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Digital inequality in Austria: Empirical evidence from the survey of the OECD "Programme for the International Assessment of Adult Competencies"☆

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A B S T R A C T

Digitisation and rapidly emerging new technologies are transforming many aspects of life such as education, work, and leisure. These changes lead to a growing demand for new skills related to ICT use, computer literacy, internet use, or technical digital skills. However, the extensive literature on digital inequality provides evidence for significant differences in computer skills along the usual dimensions of social inequality. Due to the omnipresence of digital technologies in everyday life, it is all the more important to know the extent of digital inequality to be able to take appropriate measures to ensure that social participation does not degenerate into a question of social stratification in the Digital Age. In this paper, we provide empirical evidence for socio-economic digital inequality in Austria using survey data from the "Programme for the International Assessment of Adult Competencies" (PIAAC) conducted in 2011/2012.[1] We show, for Austria, that higher socio-economic background is positively related to digital problem-solving while being female is negatively correlated. However, when controlling for ICT engagement in everyday life, the positive effect of the socio-economic background only remains significant for groups of people with a very high socio-economic background while the effect of gender becomes statistically insignificant. Furthermore, based on Eurostat data we cannot identify a uniform trend towards a decline of digital inequality since 2012. Our results indicate that disadvantaged population groups in Austria should be encouraged and enabled to integrate ICT usage in their everyday life to reduce digital inequality.

1. Introduction

The almost-all-encompassing digital transformation of society poses new challenges for people as they are expected to acquire skills and competencies to handle and use digital technologies. The recent literature in economics on the impact of technological change on labour markets highlights the growing importance of technology-complementing skills for the labour force [1–5]. Given the expected changes in occupations, there is a consensus that the demand for (more or less) new skills will increase. Moreover, the growing demand for these skills is not limited to specific professions but covers the whole world of work since the share of employment in jobs characterised by medium or high degrees of digitisation has increased significantly since 2002 [3] and is expected to do so in the future [2].

In view of these developments, the "old" issue of the digital divide is once again becoming more topical. The extensive research on the digital divide, or more recently on digital inequality, highlights the problems associated with the unequal distribution of digital skills across and within population groups (e.g., [6–18]). According to this body of literature, existing patterns of social inequality will be reproduced and amplified in the Digital Age not only because of the unequal access to digital technologies, but also because of differences in computer skills along the usual dimensions of social inequality. Furthermore, digital technologies affect many spheres of everyday life beyond the world of work. Consequently, it is important to know the extent of digital inequality and to identify the disadvantaged groups to develop strategies ensuring that social participation in the Digital Age is inclusive.

Since previous studies have shown that socio-economic background (e.g. [16]) and gender (e.g [18]) affect ICT and computer literacy, which belong to the set of digital skills, the central research question of this article is: What impact do socio-economic background and gender have on digital competencies in the Austrian workforce? The article

contributes to the empirical research on digital inequality focusing on the case of Austria by analysing the cognitive skill domain "digital problem solving" from the representative survey data provided by the OECD "Programme for the International Assessment of Adult Competencies" (PIAAC) regarding parental socio-economic background and gender, among others.

But since the PIAAC survey has only been conducted once in each participating country, this data set can only be used to document the situation in Austria in 2011/2012. Our analysis thus lacks a time dimension — a weakness that can often be found in research on digital inequality [14]. To overcome this drawback, we use aggregated Eurostat data on ICT use and digital competence levels in Austria between 2012 and 2019 to provide evidence for the changing nature of digital inequality over time. Since technology acceptance models (TAM) predict that the use of technologies increases over time irrespective of individual differences [19,20], one should be able to see rising ICT use across different population groups. But whether this helps to overcome digital inequality depends on the rate of changes in ICT use of the digital 'forerunners' compared to the digital 'laggards'. This leads to our second research question: In Austria, has digital inequality in terms of ICT use and derived digital skill levels decreased between 2012 (or 2015 depending on data availability) and 2019?

The remainder of the paper is structured as follows: Section 2 presents a literature review on digital inequality research. In Section 3 we describe the data, variables, methods and present the results of the empirical analysis of digital inequality in Austria in 2011/2012 based on PIAAC. In Section 4 we analyse time series data on ICT use and digital competence levels from Eurostat to study whether digital inequality has decreased since 2012 (or 2015 depending on data availability for the variables of interest). Section 5 concludes the paper.

2. Literature review

In light of recent technological advancements, for example in the area of artificial intelligence and big data, several studies predict a replacement of jobs by digital technologies ranging between less than 10% up to more than 50% [2,4,21,22]. Even though the reliability of such estimates is always disputable (see [23]), it is safe to say that the task and skill content of occupations has already been subject to significant changes due to computerisation. For instance, the share of jobs requiring high "digital skills" in the US has increased dramatically from 5% in 2002 to 23% in 2016 according to Muro et al. [3]. In addition to the changing nature of jobs and occupations and employment shifts, the economics literature demonstrates that there is a wage premium for digital skills [24,25]. For example, Grundke et al. [26] find evidence that workers in digital intensive sectors are generally better rewarded compared to workers in other sectors. They argue that, if the demand for certain skills (and skill bundles) is higher than their supply by the workforce, the reward will increase, while the rewards for other skills will decrease. These skill shortages could lead to income inequality, but also to unemployment of workers not possessing the types of skills demanded. Consequently, with these two empirical observations in mind, the well-known issue of the so-called "digital divide" (e.g., [8]) is more topical than ever. Digital divide research is motivated by the hypothesis that socio-economic inequality affects inequality in the access to (first-level divide) as well as the use of (second-level divide) digital information and communication technologies [10]. When digital divide research emerged in the 1990s, it mainly focused on access differences across varying segments of societies [27]. More recently, research has shifted to the analysis of variations in what people do when using computers, e.g. how they use the internet, which is found to be influenced by socio-economic inequalities [9,10]. Existing forms of social inequality therefore shape the patterns of digital inequality [7,10,28]. van Deursen et al. [13]

discuss this relationship as the stratification hypothesis[2] for which they describe two underlying mechanisms. The first, amplification, refers to the observation that rising social inequality not only manifests itself in digital inequality, but that this digital inequality also reinforces existing stratification. The second, the power law, which suggests that if there is digital inequality, patterns of polarisation emerge, i.e. a rising share of people engaging in capital-enhancing ICT use and a rising share of people who benefit comparatively less from ICT usage. The stratification hypothesis regarding digital inequality in OECD countries is well-studied and several scholars confirm that inequalities along socio-demographic dimensions such as age, ethnicity, gender, educational background or economic status affect internet usage, internet skills and internet outcomes [6–12,17,29–32]. For instance, Hargittai [11] shows that groups with more socio-economic resources are more likely to use the internet in ways that are personally beneficial. Studying college students, an already privileged group, they find that internet use reflects inhabited societal positions. Those with more privileged background use the internet more frequently and in more diverse ways and exhibit higher levels of know-how (second-level divide). Moreover, they have a higher degree of internet use autonomy as they have better resources in the sense of laptop ownership or access locations (first-level divide). Similar results are reported by Zillien and Hargittai [12] who reveal differences in capital-enhancing online activities related to social status. More precisely, high-status users engage to a greater extent than less privileged people in activities that "may lead to more informed political participation (seeking political or government information online), help with one's career advancements (exploring career or job opportunities on the Web), or consulting information about financial and health services"[33, p.606]. Hence, these differences in usage patterns of the internet may contribute to reproducing existing patterns of social inequality as different activities affect opportunities to varying degrees — with people already facing fewer opportunities, falling even further behind. Furthermore, patterns of socio-economically driven digital inequality already manifests itself among children. A recent meta-study on the relationship between socio-economic status and ICT skills of K-12[3] students concludes that educational status-related inequalities regarding the usual domains of literacy and numeracy, also exist for the domain of ICT literacy although to a smaller extent [16].

Apart from socio-economic status, there are also notable gender differences for computer and information literacy. For example, an analysis by Punter et al. [18] of students' test scores on the International Computer and Information Literacy Study (ICILS) 2013 shows a gender gap — however in favour of girls. According to the authors, 14-year-old girls outperform boys on the dimensions related to sharing and communication of as well as evaluating and reflecting on information, while there is no significant difference for applying technical functionality (computer literacy). But as Punter et al. [18] note, the better performance at sharing and communicating information may simply be due to the fact that girls perform better at reading literacy. As another possible explanation, they highlight that girls are more communication-oriented users of ICT.

Several other aspects influence the use of digital technologies. Among these, a positive relationship of higher education and frequency of internet usage and a negative relationship of higher age and frequency of internet usage are well established, as well as persisting differences regarding internet access and quality of connectivity between urban and rural regions [11,34,35].

To summarise, the extensive literature on the digital divide and digital inequality points to the importance of the traditional dimensions of social inequality in shaping the differences in internet and ICT use

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[2] Ragnedda [28] provides an interesting account on social stratification in the digital world from a neo-Weberian perspective.

[3] This American expression comprises primary and secondary education and is short for from kindergarten to $12^t h$ grade.

within and across population groups. However, to the best of our knowledge there is no comprehensive analysis of the extent of digital inequality in Austria going beyond the use of ICT. We will therefore study the stratification hypothesis by analysing how the commonly known dimensions of social inequality are related to the competencies needed to solve problems in technology-rich environments.

3. Is there digital inequality in Austria?

3.1. Data

For the analysis we use the Austrian survey data generated by the "Programme for the International Assessment of Adult competencies" (PIAAC) launched by the OECD. 24 countries[4] participated during the first round of data collection in 2011/2012. The main data collection in Austria took place between August 2011 and March 2012. The survey consists of two parts: first, a background questionnaire on demographic characteristics, education and training, social and linguistic background, employment status and income as well as on generic skills used in everyday life and in the workplace. Second, the direct assessment within the skill domains literacy, numeracy and problem solving in technological rich environments (henceforth PSTRE or *digital problem-solving*). In total, 5130 people (16 to 65 years old) participated in the PIAAC survey in Austria which was carried out by Statistics Austria. For our analysis we only use those respondents with proven ICT knowledge (71.6% of female and 74.9% of male participants) who took part in the PSTRE assessments. This means we do not include people with insufficient ICT skills (9.6% of the participants never used a computer and 4% failed the ICT core stage) or people who refused to take part in the PSTRE assessment (11.3%). While little can be said about the group of people who refused to participate in the assessment, we can assume that by excluding the participants without sufficient ICT knowledge, we underestimate the extent of digital inequality. Furthermore, as we are especially interested in the "readiness" of the Austrian workforce for the digital transformation, we restrict our sample to the employed and self-employed. This leaves us with 2542 observations, with 1303 men and 1239 women.

3.2. Variables

Based on the literature review, we consider the following variables as important for analysing digital inequality in Austria.

Digital competencies. To study digital inequality in Austria, we examine the distribution of digital competencies. Digital competencies are a set of skills that can be media-related, e.g. handling soft- and hardware, but also content-related, e.g. targeted use of computers to achieve personal goals [9]. Other definitions of digital competencies are outlined in media studies (e.g., [36]) and they comprise, for instance, dealing with the handling of digital security issues, but also social and creative aspects of the usage of digital content. Frequently, basic skills, such as literacy, are considered a precondition for the usage of digital media as well. Another concept of digital competencies is digital literacy. In a recent study Chetty et al. [37] provide an overview of different concepts of digital literacy and a framework to assess the identified components of digital literacy. According to this framework, five dimensions of literacy constitute digital literacy: information literacy (ability to access, evaluate and create digital content), computer literacy (the ability to use

hard- and software), media literacy (the ability to navigate, create and criticise texts, sounds, videos etc.), communication literacy (the ability to develop and apply non-linear interaction) and technological literacy (the ability to use, invent or evaluate different tools for life situations). Hence, digital literacy is a multi-dimensional and evolving concept where the sub-components need to be well defined and adjusted in line with evolving and changing technologies.

Building on these concepts of digital competencies and/or digital literacy, we study how the participants in the PIAAC survey scored on the PSTRE-tests. The digital problem-solving skills are defined as:

> "[…] the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks. The assessment focuses on the abilities to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer network".
>
> [p. 20 [38]]

The PSTRE concept therefore goes beyond the domain of computer (literacy) skills by focusing on assessing the abilities to solve problems using computer-based information. These are related to a range of cognitive, pre-dominantly analytical, skills such as evaluating information. The PSTRE-score is measured on a continuous scale from 0 to 500 points. The scales are subdivided into 4 "proficiency levels" for PSTRE (below Level 1 and Level 1, Level 2, Level 3). A description of the proficiency levels for PSTRE is provided in the Appendix.

Socio-economic background. Digital inequality research points to the importance of socio-economic background for the personally beneficial usage of digital tools, e.g. Zillien and Hargittai [12]. To approximate socio-economic background in the PIAAC data, we use the question: "About how many books were there in your home when you were 16 years old? Do not include magazines, newspapers or schoolbooks. To give an estimation, one metre of shelving is about 40 books". The choice of this variable is inspired by the sociological literature which suggests that books at home are a powerful indicator for the background of people's families [39].[5] Furthermore, as books at home at age 16 is independent from the survey respondent's choice, it eliminates the reverse causality problem, which would occur with other variables related to socio-economic status such as the respondent's educational attainment or occupation.

Gender. As the literature review shows, there are significant differences with regard to internet and ICT use between the sexes. Explanations in the social sciences emphasise cultural factors related to persistent gender norms or social expectations (e.g., [41]). Given that PSTRE assesses the cognitive processes of problem solving using digital technology, a gender gap might indicate that the underlying mechanisms to form these skills may be gender-biased. However, it is difficult to identify sociocultural determinants of skill formation by using quantitative methods. We therefore restrict the analysis to the documentation of gender differences with regard to digital problem-solving in 2011/2012.

For example, Fig. 1 shows the distribution of employed men and women in Austria across the four proficiency levels in PSTRE. While 52.3% of men are highly proficient (Level 2 and 3), this is true for 44.8% of women.

Table 1 shows the gender gap in PSTRE by socio-economic background. The largest differences in absolute as well as in relative terms can be observed in the group with low socio-economic background, while the smallest difference can be observed between men and women who said they had more than 200 books at home at age 16.

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[4] Australia, Belgium, Denmark, Germany, Estonia, Finland, France, Ireland, Italy, Japan, Canada, Korea, Netherlands, Norway, Austria, Poland, Russian Federation, Sweden, Slovakia, Spain, Czech Republic, USA, UK and Cyprus. In 2013 Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey followed. In 2017 Data on Ecuador, Hungary, Kazakhstan, Mexico, Peru, United States was added. The 2nd cycle of data collection will take place during 2021 and 2022.

[5] Its validity as a predictor of social status is, however, not uncontested. See for instance Engzell [40].
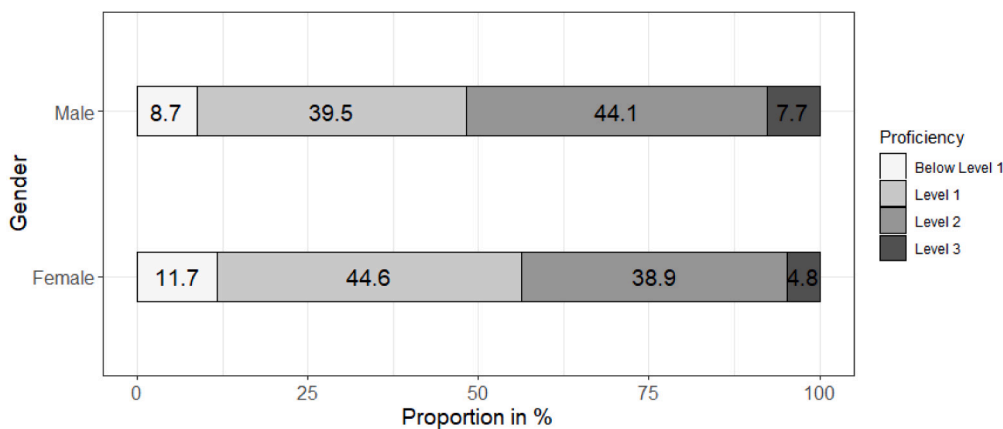
Fig. 1. Proficiency Levels.

Table 1
Difference of mean PSTRE-scores between men and women.

Books at Home at Age 16	DiffAbs	Diff. in %
10 books or less	−13.86	−5.11
11 to 25 books	−9.56	−3.49
26 to 100 books	−7.50	−2.58
101 to 200 books	−11.56	−3.84
More than 200 books	−7.23	−2.37

Table 2
Differences in mean PSTRE-scores by socio-economic background.

Books at Home at Age 16	N	Mean	DiffAbs	Diff. in %
Men				
10 books or less	99	271.40	0.00	0.00
11 to 25 books	190	274.13	2.73	1.01
26 to 100 books	495	291.15	17.01	6.21
101 to 200 books	225	300.93	9.78	3.36
More than 200 books	294	304.69	3.76	1.25
Women				
10 books or less	74	257.54	0.00	0.00
11 to 25 books	140	264.58	7.03	2.73
26 to 100 books	445	283.65	19.07	7.21
101 to 200 books	249	289.37	5.72	2.02
More than 200 books	331	297.46	8.09	2.80

Table 2 shows the differences in digital problem solving between different socio-economic groups by gender. For both men and women, we can observe a jump in the mean PSTRE-score between people with 11 to 25 books at home and people with 26 to 100 books at home.

Other variables. To control for other influential variables identified in the empirical research on ICT skills, we use age, education in terms of years of schooling and urbanisation. While we expect age to be negatively correlated with digital problem solving, we expect a positive correlation between years of schooling and PSTRE — however, the direction of causality is unclear.

We expect the degree of urbanisation to be positively correlated with digital problem-solving due to a small but nevertheless existing digital divide between densely and thinly populated areas regarding internet access in Austria in 2011/2012 (see Fig. 2). Furthermore we control for the variable test language indicating whether the test was taken in the native language to approximate for migration background. However, by focusing on language, we pick only one dimension along which people with migration background face disadvantages in society. This means we take into account that test results may be affected by poor language skills.

Finally, to capture ICT-affinity of participants, we include the index of ICT use in everyday life. This index is derived from variables presented in Table A.6 in the Appendix. These variables are measured on a Likert scale with the categories "Never", "Less than once a month", "Less than once a week but at least once a month", "At least once a week but not every day" and "Every day". The derived index is categorised as Warm's mean weighted likelihood estimation with five different levels of ICT engagement ranging from "Less than 20%" indicating low engagement in terms of frequency (i.e. never or less than once a month) and number of activities to "80%" or more representing high engagement (at least weekly used across a higher number of activities). In line with existing empirical research on internet use, e.g. Helsper [15], Zillien and Hargittai [12] or more recently van Deursen et al. [13], we expect that a low socio-economic background and female gender is associated with a lower degree of ICT usage. This is confirmed by the data presented in Fig. 3. It can be seen, that the number of men and women varies significantly in the different categories describing ICT use in everyday life. Especially in the groups with low socio-economic background (10 books or less), there are almost no women in the top quintiles of ICT use. For people with higher socio-economic background, the difference between the number of women in top quintiles is lower. In other words, as the socio-economic background rises, the gap in ICT engagement between men and women decreases. Furthermore, it can be seen from Fig. 3 that there is a rightward shift of the distribution of men and women across ICT use quintiles as the number of books increases.

Hence, the descriptive evidence already uncovers patterns of digital inequality between sexes and people with different socio-economic background in terms of digital problem solving as well as ICT usage. In the next section we turn to regression analysis to determine the statistical significance and magnitude of these effects.

3.3. Regression analysis

3.3.1. Data preparation

The variables used in the econometric analysis (see Table 3) are of categorical and continuous nature. We use the categorical variable "books at home at age 16" distinguishing between five levels: less than 10 books, 11 to 25 books, 26 to 100 books, 101 to 200 books and more than 200 books. The reference category in the estimations is less than 10 books. The gender dummy takes the value 1 if the respondent is female and 0 if the respondent is male. The language dummy takes the value 1 if the respondent is a non-native speaker and 0 otherwise. Years of schooling and age are continuous variables and centred at the mean. While this neither affects the size nor the significance of the coefficients, it allows for a more meaningful interpretation of the intercept, i.e. the intercept of model specifications including these
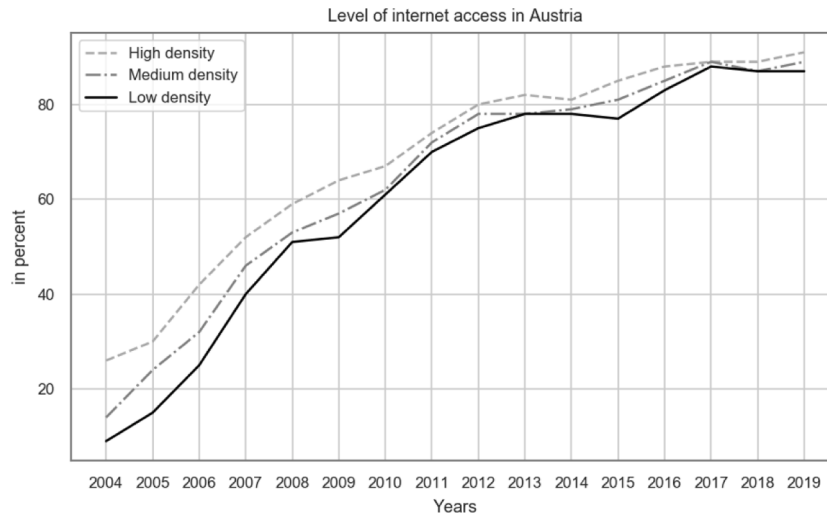
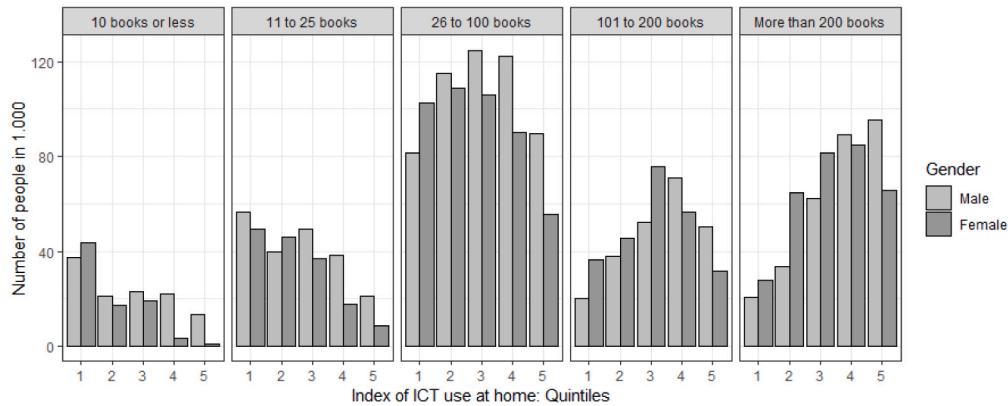**Fig. 2.** Level of Internet access by degree of urbanisation 2004–2019.

Fig. 3. ICT use in everyday life by socioeconomic background and gender.

variables refers to people of the mean age or mean years of schooling rather than to hypothetical values of 0. Urbanisation is a categorical variable with three outcomes and we re-scaled it to range between 0 and 1, where 0 indicates low urbanisation, 0.5 indicates medium urbanisation and 1 indicates high urbanisation. Finally, we use the index of ICT skills used in everyday life categorised from 1 to 5 where each value indicates quintiles (from low to high) of ICT engagement, i.e. higher values refer to relatively higher degree of ICT engagement.

3.3.2. Econometric specification

We use OLS regression to determine how socio-demographic variables are related to digital problem solving. In order to analyse differentials in PSTRE, we estimate a linear regression model. Doing so enables to test whether the effects of individual characteristics and socio-economic background systematically differ between population groups. The econometric model is given by the following equation,

$$PSTRE_i = \alpha + \beta_1 F_i + \delta_1 F_i \cdot S_i + \beta_2 \mathbf{I}_i + \delta_2 \mathbf{I}_i \cdot S_i +$$
$$\beta_3 \mathbf{C}_i + \delta_3 \mathbf{C}_i \cdot S_i + \beta_4 ICT_i + \delta_4 ICT_i \cdot S_i + \beta_5 S_i + \epsilon_i,$$
(1)

where the dependent variable $PSTRE_i$ is the PSTRE-score of individual i, F_i is the gender dummy, S_i is the ordinal variable "books at home at age 16" approximating socio-economic background and ϵ_i is the error term. The vector $\mathbf{I}_i$ contains the individual characteristics age and native speaker, the vector $\mathbf{C}_i$ comprises factors related to individual choice, i.e. education and urbanisation, and finally, ICT_i is the ordinal

Table 3
Overview of independent variables.

Independent Var.	Description	Values/Levels
F	Sex	0: Male 1: Female
S	Books at home	1: 10 books or less 2: 11 to 25 books 3: 26 to 100 books 4: 101 to 200 books 5: More than 200 books
$\mathbf{I}$	Age Language	Age in years (centred at mean) 0: Native Speaker 1: Non-Native Speaker
$\mathbf{C}$	Education Urbanisation	Years of schooling (centred at mean) 0: Low density 0.5: Medium density 1: High density
ICT	ICT skill use in everyday life	1: Lowest 20% 2: > 20% to 40% 3: > 40% to 60% 4: > 60% to 80% 5: > 80%

Table 4
Summary Statistics of Explanatory Variables.

Variable	Mean	Median	Min	Max	SD
Female	0.48 (0.010)				
Age	38.32 (0.231)	38.00	16.00	65.00	11.29 (2.582)
Non-native lang.	0.05 (0.005)				
Years of Schooling	12.66 (0.048)	12.00	7.00	19.00	2.42 (0.185)
Urbanisation	0.48 (0.009)	0.00	1.00	3.00	0.42 (0.002)

index of ICT skill use in everyday life. Each independent variable is interacted with the proxy for socio-economic background to test for differences between groups with different socio-economic backgrounds. We used a step-wise regression approach to show how statistical significance changes when each set of explanatory variables is added. With each set of independent variables we control for different effects identified in the literature review on digital inequality. In the first model, only a gender dummy was used. For the second model, socio-economic background was included. The individual, unchangeable characteristics (age centred at the mean and language dummy) were added next, followed by the variables education (years of schooling centred at the mean) and urbanisation and finally, the ICT use index was included to capture respondent's familiarity with digital technologies. In addition we interacted each of the explanatory variables with socio-economic background to catch potential moderator effects. For example, socio-economic background may have a smaller effect for better-educated people as they might also be employed in high-skill jobs for which it is more likely to be confronted with digital technologies.

For all data work and the estimation we used R and the svyPV package, which was developed to conduct calculations taking into account plausible values and survey weights in complex test survey designs.

3.3.3. Results
The summary statistics of the independent variables are presented in Table 4 while for the ICT skill index variable, the distribution by gender and socio-economic background are provided in Fig. 3.

Model 1 and model 2 confirm what can also be seen in the descriptive analysis: in Austria, women's PSTRE-score is on average 7.36 points lower than men's and this result is statistically significant at the 1%-level. Model 2 confirms that on average, higher socio-economic background is positively related to people's PSTRE-score. However, this effect is only statistically significant if the number of books at home is larger than 26. For instance, men with 26 to 100 books at home score on average 19 points higher than men from the reference group with less than 10 books at home. The size of the effect increases with socio-economic background in absolute terms but the relative gain from additional books becomes smaller when the number of books is greater than 100. Of the control variables, only age and years of schooling are statistically significant. As expected, age is negatively correlated with PSTRE (each additional year is associated with a reduction of PSTRE by between 0.69 and 0.8 in the different models). Years of schooling is positively correlated with PSTRE, i.e. one additional year of schooling is associated with a higher PSTRE-score of 3.89 or 3.24. None of the interaction terms are statistically significant. Hence, socio-economic background does not have a moderating effect. While adding control variables reduces the statistical significance of gender, socio-economic background remains statistically significant at the 1%-level. However, this changes once we include the ICT use index in model 5. In this specification only having more than 200 books remains statistically significant at the 5%-level while the gender-dummy is not statistically significant anymore. This implies that using ICT in

everyday life is positively correlated with PSTRE in Austria, but the direction of causality is unclear. On the one hand, the test to assess digital problem solving measures skills that are related to the tasks captured by the ICT use index and consequently one could expect a learning-by-doing effect as discussed in van Dijk [8] and Matzat and Sadowski [42]. On the other hand, people with higher digital problem solving abilities might be more interested in using ICT in everyday life. In either case, a closer look at the ICT use index (see Fig. 3) shows that the number of men and women falling into different categories of ICT engagement, varies significantly across different levels of socio-economic background. Furthermore, for men as well as women, ICT use increases with socio-economic background. Together with the regression results, this indicates that a reduction in digital inequality can partly be achieved by encouraging ICT use in everyday life for more disadvantaged groups. (See Table 5.)

4. Digital inequality in Austria today: trends in ICT use and digital skills since 2012

As stated in the introduction, our results only provide a snapshot of the situation in Austria in 2011/2012, thus, we cannot infer how digital inequality has developed since 2012. We try to overcome this limitation by analysing data on ICT usage in Austria from 2012 until 2019 and data on digital skills from 2015 until 2019 provided by Eurostat.

According to technology acceptance models (TAM), the use of new technologies increases over time regardless of individual characteristics [19,20]. Furthermore, the regression results suggest that differences in PSTRE reflect inequalities in terms of ICT engagement in everyday life. Therefore, increases in ICT use may be beneficial in terms of developing higher levels of digital problem solving skills.

However, whether increasing technology adoption can help to overcome digital inequality (in terms of ICT use) is not clear (see e.g., [13,28]): On the one hand, proponents of the 'normalisation' hypothesis argue that initial differences in access to and consequently use of new technologies disappear as they become cheaper and/or more user-friendly. On the other hand, the 'stratification' hypothesis puts forward that digital inequalities not only mirror but also reinforce the already existing inequalities and if digital 'forerunners' stay ahead in adopting new technologies, time will not affect digital inequality if the underlying structures of social stratification remain unchanged.

In an attempt to shed light on the evolution of digital inequality in Austria over time, we present descriptive evidence on changes in ICT use, starting in 2012, and derived digital skill levels based on self-reported tasks, starting in 2015, by socio-economic background (income quartiles), gender, age groups and the degree of urbanisation.

4.1. Data

To investigate the development of ICT use and digital skills over time, we use data from the Eurostat survey on ICT usage in households and by individuals (Eurostat [$isoc_c i_a c_i$] and [$isoc_s k_d skl_l$]). These are collected via telephone interviews on an individual or household level and are recorded along several background characteristics of the respondents including gender, income (quartiles), age (groups) and degree of urbanisation. The Eurostat survey covers a variety of variables related to ICT usage but we restrict our analysis to those similar to the variables of ICT use obtained by the PIAAC survey. Specifically, we analyse the share of individuals sending/receiving emails, telephoning, seeking information on goods and services online (Information — Goods/Services), internet banking and selling goods and services online (Selling — Goods/Services) from 2012 until 2019. Furthermore, we study the share of individuals who use a word processor software (Word processor) or have written a computer programme using a specialised programming language (Coding) from 2015 until 2019.[6]

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[6] We do not analyse using spreadsheet software because this variable is only available for 2012 and 2014.

Table 5
Regression Results.

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	291.54***	271.40***	274.72***	278.30***	262.00***
	(1.181)	(4.295)	(4.130)	(5.293)	(8.537)
Female	−7.36***	−13.86**	−14.70**	−12.06**	−7.88
	(1.609)	(6.243)	(6.214)	(6.283)	(5.949)
Books (at age 16)					
Ref.cat. = Less than 10 books					
11 to 25 books		2.73	1.03	3.68	6.70
		(4.940)	(6.081)	(6.081)	(9.643)
26 to 100 books		19.74***	16.97***	11.54**	10.81
		(4.771)	(4.572)	(5.776)	(8.735)
101 to 200 books		29.52***	225.34***	17.47***	13.15
		(5.176)	(4.900)	(5.978)	(9.987)
More than 200 books		33.28***	29.53***	19.76***	21.07**
		(5.023)	(4.957)	(6.029)	(9.838)
Control Variables					
Age (centred at mean)			−0.69***	−0.78***	−0.80***
			(0.261)	(0.263)	(0.262)
Non-native language			−15.51	−9.381	−14.49
			(9.742)	(9.389)	(9.969)
Education (Yrs. of schooling)				3.89***	3.24**
				(1.341)	(1.366)
Urbanisation				0.19	0.79
				(8.055)	(7.556)
ICT use at home index					6.20**
					(2.555)
Interaction terms					
Female : Books		Yes	Yes	Yes	Yes
Books : Age			Yes	Yes	Yes
Books : Language			Yes	Yes	Yes
Books : Education				Yes	Yes
Books : Urbanisation				Yes	Yes
Books : ICT use					Yes
Working.2.logLR	31.23***	309.39***	479.57***	660.89***	782.93***
No. Obs.	2425	2425	2425	2425	2425

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Note: Due to space constraints, the reported results are those discussed in the text. The full table of results is provided in the Appendix.

In addition to ICT usage, Eurostat reports the share of individuals with low digital skills, basic digital skills and above basic digital skills.[7] These can be interpreted, albeit with caution, as below Level 1, Level 1, and Level 2+3 of PIAAC's PSTRE-scores, respectively. In contrast to PIAAC data, the levels of digital skills are based on self-reported tasks, which are then categorised according to the EU Digital Competence Framework for citizens.[8] Nonetheless, we can use the derived digital skill levels to discover directions of change for different population groups from which we can draw tentative conclusions for the importance of digital inequality in Austria today.

4.2. Results

4.2.1. Digital skills

As a measure of socio-economic background, we use information on income quartiles. Fig. 4(a) shows the share of people with low, basic and above basic digital skills in each quartile of the income distribution in 2015 and 2019. Within the group of people reporting low digital skills, the share of individuals in the lowest income quartile (Q1) and the highest income quartile (Q4) decreased, while it increased

for the second lowest (Q2) and second highest (Q3) between 2015 and 2019. For basic digital skills, the share of individuals fell in all income quartiles except for Q1. At the same time, the share of people with above basic digital skills (the highest skill level category) increased for all income quartiles between 2015 and 2019. These results indicate a tendency towards an overall improvement of digital skill levels for people in the top and bottom quartile of the income distribution, while the development for the second and third income quartile resembles a polarisation pattern, i.e. increasing shares for low and above basic digital skills and decreasing shares for basic digital skills.[9]

Finally, despite the overall improvement within the group reporting above basic digital skills regardless of socio-economic background, the gap between the richest quartile and the rest widened since the share of the former increased the most. This indicates that the development of digital inequality with respect to socio-economic background seems to be in line with the stratification hypothesis.

As displayed in Fig. 4(b), the trends for different levels of digital skills are similar for men and women. The share of people with low digital skills as well as above basic skills increased, while the share of people with basic skills decreased. Comparing the relative changes within each group reveals that the gap between men and women has narrowed between 2015 and 2019. Most importantly, for the group reporting above basic digital skills, the share of women increased by 32%, while the share of men only increased by 8%. Hence, within the group of digitally skilled people the gender gap diminished.

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[7] The share of people reporting no digital skills is only around 1% and has not changed over time. We therefore decided to not include them in the analysis. Furthermore, to be consistent with the analysis based on PIAAC, we excluded those people whose digital skills could not be assessed as they reported not having had used the internet in the last 3 months before the interview. For the whole population this share decreased from 16% to 12% indicating increasing technology adoption.

[8] See Vuorikari et al. [43] for a detailed description of the DigComp framework.

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[9] Note that the share of people who did not use the internet 3 months prior to the interview decreased by 7 percentage points for Q1, 1 percentage point for Q2, 7 percentage points for Q3 and 5 percentage points for Q4.
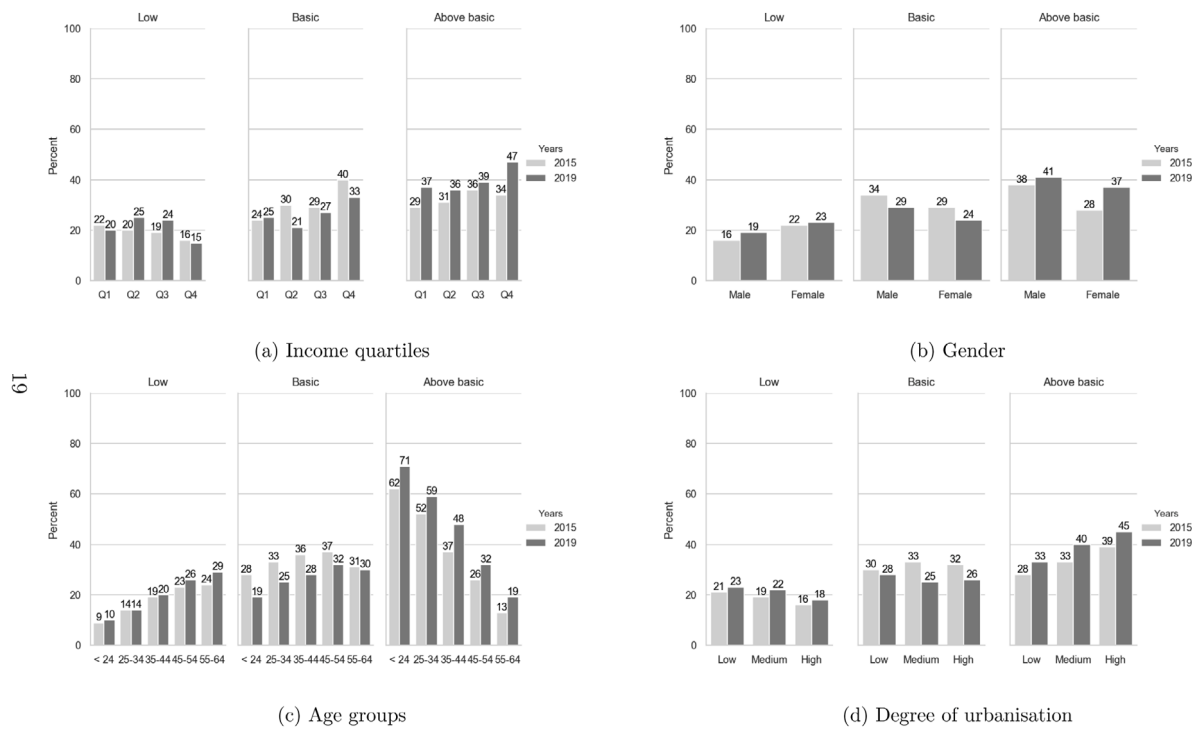
(a) Income quartiles

(b) Gender

(c) Age groups

(d) Degree of urbanisation

Fig. 4. Level of digital skills by share of people according to different background characteristics.

Because of the relatively short observation period of only 4 years, we do not expect large changes for different age cohorts. As can be seen from Fig. 4(c), the direction of change is the same for all age groups with rising shares of individuals with low and above basic digital skills and falling shares of individuals with basic digital skills. The most pronounced developments can be observed for people with advanced digital skills. In relative terms, the share of the oldest age group (55–64 years) among the digitally skilled increased the most, suggesting that the gap between old and young, albeit still large in absolute terms, decreased. While the gap between older and younger adults narrowed for the digitally skilled, it widened for people with low and basic digital skills. Consequently, we cannot identify a uniform trend regarding digital inequality between different age cohorts.

Fig. 4(d) reveals similar patterns as Fig. 4(c) displaying an increasing proportion of Austrians with poor and advanced digital skills and a decreasing share of people with basic digital skills in all types of urbanisation areas. However, based on the relative changes between 2015 and 2019, we can observe that people living in thinly populated and intermediate-density areas have caught up with people living in densely populated areas.

4.2.2. Internet activities

Fig. 5 shows similar trends for the different internet activities by socio-demographic characteristics. In line with predictions from technology acceptance models, there is a general increase in the use of email, telephoning and internet banking. At the same time the share of people seeking information on goods and services decreased while the share of people selling goods and services remained more or less constant between 2012 and 2019.

As shown in Fig. 5(a), the proportion of people in the lowest income quartile was smallest for most of the selected internet activities in 2012. By 2019 this has changed and now the second income quartile exhibits the lowest shares of users for each activity. The change is particularly noticeable for telephoning: while in 2012 between 22 to 24% used the internet for telephoning, in 2019 this is the case for 50% of people in the lowest income quartile, 36% of people in Q2 and 39% in each of the

two top income quartiles. Nonetheless, for all other exemplary internet activities one can observe a narrowing of the usage gap between the rich and the poor.

Fig. 5(b) reveals comparable trends in internet use for men and women over time: the proportion of people using email, telephony and internet banking increased, while the share of people seeking information about goods/services and selling goods/services online decreased. The share of women using the internet is smaller for all activities than that of men but the differences are small and for some activities, like telephoning, it hardly exists by 2019.

Differences in the shares of the old and young adults participating in the selected internet activities (Fig. 5(c)) diminished. Hence, the results on internet activities seem to support the normalisation hypothesis. Similarly, the gap between people living in thinly and people living in densely populated areas narrowed (Fig. 5(d)).
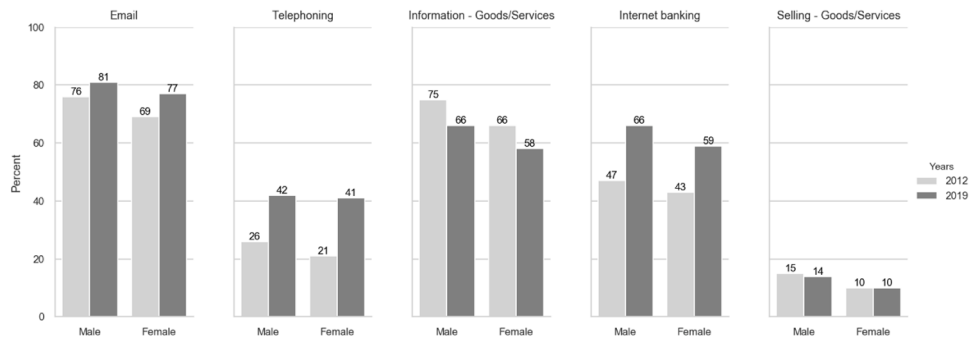
4.2.3. Computer use

Fig. 6 shows that, in general, computer use has not changed significantly between 2015 and 2019. Accordingly, digital inequality still exists, as computer use varies according to the socio-demographic characteristics of users. Looking at income quartiles (Fig. 6(a)), a positive relationship between using word processors and income can be observed. Nevertheless, the gap between the lowest income quartile and the rest decreased, while the difference between the second/third quartile and the top quartile increased. The gap within the group of people who report to have written code in a programming language (coding) remained stable. However, in 2019 the share of people in the second income quartile is lowest for using a word processor and coding but the differences are only minor.

Fig. 6(b) shows that the share of men using a word processor exceeds the share of women in 2015 as well as in 2019 but the gap decreased from 13 percentage points in 2015 to 7 percentage points in 2019. The proportion of men coding remained stable over time at 13% while it increased for women from 3% to 4%. Hence, the gender gap for coding decreased marginally but coding is still a male-dominated activity.
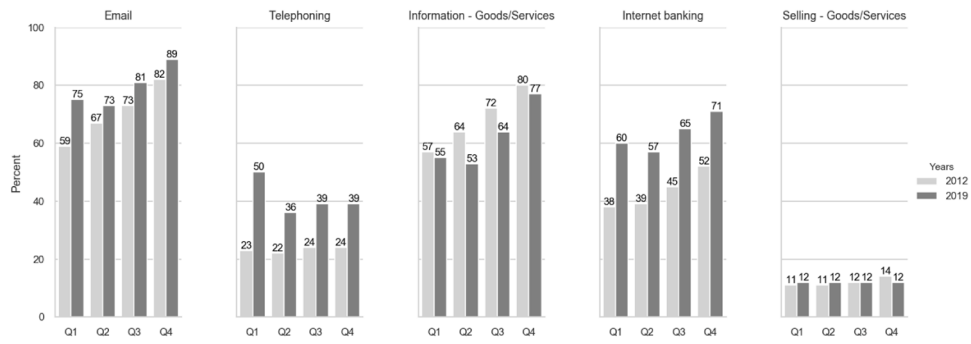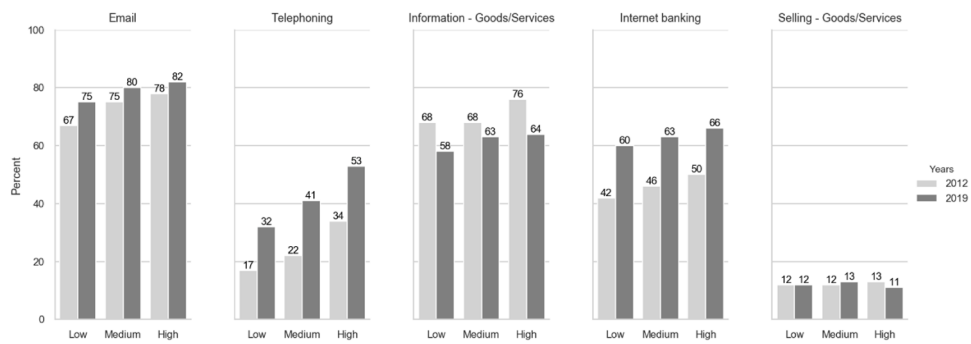
(a) Income quartiles

(b) Gender
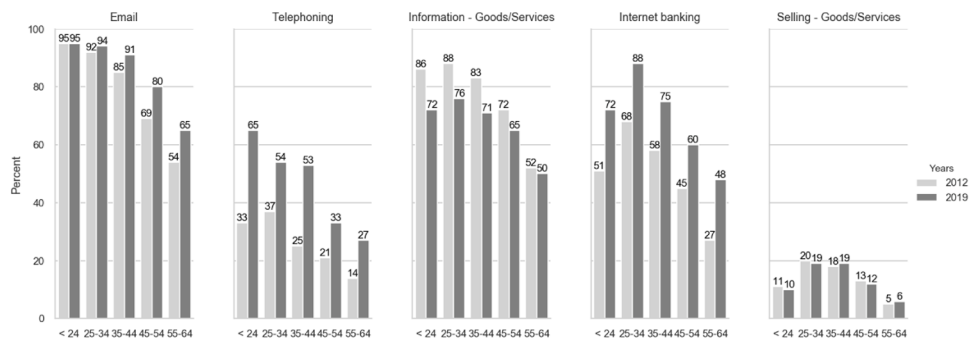
(c) Age groups

(d) Degree of urbanisation

Fig. 5. Internet activities by share of individuals according to background characteristics.

(a) Income quartiles

(b) Gender

(c) Age groups

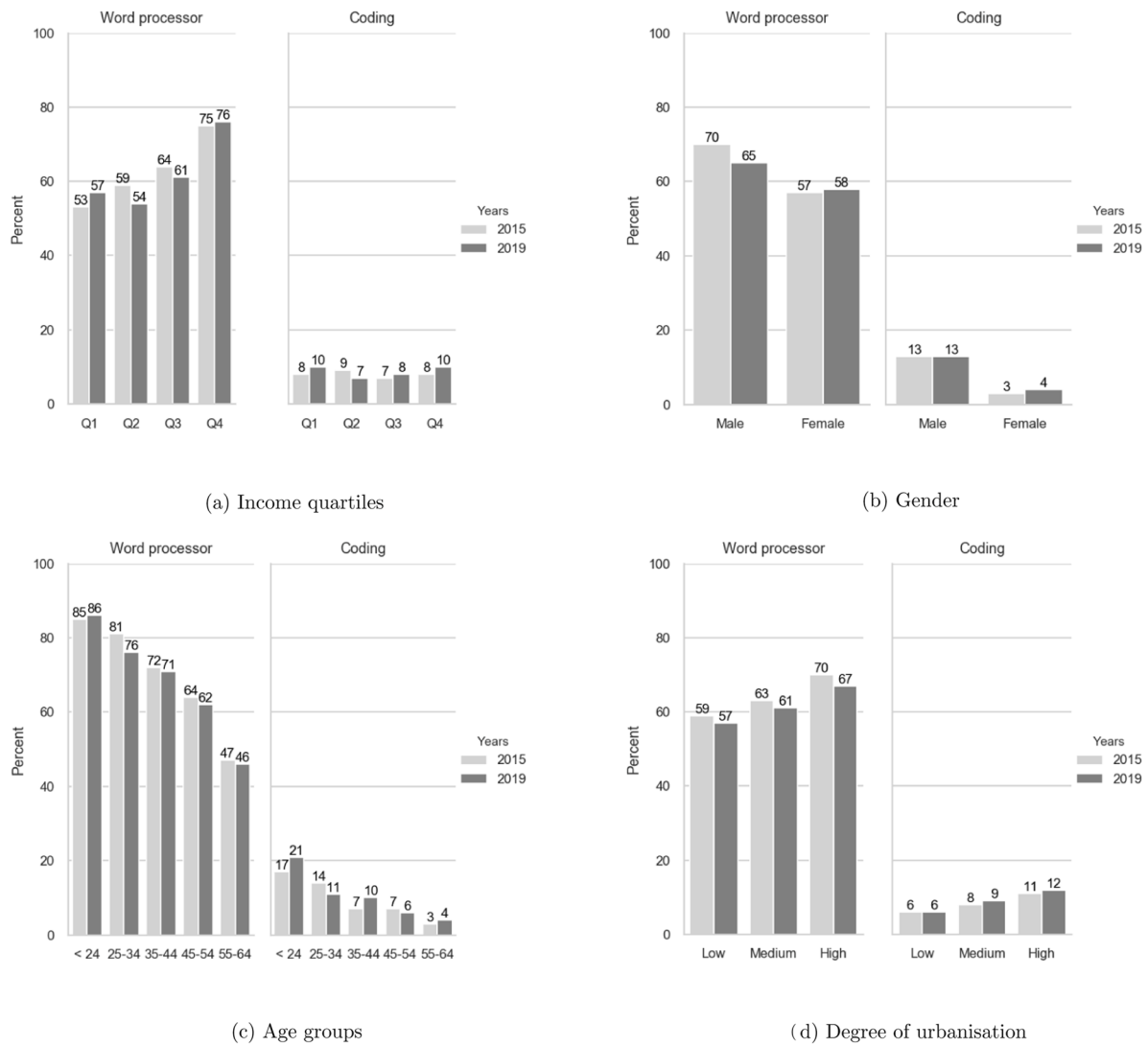(d) Degree of urbanisation

Fig. 6. Computer use by share of individuals according to different background characteristics.

As expected there is a negative relationship between computer use and age (see Fig. 6(c)). In particular, the absolute gap between the youngest (16–24) and the oldest (55–64) age cohort is large at 38 percentage points in 2015 and 40 percentage points for word processing in 2019. Similarly the absolute gap for coding between young adults and people aged 55 to 64 widened as the proportion of the young increased from 17 to 21% while that of the old increased from 3 to 4%. Thus, computer use by age groups provides evidence for the stratification hypothesis.

Finally, Fig. 6(d) displays that computer use is positively related to the degree of urbanisation. Since 2015 the use of word processors decreased while it increased for coding regardless of population densities but the changes in the size of the gaps are negligible small.

To summarise, we cannot identify a uniform development of decreasing digital inequality but rather a variety of patterns associated with different socio-demographic characteristics and dimensions of ICT use and digital skills. In line with predictions of technology acceptance models, usage of internet for communication purposes (email, telephoning) increases over time. This is not surprising in light of the fast adoption of portable computers or handheld devices (e.g. smartphones or tablets) to access the internet away from home or work, which rose from 45% in 2012 to 82% in 2019 in Austria [44]. Moreover, the

proportion of people using online banking has increased significantly over the period of 7 years regardless of socio-demographic differences. Even though the absolute gap in internet use persists – apart from the small gender gap – digital inequalities in terms of internet use decreased. Similarly, digital inequality in terms of digital skills still exist in 2019 but no clear trends over time can be observed. On the one hand, within the group of the digitally skilled people, inequality increased between the richest income quartile and the rest. On the other hand, within this group of people with advanced digital skills, inequality decreased between men and women as well as between old and young age cohorts.

While these results provide important additional information on trends in ICT use and digital skills over time, they are not directly comparable to the analysis based on PIAAC. Firstly, ICT use is not

reported separately for ICT use at home and at work and consequently usage inequalities might reflect occupational segregation rather than actual differences in ICT use. Secondly, the level of digital skills is based on the categorisation of self-reported tasks carried out using ICT and may thus exhibit response bias. Future releases of PIAAC data, however, will allow to study the development of the test variable digital problem-solving as well as ICT usage gaps over time in more depth.

5. Conclusion

Our findings support the initial hypothesis that existing patterns of inequality are reflected in the distribution of digital problem solving skills in Austria. Our results further highlight that differences in PSTRE are closely related to differences in ICT usage in everyday life.

More precisely, the econometric analysis confirms that there is a negative relationship between female gender and the PSTRE score. Moreover, there is a positive relationship between PSTRE and higher socio-economic background. Both findings are robust when controlling for age, education, language and urbanisation where only age and education are statistically significant with the expected signs, thus confirming results from existing research on digital inequality in OECD countries (e.g., [7,11,13,15,17,32,34]). However, once ICT-affinity is included in the regression, gender becomes insignificant while only the top socio-economic background category remains statistically significant. This is not surprising since our data show that, in line with existing research, ICT (in particular internet) use is itself characterised by differences with regard to gender (e.g., [15,18,32]) and socio-economic background (e.g.,[12,16,30,31]). Even though we cannot say anything about the direction of causality based on the regression results, it is reasonable to assume that ICT-familiarity increases digital problem solving because the test items of the PSTRE-test are comprised of tasks which are related to the variables included in the ICT use index. These estimation results for the ICT use index and PSTRE score may indicate that digital problem solving is a learning-by-doing type of skill which is in line with the findings from a study on Dutch internet users by Matzat and Sadowski [42] and a briefing note published by the "European Centre for the Development of Vocational Training" [45]. Hence, the differences in PSTRE in Austria reflect differences in ICT use in 2011/2012 — which should ideally be analysed taking into account the socio-cultural factors shaping usage behaviour.

However, as our analysis of aggregated Eurostat data has shown, some differences in ICT use lost in importance by 2019 (e.g. gender and age-related inequalities in internet use), while other digital inequalities, i.e. among the group of people with advanced digital skills, are still comparatively pronounced. While this analysis provides interesting additional insights concerning the development of digital inequality, the time span covered is very short. Consequently, further research is needed to investigate the development of digital inequality over time within and across countries. The data from PIAAC are promising in this regard because it will be conducted every ten years. Thus, once the new data are made available,[10] changes over time can be investigated more thoroughly.

Nevertheless, based on the results of our analysis, we can conclude that it is advisable to foster ICT usage of disadvantaged groups to reduce digital inequality. To this end, digital devices have to be made available because as the recent experiences with homeschooling and remote work during the Covid-19-pandemic have revealed, even today, with the high availability of digital devices in households and widespread internet access, the first-level divide still plays a role.[11] This can be addressed by financial support for low-income households for the acquisition of personal computers or laptops to use at home. Moreover, fears of contact with the technologies must be reduced, which could be achieved by information campaigns to foster self-learning in combination with formal education initiatives targeted at disadvantaged groups. For example, governments should support employers to provide on-the-job-training and invest in training programmes to enable employees to develop digital skills. However, further analysis is needed to uncover what parts of ICT use affect digital problem solving in particular and why, for example, the number of women using ICT in everyday life, especially those with low socio-economic background, was so low in Austria in 2011/2012. Future research should therefore not only focus on identifying which forms of ICT use increase digital problem solving for different groups, but also use cross-country analysis to determine whether different intangible socio-cultural factors shaping using behaviour, such as social norms, influence the digital gender gap and whether different welfare state regimes have an impact on socio-economic differences in digital skills as they may affect underlying socio-economic inequalities. The latter may provide evidence for the importance of addressing societal inequalities rather than making it the individual's responsibility to bridge the digital divide which is put forward in van Deursen et al. [13].

Finally, one last limitation of our analysis has to be pointed out. We do not include those 20% of the sample who did not take part in the PSTRE-assessment, i.e. people who either opted out to take the test or who did not have the minimum level of skills required to participate in the computer-based assessment. But with regard to the ongoing digitisation of all realms of society, future work has to also take a closer look at this group of digital outsiders to inform policy makers on the people most vulnerable to the changes brought about by the Digital Transformation.

CRediT authorship contribution statement

Stella Sophie Zilian: Conceptualization, Methodology, Formal analysis, Visualization, Writing - original draft. **Laura Samantha Zilian:** Conceptualization, Methodology, Visualization, Writing - review & editing.

Appendix

See Tables A.6–A.8.

Table A.6

Variables used for ICT use index in PIAAC.

Code in PIAAC	Description
H_Q05a	Use email
H_Q05c	Use the internet in order to better understand various issues
H_Q05d	Conduct transactions on the internet (selling or buying products, services or banking)
H_Q05e	Use spreadsheet software
H_Q05f	Use a word processor
H_Q05g	Use a programming language to programme or write computer code
H_Q05h	Participate in real-time discussion on the internet (online conferences, chat groups)

Table A.7

Regression results.

Variable	Mean	SE	t.value	Pr.t
(Intercept)	291.540***	1.181	246.779	0.000
female	−7.361***	1.609	−4.574	0.000
(Intercept)1	271.405***	4.295	63.191	0.000
female1	−13.862**	6.243	−2.220	0.029
books_num11 to 25 books	2.729	4.940	0.552	0.582
books_num26 to 100 books	19.743***	4.771	4.138	0.000
books_num101 to 200 books	29.522***	5.176	5.703	0.000
books_numMore than 200 books	33.281***	5.023	6.625	0.000
female:books_num11 to 25 books	4.306	7.306	0.589	0.557
female:books_num26 to 100 books	6.362	6.655	0.956	0.342
female:books_num101 to 200 books	2.302	6.549	0.352	0.726
female:books_numMore than 200 books	6.636	7.359	0.902	0.370
(Intercept)2	274.716***	4.130	66.511	0.000
female2	−14.703**	6.214	−2.366	0.020
books_num11 to 25 books1	1.034	4.667	0.222	0.825
books_num26 to 100 books1	16.972***	4.572	3.712	0.000
books_num101 to 200 books1	25.336***	4.900	5.170	0.000
books_numMore than 200 books1	29.534***	4.957	5.959	0.000
age_c	−0.690***	0.261	−2.649	0.010
nat_lang	−15.514	9.742	−1.593	0.115
female:books_num11 to 25 books1	6.370	7.240	0.880	0.382
female:books_num26 to 100 books1	6.119	6.610	0.926	0.357
female:books_num101 to 200 books1	3.567	6.594	0.541	0.590
female:books_numMore than 200 books1	6.936	7.422	0.934	0.353
books_num11 to 25 books:age_c	0.078	0.340	0.229	0.820
books_num26 to 100 books:age_c	−0.104	0.275	−0.378	0.706
books_num101 to 200 books:age_c	−0.336	0.310	−1.085	0.281
books_numMore than 200 books:age_c	−0.197	0.295	−0.666	0.507
books_num11 to 25 books:nat_lang	−1.510	13.883	−0.109	0.914
books_num26 to 100 books:nat_lang	0.767	11.281	0.068	0.946
books_num101 to 200 books:nat_lang	4.827	14.770	0.327	0.745
books_numMore than 200 books:nat_lang	−1.941	13.575	−0.143	0.887
(Intercept)3	278.299***	5.293	52.578	0.000
female3	−12.056*	6.283	−1.919	0.059
books_num11 to 25 books2	3.679	6.081	0.605	0.547
books_num26 to 100 books2	11.537**	5.776	1.997	0.049
books_num101 to 200 books2	17.466***	5.978	2.922	0.005
books_numMore than 200 books2	19.761***	6.029	3.278	0.002
age_c1	−0.783***	0.263	−2.972	0.004
nat_lang1	−9.805	9.389	−1.044	0.300
YRSQUAL	3.886***	1.341	2.897	0.005
urban	0.195	8.055	0.024	0.981
female:books_num11 to 25 books2	6.539	6.994	0.935	0.353
female:books_num26 to 100 books2	4.367	6.653	0.656	0.513
female:books_num101 to 200 books2	1.503	6.822	0.220	0.826
female:books_numMore than 200 books2	3.704	7.543	0.491	0.625
books_num11 to 25 books:age_c1	0.071	0.335	0.212	0.833
books_num26 to 100 books:age_c1	−0.094	0.275	−0.342	0.733

Table A.7 (*continued*).

Variable	Mean	SE	t.value	Pr.t
books_num101 to 200 books:age_c1	−0.358	0.315	−1.134	0.260
books_numMore than 200 books:age_c1	−0.196	0.300	−0.653	0.515
books_num11 to 25 books:nat_lang1	−5.105	13.373	−0.382	0.704
books_num26 to 100 books:nat_lang1	−7.582	10.974	−0.691	0.492
books_num101 to 200 books:nat_lang1	−4.821	13.197	−0.365	0.716
books_numMore than 200 books:nat_lang1	−10.470	13.919	−0.752	0.454
books_num11 to 25 books:YRSQUAL	0.400	1.681	0.238	0.813
books_num26 to 100 books:YRSQUAL	−0.338	1.441	−0.235	0.815
books_num101 to 200 books:YRSQUAL	−0.999	1.608	−0.621	0.536
books_numMore than 200 books:YRSQUAL	−2.218	1.357	−1.634	0.106
books_num11 to 25 books:urban	−7.356	10.231	−0.719	0.474
books_num26 to 100 books:urban	7.973	8.885	0.897	0.372
books_num101 to 200 books:urban	7.774	8.918	0.872	0.386
books_numMore than 200 books:urban	8.180	8.773	0.932	0.354
(Intercept)4	261.996***	8.537	30.690	0.000
female4	−7.876	5.949	−1.324	0.189
books_num11 to 25 books3	6.701	9.643	0.695	0.489
books_num26 to 100 books3	10.809	8.735	1.238	0.220
books_num101 to 200 books3	13.148	9.987	1.317	0.192
books_numMore than 200 books3	21.066**	9.838	2.141	0.035
age_c2	−0.797***	0.262	−3.042	0.003
nat_lang2	−14.486	9.969	−1.453	0.150
YRSQUAL1	3.240**	1.366	2.373	0.020
urban1	0.789	7.556	0.104	0.917
icthome_c	6.205**	2.555	2.428	0.017
female:books_num11 to 25 books3	3.893	6.616	0.588	0.558
female:books_num26 to 100 books3	1.665	6.299	0.264	0.792
female:books_num101 to 200 books3	−0.187	6.426	−0.029	0.977
female:books_numMore than 200 books3	1.325	7.158	0.185	0.854
books_num11 to 25 books:age_c2	0.128	0.326	0.391	0.697
books_num26 to 100 books:age_c2	−0.040	0.275	−0.146	0.884
books_num101 to 200 books:age_c2	−0.195	0.313	−0.622	0.536
books_numMore than 200 books:age_c2	−0.119	0.300	−0.397	0.693
books_num11 to 25 books:nat_lang2	−0.231	13.719	−0.017	0.987
books_num26 to 100 books:nat_lang2	−3.254	11.196	−0.291	0.772
books_num101 to 200 books:nat_lang2	1.893	13.507	0.140	0.889
books_numMore than 200 books:nat_lang2	−4.918	13.816	−0.356	0.723
books_num11 to 25 books:YRSQUAL1	0.696	1.709	0.407	0.685
books_num26 to 100 books:YRSQUAL1	−0.319	1.492	−0.214	0.831
books_num101 to 200 books:YRSQUAL1	−0.834	1.665	−0.501	0.618
books_numMore than 200 books:YRSQUAL1	−1.866	1.394	−1.339	0.185
books_num11 to 25 books:urban1	−8.689	9.633	−0.902	0.370
books_num26 to 100 books:urban1	6.373	8.406	0.758	0.451
books_num101 to 200 books:urban1	3.809	8.407	0.453	0.652
books_numMore than 200 books:urban1	6.271	8.286	0.757	0.451
books_num11 to 25 books:icthome_c	−1.233	2.895	−0.426	0.671
books_num26 to 100 books:icthome_c	−0.549	2.537	−0.217	0.829
books_num101 to 200 books:icthome_c	0.408	2.882	0.142	0.888
books_numMore than 200 books:icthome_c	−1.850	2.968	−0.623	0.535

Table A.8
Proficiency levels.

Proficiency Level	Score	Description
Below Level 1	Below 241 points	Tasks are based on well-defined problems involving the use of only one function within a generic interface to meet one explicit criterion without any categorical or inferential reasoning, or transforming of information. Few steps are required and no sub-goal has to be generated.
Level 1	241 to less than 291 points	At this level, tasks typically require the use of widely available and familiar technology applications, such as e-mail software or a web browser. There is little or no navigation required to access the information or commands required to solve the problem. The problem may be solved regardless of the respondent's awareness and use of specific tools and functions (e.g. a sort function). The tasks involve few steps and a minimal number of operators. At the cognitive level, the respondent can readily infer the goal from the task statement; problem resolution requires the respondent to apply explicit criteria; and there are few monitoring demands (e.g. the respondent does not have to check whether he or she has used the appropriate procedure or made progress towards the solution). Identifying content and operators can be done through simple match. Only simple forms of reasoning, such as assigning items to categories, are required; there is no need to contrast or integrate information.
Level 2	291 to less than 341 points	At this level, tasks typically require the use of both generic and more specific technology applications. For instance, the respondent may have to make use of a novel online form. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) can facilitate the resolution of the problem. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, though the criteria to be met are explicit. There are higher monitoring demands. Some unexpected outcomes or impasses may appear. The task may require evaluating the relevance of a set of items to discard distractors. Some integration and inferential reasoning may be needed.
Level 3	Equal to or higher than 341 points	At this level, tasks typically require the use of both generic and more specific technology applications. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g. a sort function) is required to make progress towards the solution. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, and the criteria to be met may or may not be explicit. There are typically high monitoring demands. Unexpected outcomes and impasses are likely to occur. The task may require evaluating the relevance and reliability of information in order to discard distractors. Integration and inferential reasoning may be needed to a large extent.

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