessing competencies for private and professional purposes rather than assessing mere knowledge about ICT (like e.g. Lennon, Kirsch, Von Davier, Wagner, and Yamaamoto, 2003) or the self-estimation about internet skills. Especially when comparing the results of van Deursen et al. (2011) and van Deursen et al. (2015) one can see that skills or competency measures rarely result in gender effects but self-evaluations quite often. Finding just a marginal effect of gender may also be a result of the intersectional approach of this study that doesn't specifically look at gender in and of itself, but instead as it is placed in the context of other socialization factors. This study analyzed how far the different factors contribute to PS-TRE, which contrasts with previous OECD (2015) analyses that analyzed the percentages of populations that fall within different competency levels. Considering that the mean PS-TRE score of the subsample of employed people with computer use at work and at home was very close to the border between competency levels I and II, it is obvious that small deviations from the mean will result in falling either into the one or the other competency level. Thus, analyses of the proportions of people comprising at least competency level II (like OECD, 2015) may strongly overestimate relatively small differences. Finally, although the results revealed just marginal effects of gender on ICT skills, there are still prevalent gender stereotypes about these (see e.g. Ertl and Helling, 2011). According to the van Deursen et al. (2015) model, such attitudes are the starting point affecting other kind of self-estimations and are therefore spreading widely into the self-concept of females in the context of computer and internet usage, access, and skills. Thus, gender stereotypes may, although competency scores are equivalent, result in further impairments regarding the individual's career paths (see e.g. Ertl and Tarnai, 2017).

As Fig. 2 clearly shows, the impact of education was lower for PS-TRE than for the two other competency domains. This finding is of importance for classifying the results of van Deursen et al. (2011; 2015) and Helsper and Eynon (2010): when looking at digital divide, it becomes very clear that education produces less heterogeneity for PS-TRE than for literacy and numeracy. This means that, although education has a big impact on the digital skills, it is rather mitigating digital divide—an aspect that studies only focusing on digital skills without context fail to reveal. The impact of education was highest for the subsample of employed people with computer use at work and at home. On the same level, but with relatively less impact compared to age (generation), it was also important for the subsample of people out of the labor force, and nearly lost its impact for the subsample of employed people with computer use only at home. This effect may be Janus-headed and show positive as well as negative aspects of the educational system. Education may compensate for the effects of age (a person's generation), i.e. older but better-educated people may show higher levels of competencies than younger, less-educated ones.

Education may furthermore compensate for gender and migration background if an individual finds his or her way into the right kind and level of education. If not, then this person may lag even further behind. Education remains a major factor for explaining scores in PS-TRE, even after controlling for an individual's generation and migration background. In contrast, endeavors for further education/training on the job had only marginal impacts in all analyses. It's therefore important to recognize that the main drivers for the development of PS-TRE may be found in school, not later education. Therefore, the actual issue should be to strengthen the efforts of education to prepare students for a technology-rich world. Comparing these results with the results of the Austrian study (Ertl and Tarnai, 2017), one has to realize that education explains in Germany almost twice as much variance compared to Austria. This difference for relatively close countries calls for further cross-national comparisons regarding impact factors.

Finally, the paper looked at individual computer use at home to get an estimation of how this factor would complement the explanation of the scores in PS-TRE. We found some effects regarding this variable. It was a major factor only for the subsample of employed people with computer use only at home. This indicates that individual activity may partially compensate for socio-demographic factors, particularly for people that don't use technology in their professional life. One may discuss how far computer competency predicts computer use (e.g. the model of van Deursen and van Dijk, 2015) or computer competency develops in the context of computer use. Yet, it seems reasonable to consider mutual interaction. Particularly the result that employed persons without computer use at work scored noticeably lower indicates that computer use is a prerequisite for competency development.

So, what does this mean for digital divide? First, the PIAAC study reveals that slightly less than 12 % had no experience in computer use or failed the basic computer test. These persons in the age of 16–64 years meet the traditional criterium of digital divide as not even being able to have access to digital tools (see also van Dijk, 2006v). Furthermore, we can see that these persons also suffer regarding their literacy and numeracy skills and therefore they are highly endangered for keeping track with the societal developments (see Zabal et al., 2013, p. 68). Considering the persons that took part in the evaluation of PS-TRE, we first must state that all three groups show only competencies on level I that just relates to basic computer competencies (see Zabal et al., 2013, p. 66). This means that none of these groups has on average medium or high computer competency. Systematically, employed persons that use computer only at home show the lowest skill. Thus, impairment in access to computers at work is also related to lower computer competencies, which could also be explained by the van Deursen and van Dijk (2015) model or vice versa which means that persons with lower competencies find themselves in lower profession jobs. For them, generation became the predominant factor for computer competency and was rather marginalizing the effect of education (which is prevalent in the other groups). The group of persons out of the labor force scored noticeably higher, but the explained variance is more than one third higher as for the other two groups. With more than 40 % variance only explained by socio-demographic factors, this group is much more subject to multiple impairments than the other two with more than 30 % only explained by age (generation) and education. Looking at these three sub-groups, one could see the specific advantages of the intersectional approach. Comparing to the baseline of employed persons with computer use at work and at home, both other groups score clearly lower regarding their competency in PS-TRE. Furthermore, one can see that the factors explaining the variances show different patterns. Thus, looking at the intersections could identify groups that are especially impaired and endangered in lagging behind regarding digital divide.

Limitations

This study analyzed the PIAAC sample that aims at ensuring representativity for the German population. However, PS-TRE could not

be assessed for more than 15 %. Looking at the scores for literacy and numeracy in Table 1, it needs to be acknowledged that the assessment of PS-TRE excludes the very low skilled people in the analysis, e.g. people with no computer experience that scored 80 points or two competency levels lower in numeracy than the subsample of employed people with computer use at work and at home (60 points or 1 competency level less for literacy). Thus, the aspects of intersectionality that lead to these very low skills may in fact be underestimated in this study.

9. Conclusions

The most important conclusion of this paper is that the impact of the different factors varies with respect to the sub-group analyzed and that the hierarchical analysis can provide more insights into interactions and intersections between the different factors. Research on large scale data should acknowledge that these effects aim to avoid "horse race" comparisons when it comes to the variations of specific factors but consider such intersections.

The second aspect involves the development of PS-TRE competencies. Even if the PIAAC measurement specifically operationalizes private *and* professional purposes, individuals using a computer at work show higher competency levels. This means that society should ensure access to learning opportunities for people that are not in these kinds of professions. Access initiatives should have their focus on intersectionally underprivileged groups to mitigate the digital divide.

The third aspect relates to un-doing gender (see Faulstich-Wieland, Weber, and Willams 2004) in PS-TRE. Results have shown that the impact of gender on PS-TRE is—counter to stereotypic attributions—rather marginal. Acknowledging this allows people a more appropriate estimation of their own PS-TRE competencies and opens pathways for professional development. However, this requires dissolving gender stereotypic attribution patterns of computer competencies as a male domain (see Ertl and Helling, 2011).

Looking finally at the impact of the socio-demographic variables, it's seen that they can explain more than 25 % of the variance in PS-TRE, which can be a huge burden for intersectionally impaired people. The main factors however go beyond race, class, and gender; they primarily include a person's generation, educational background (even if this is influenced by class), and migration background. Therefore, one must acknowledge that intersectionality in PS-TRE has to expand its perspectives to include more and other variables beyond just race, class, and gender in an overall effort to provide equal chances for as many people as possible.

Reflecting on the 25%–42% explained variance for the OLF subsample, may lead to Janus-headed conclusions. One the one hand one could think that this is a quite low amount of explained variance because it leaves quite a lot to other factors. However, these 25%–42% are just explained by the individual's socio-demographic characteristics—biases that the individual can't change by itself. We have seen that the sub-sample of employed persons with computer use only at home worked on average in lower income professions: persons of this sub-sample just earned 58 % of the income of the sample of employed persons with computer use at work and at home. The impact of education was far less than 10 % in any of the competencies for this subsample in contrast to the other two sub-samples. This means that the differences in variances, in the sizes we found, make a difference for the individuals when increasing or decreasing the chances for a well-paid job—and for the CoVid19 situation distinguishing between working at home or getting laid off.

Author statement

All authors contributed to the study conception and design. All authors have written and commented on previous versions of the manuscript. All authors read and approved the final manuscript.

References

Bureau of Labor Statistics, 2020. The Employment Situation – April 2020. Retrieved on 4th of June 2020 from. https://www.bls.gov/news.release/pdf/empsit.pdf.

Crenshaw, K., 1991. Mapping the margins: intersectionality, identity politics, and violence against women of color. Stanford Law Rev. 43 (6), 1241–1299. https://doi.org/10.2307/1229039.

Destatis (Statistisches Bundesamt), 2018. Bevölkerung (ab 15 Jahren): Deutschland, Jahre, Geschlecht, Altersgruppen, Allgemeine Schulausbildung (12211-0040) [xlx]. Retrieved from:. https://www-genesis.destatis.de/genesis/online/data;jsessionid=819E1AA21364BB43B00B287AA463A42A.tomcat_GO_2_1?operation=abruftabelleAbrufen&selectionname=12211-0040&levelindex=1&levelid=1533630223471&index=1.

Dubrow, J., 2013. Why should we account for intersectionality in quantitative analysis of survey data? In: Kallenberg, V., Meyer, J., Müller, J.M. (Eds.), Intersektionalität und Kritik. Springer VS, Wiesbaden, pp. 161–189.

Else-Quest, N.M., Hyde, J.S., 2016a. Intersectionality in quantitative psychological research: I. Theoretical and epistemological issues. Psychol. Women Q. 40 (2), 155–170. https://doi.org/10.1177/0361684316629797.

Else-Quest, N.M., Hyde, J.S., 2016b. Intersectionality in quantitative psychological research: II. Methods and techniques. Psychol. Women Q. 40 (3), 319–336. https://doi.org/10.1177/0361684316647953.

Engle, S., Stromme, J., & Zhou, A., Staying at Home: Mobility Effects of COVID-19 (April 3, 2020). Available at SSRN: https://ssrn.com/abstract=3565703 doi:10.2139/ssrn.3565703.

Ertl, B., Helling, K., 2011. Promoting gender equality in digital literacy. Journal of educational computing research 45 (4), 477–503. https://doi.org/10.2190/EC.45.4.f.

Ertl, B., Tarnai, C., 2017. Technologiebasierte Problemlösekompetenz im Kontext der PIAAC Studie. Zeitschrift für Bildungsforschung 7 (2), 165–180. https://doi.org/10.1007/s35834-017-0186-3.

Faulstich-Wieland, H., Weber, M., Willems, K., 2004. Doing Gender im heutigen Schulalltag. Empirische Studien zur sozialen Konstruktion von Geschlecht in schulischen Interaktionen. Veröffentlichungen der Max-Traeger-Stiftung Bd. 39. Juventa, Weinheim.

Ferrari, A., 2013. DIGCOMP: A Framework for Developing and Understanding Digital Competence in Europe. Publications Office of the European Union, Luxembourg. https://doi.org/10.2788/52966.

Field, A., Miles, J., Field, Z., 2019. Discovering Statistics Using SPSS, 5th ed. Sage, Los Angeles.

Fraillon, J., Schulz, W., Ainley, J., 2013. International Computer and Information Literacy Study: Assessment Framework. Retrieved on 23rd of April, 2018 from. https://research.acer.edu.au/cgi/viewcontent.cgi?article=1010&context=ict_literacy.

Friemel, T.N., 2016. The digital divide has grown old: determinants of a digital divide among seniors. New Media Soc. 18 (2), 313–331.

Hancock, A.-M., 2007. When multiplication doesn't equal quick addition: examining intersectionality as a research paradigm. Perspect. Politics 5 (1), 63–79. https://doi.org/10.1017/S1537592707070065.

Helsper, E.J., Eynon, R., 2010. Digital natives: Where is the evidence? Br. Educ. Res. J. 36 (3), 503–520. https://doi.org/10.1080/01411920902989227.

Lennon, M., Kirsch, I., Von Davier, M., Wagner, M., Yamamoto, K., 2003. Feasibility Study for the PISA ICT Literacy Assessment: Report to Network A. Retrieved on 11th of April 2018 from. . http://www.oecd.org/education/school/programmeforinternationalstudentassessmentpisa/33699866.pdf.

McCall, L., 2005. The complexity of intersectionality. Signs J. Women Cult. Soc. 30 (3), 1771–1800.

OECD, 2013a. OECD Skills Outlook 2013: First Results From the Survey of Adult Skills. OECD, Paris, France. https://doi.org/10.1787/9789264204256-en.

OECD, 2013b. Technical Report of the Survey of Adult Skills (PIAAC). OECD Publishing, Paris.

OECD, 2014. Creative Problem Solving: Students' Skills in Tackling Real-Life Problems. OECD, Paris, France. https://doi.org/10.1787/9789264208070-en.

OECD, 2015. Adults, Computers and Problem Solving: What's the Problem? OECD, Paris, France. https://doi.org/10.1787/9789264236844-en.

Ponocny-Seliger, E., Ponocny, I., 2014. Genderunterschiede in PIAAC. In: STATISTIK AUSTRIA (Ed.), Schlüsselkompetenzen von Erwachsenen - Vertiefende Analysen der PIAAC-Erhebung 2011/2012. STATISTIK AUSTRIA, Wien, pp. 170–187.

Prensky, M., 2001. Digital natives, digital immigrants part 1. Horizon 9 (5), 1–6. https://doi.org/10.1108/10748120110424816.

Rammstedt, B. (Ed.), 2013. Grundlegende Kompetenzen Erwachsener im internationalen Vergleich: Ergebnisse von PIAAC 2012. Waxmann, Münster 2013.

Rammstedt, B., Martin, S., Zabal, A., Konradt, I., Maehler, D., Perry, A., et al., 2016. Programme for the International Assessment of Adult Competencies (PIAAC), Germany – Reduced Version (Version 2.2.0) [ZA5845]. GESIS Data Archive, Cologne. doi:10.4232/1.12660. .

Rouet, J.-F., Bétrancourt, M., Britt, M.A., Bromme, R., Graesser, A.C., Kulikowich, J.M., et al., 2009. PIAAC Problem Solving in Technology-Rich Environments: A Conceptual Framework (OECD Education Working Paper Nr. 36). OECD, Paris.

Stöger, E., Peterbauer, J., 2014. Informell, nicht-formal, formal – die Bedeutung dieser Lernorte für die PIAAC-Schlüsselkompetenzen und die berufliche

Handlungsfähigkeit. In: STATISTIK AUSTRIA (Ed.), Schlüsselkompetenzen von Erwachsenen - Vertiefende Analysen der PIAAC-Erhebung 2011/2012. STATISTIK AUSTRIA, Wien, pp. 98–125.

Tsetsi, E., Rains, S.A., 2017. Smartphone Internet access and use: extending the digital divide and usage gap. Mob. Media Commun. 5 (3), 239–255.

van Deursen, A., van Dijk, J., 2010. Internet skills and the digital divide. New Media Soc. 13 (6), 893–911. https://doi.org/10.1177/1461444810386774.

van Deursen, A.J.A.M., van Dijk, J.A.G.M., 2015. Toward a multifaceted model of internet access for understanding digital divides: an empirical investigation. Inf. Soc. 31 (5), 379–391. https://doi.org/10.1080/01972243.2015.1069770.

van Deursen, A.J.A.M., van Dijk, J.A.G.M., Peters, O., 2011v. Rethinking Internet skills: the contribution of gender, age, education, Internet experience, and hours online to medium- and content-related Internet skills. Poetics 39 (2), 125–144. https://doi.org/10.1016/j.poetic.2011.02.001.

Van Deursen, A.J., Van Dijk, J.A., 2014. The digital divide shifts to differences in usage. New Media Soc. 16 (3), 507–526.

van Dijk, J.A.G.M., 2006v. Digital divide research, achievements and shortcomings. Poetics 34 (4), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004.

Walby, S., Armstrong, J., Strid, S., 2012. Intersectionality: multiple inequalities in social theory. Sociology 46 (2), 224–240. https://doi.org/10.1177/0038038511416164.

Zabal, A., Martin, S., Klaukien, A., Rammstedt, B., Baumert, J., Klieme, E., 2013. Grundlegende Kompetenzen der erwachsenen Bevölkerung in Deutschland im internationalen Vergleich. In: Rammstedt, B., Ackermann, D. (Eds.), Grundlegende Kompetenzen Erwachsener im internationalen Vergleich: Ergebnisse von PIAAC 2012. Waxmann, Münster, pp. 31–76.

Zabal, A., Martin, S., Massing, N., Ackermann, D., Helmschrott, S., Barkow, I., Rammstedt, B., 2014. PIAAC Germany 2012: Technical Report. Waxmann, Münster.