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Do Basic Digital Skills Help in the Labor Market? Evidence from a Repeated Assessment

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Abstract

Introduction: This article focuses on the labor market outcomes of acquisition of basic digital skills. A review of similar previous studies suggests that the present article is the first to focus on basic digital skills, to be based on a repeated measurement of these skills and to take account of a wide range of labor market outcomes. **Research Aim:** Our aim is to empirically test whether the acquisition of basic digital skills leads to an improved professional situation. **Method:** After outlining hypothetical underlying causal mechanisms, we use a unique panel dataset from a repeated assessment carried out in Poland and propensity score weighting technique to obtain two comparable groups of adults. **Results:** No significant effect of the acquisition of basic digital skills is found, with most effect estimates approaching zero. Additional strands of analysis indicate two probable reasons of this apparent lack of impact. First, most of adults who acquired basic digital skills did not obtain jobs requiring these skills. Second, what seems to be rewarded in the labor market is experience using work-relevant software, rather than possessing basic digital skills. **Conclusion:** A policy implication is that the education and training system should provide individuals with more than basic digital skills to increase their employability.

Keywords: **digital skills, ICT skills, employment, wages, propensity score weighting, PIAAC**

Czy podstawowe umiejętności cyfrowe pomagają na rynku pracy? Wyniki z badań opartych na wielokrotnej ocenie

Streszczenie

Wprowadzenie: Artykuł koncentruje się konsekwencjach nabycia podstawowych umiejętności cyfrowych na rynku pracy. Przegląd wcześniejszych podobnych badań sugeruje, że jest to pierwszy artykuł, który porusza ten temat, opierając się na powtarzalnym pomiarze podstawowych umiejętności cyfrowych oraz uwzględniającw tak wiele wskaźników charakteryzujących sytuację zawodową osoby. **Cel badań:** Empiryczne sprawdzenie, czy nabycie podstawowych umiejętności cyfrowych prowadzi do poprawy sytuacji zawodowej. **Metoda badań:** Po zidentyfikowaniu hipotetycznych mechanizmów przyczynowych wykorzystano unikalny zbiór danych panelowych z powtórzonego dwukrotnie badania podstawowych umiejętności cyfrowych przeprowadzonego w Polsce oraz technikę propensity score weighting, aby uzyskać dwie porównywalne grupy osób dorosłych. **Wyniki:** Nie stwierdzono istotnego wpływu nabycia podstawowych umiejętności cyfrowych na sytuację zawodową, a oszacowania większości efektów były zbliżone do zera. Dodatkowe analizy wskazują na dwie prawdopodobne przyczyny tego sugerowanego braku efektów. Po pierwsze, większość dorosłych, którzy nabyli podstawowe umiejętności cyfrowe, nie podjęła pracy wymagającej tych umiejętności. Po drugie, tym, co wydaje się być nagradzane na rynku pracy, jest doświadczenie w korzystaniu z oprogramowania istotnego dla danego stanowiska, a nie samo posiadanie podstawowych kompetencji cyfrowych. **Wnioski:** Na podstawie tych analiz można sformułować istotny dla polityki publicznej wniosek, że system edukacji powinien zapewniać jednostkom umiejętności wykraczające poza podstawowe kompetencje cyfrowe, aby skutecznie zwiększać ich szanse na rynku pracy.

Słowa kluczowe: **umiejętności cyfrowe, kompetencje cyfrowe, rynek pracy, wynagrodzenia, propensity score weighting, PIAAC**

1. INTRODUCTION

Promoting digital literacy constitutes a major public policy issue, as acknowledged by national governments and international organizations such as the European Union. The increasing role of digital skills in the economy seems evident. There is, however, little empirical research showing if, when and how acquisition of basic digital skills actually helps improve one's labor market outcomes, such as employment, wage, or other aspects of job quality. This article is meant to provide evidence in this respect, using a repeated measurement of basic digital skills carried out in Poland between 2011 and 2015. There are many hypothetical causal mechanisms that may link the mastery of basic digital skills to the improvement of an individual's professional situation. Nine of them are briefly described below.

Hypothesis 1 (human capital theory). An employee acquiring basic digital skills becomes more productive. For this reason, the employer is likely to offer the employee better working conditions, such as a wage increase. This explanation of the relationship between human capital and earnings is in line with the human capital theory advanced by Becker (1993).

Hypothesis 2 (required skills). Hypothesis 2 may be considered a stronger version of Hypothesis 1 or an alternative hypothesis which shifts the focus from human capital to job characteristics. Basic digital skills are a precondition for performing some jobs, so that the productivity of a person without these skills is null. Hence, basic digital skills give access to a wider range of jobs, including some of relatively high quality. Acquiring these skills makes it possible to get a new, better job which requires them, and this translates into an improved professional situation. One approach that can explain how this mechanism operates is the job competition theory (also known as labor queue theory) formulated by Thurow (1975), which suggests that lower employee training costs act as an incentive to hire a given person rather than another. A more elaborate explanation is that jobs which rely on digital skills coincide with those which include abstract tasks, and in the labor market there is a wage premium for performing abstract tasks (Falck et al., 2016).

Hypothesis 3 (signaling theory). The information that a person has acquired basic digital skills is a signal for an employer that this individual is a productive employee. For this reason, employers are likely to hire such individuals and offer them better working conditions. The difference between hypothesis 1 and hypothesis 3 is that the latter does not assume that basic digital skills necessarily increase productivity. Instead, the employer may believe that those who possess these skills are likely to have other abilities or characteristics which increase their productivity as employees. Hypothesis 3 is based on the job market signaling model (Spence, 1973).

Hypothesis 4 (digital career literacy). Basic digital skills enable individuals to develop a more advanced competence – digital career literacy, which consists of 'knowledge, skills and attitudes that are employed to pursue a career […] [making] use of the online environment' (Hooley, 2012: 5). Hence, some people who have acquired basic digital skills also learn how to use the internet to search for a better job, which makes them more likely to find one and improve their professional situation.

Hypothesis 5 (key enabling competence). (a) People who possess basic digital skills find it easier to develop other skills, because they use ICT to learn, for example, to take advantage of internet courses. (b) Additionally, successful acquisition of basic digital skills makes people more self-confident and encourages them to take part in further education and training. It is these subsequently acquired skills, rather than basic digital skills themselves, that lead to an improved professional situation. This hypothesis, presenting basic digital skills as a key enabling competence which facilitates learning, seems to be supported by evidence on the impact of digital literacy on academic performance (Pagani et al., 2016; Ben Youssef et al., 2022).

Hypothesis 6 (correlated skill acquisition). People who acquire basic digital skills are also more likely to acquire other skills, even though it is not the digital skills that make this possible. For example, a generally positive attitude towards learning makes an individual more likely to learn basic digital skills, but also to learn other skills. These other skills lead to improvement in the individual's professional situation, while basic digital skills do not.

Hypothesis 7 (employer bias). Employers who invest in developing their employees' skills are also likely to improve their working conditions. For example, the implementation of a technological change which increases productivity, thereby leading to higher remuneration, at the same time leads to more training. In other words, employer characteristics may simultaneously increase wages (to mention just one aspect of job quality) and the scale of employee training, generating a correlation between acquisition of basic digital skills and growth in earnings.

Hypothesis 8 (employee bias). The same characteristics of individuals (e.g. a proactive attitude) that increase their likelihood of acquiring basic digital skills simultaneously increase their chances of improving their professional situation (even though the latter effect is not mediated by the acquisition of other skills).

Hypothesis 9 (reversed causality). Individuals who have a job, particularly if it is a good quality job, are more likely to acquire basic digital skills, for example, because they are more likely to be trained by their employer or because they have more financial resources allowing them to participate in this type of training at their own expense.

A crucial and policy-relevant difference between hypotheses 1-5 and hypotheses 6-9 is that if one of the former set of hypotheses is true, the development of an individual's basic digital skills is expected to bring about improvement in their professional situation. A recommendation for public policy addressing such problems as unemployment or the digital divide would then be to train people in basic digital skills in order to improve their employment prospects. In contrast, hypotheses 6-9 do not imply that basic digital skills affect labor market outcomes, but rather that the effects of acquiring basic digital skills are spurious and that public intervention will not help. Accordingly, the primary objective of the analytical techniques used in this study is to disentangle, to the extent possible, the effects described in hypotheses 1-5 from the effects described in hypotheses 6-9. If the former type of effects is confirmed by the analysis, only then would the question arise as to which of the mechanisms described in hypotheses 1-5 is actually in place. Hence, the primary research question to be answered in this article is this: does acquisition of basic digital skills improve one's professional situation?

The rest of this research article is geared towards answering this question and organized as follows. Section 2 summarizes findings from previous, similar studies and highlights the novel features of this article. Section 3 describes the methodological aspects of the analysis presented in this article, such as the data used, control and outcome variables, causal identification strategy, and estimation of standard errors. Section 4 presents the results of the analysis. Section 5 briefly states what policy-relevant conclusion can be drawn from this study.

2. REVIEW OF PREVIOUS RESEARCH

During the literature review, 25 empirical studies which met both of the following criteria were identified:

1. They included a statistical analysis intended to estimate the impact of individuals' digital skills on their labor market outcomes.
2. They were based on individual-level data collected after the year 2000.

All of these studies are listed in Table A.6 in the appendix. Ten of them were based on PIAAC data, either from many countries or, as in this article, from a selected single country (e.g. the Netherlands). Of these 10 studies, one used data on self-reported digital skills and the remaining nine interpreted PSTRE (problem solving in technology-rich environments) score as a measure of ICT skills, sometimes in combination with ICT core test results and information about whether the respondent opted out of computer-based assessment. Only these nine studies using PIAAC data based inferences about individuals' digital skills on their performance in solving tasks. This is an important advantage offered by PIAAC, because there is evidence that self-reported skills tend to be overestimated in different degrees across demographic categories (Palczyńska and Rynko, 2021). What makes the present article unique is that it is based exclusively on ICT core test results. The rationale for this is that it focuses on basic digital skills, which are measured by the ICT core test, as will be explained in the 'Source of data' section. PSTRE score conveys information about more advanced skills, although it should be noted that PSTRE is not just another term for digital skills, but rather 'involves the intersection of the set of skills that are sometimes described as "computer literacy" (…) and the cognitive skills required to solve problems associated with information contained in various digital environments' (OECD, 2019).

Apart from PIAAC, the studies identified in the literature review used data from various other surveys, in a few cases combined with administrative data, job advertisements, or training curricula. Three studies were randomized experiments in which fictitious candidates' CVs or vignettes were presented to real hiring managers. Another randomized study assessed the effects of providing home computers to college students, demonstrated to be associated with an increase in self-reported computer skills (estimating the effects of these skills was one of the explicit goals of the study). Nine studies were not based on an experimental design, but, as in this article, applied counterfactual techniques (such as instrumental variables, fixed-effects models, Heckman's models, or propensity score matching) to identify the impact of digital skills. Twelve studies did not employ experimental designs or counterfactual techniques, but only various regression models (including random effects models). There were not many longitudinal studies, and the present article appears to be the first to be based on a repeated measurement of individuals' digital skills.

Moreover, no previous study took account of such a wide range of labor market outcomes and changes in an individual's professional situation as the present one. Sixteen studies focused on a single outcome, usually earnings, while the remaining nine studies considered two to four types of outcomes. The outcomes included most often were earnings and (un)employment, while outcomes included rarely were income, household expenditure, type of unemployment, labor force participation, labor market transitions, job stability, employer callback, declared interview invitation, hiring intention, and college enrolment. The present article appears to be the first to take into consideration job satisfaction, supervising of other employees, and promotion, in addition to employment, type of contract, and earnings.

Most studies drew conclusions from analysis of variously defined populations or samples, mostly from developed countries. No previous study focused on Poland, but several were based on data collected in many countries, including Poland. Usually, the group analyzed was restricted to working-age or prime-age individuals, and quite often to those who were employed. A few studies focused on a specific group, e.g. adult immigrants or late career workers.

Irrespective of the group analyzed, all but one study found a positive effect of digital skills. The only exception was a randomized controlled trial during which college students were given computers for home use. The study concluded that there was no evidence that computer skills had short- or medium-run effects on earnings or college enrolment. However, the experimental and control groups were not large, resulting in wide confidence intervals which made it difficult to obtain significant effects (Fairlie and Bahr, 2018). Some other studies concluded that positive effects are observed only for some categories of skills or workers (for example, generic skills or secondary school graduates), or that the effect of digital skills disappears or is even negative when the analysis controls for literacy or numeracy skills (see Table A.6 in the appendix for details).

3. DATA, MEASURES AND METHODS

3.1 Source of data – the PIAAC and postPIAAC surveys

The dataset analyzed in the study is a result of merging data from the OECD's PIAAC survey (1st cycle) and its national follow-up study, postPIAAC. Both surveys were coordinated in Poland by the Educational Research Institute (IBE). The latter was carried out only in Poland1. The PIAAC survey, or Survey of Adult Skills, was conducted in more than 30 countries, but this article is based on data gathered in Poland. These data were collected from August 2011 to April 2012. In total, 9366 interviews were administered. The sample was representative of the noninstitutionalized population aged from 16 to 65 and residing in Poland, but people aged 19-25 were oversampled and amounted to 5372 interviewees.

Interviewers administered computer-assisted personal interviews, using a background questionnaire (BQ) to collect data on the respondent's education and labor market history, job characteristics, skills applied at work and in everyday life, family background, personal traits and attitudes, demographics, etc. Direct assessment of skills followed the BQ. Four skill domains were assessed: literacy, reading components, numeracy, and PSTRE. To determine the level of respondents' skills, they were asked to solve tasks related to these domains. There were two modes of task administration: paper-based assessment (PBA)[2] and computer-based assessment (CBA). The procedure for selecting one of these modes is particularly relevant for

[1] PostPIAAC was not the only follow-up study to PIAAC. In Germany, PIAAC-L, a three-wave follow-up survey of PIAAC respondents, was conceived and conducted independently.

[2] With the exception that there was no PBA of PSTRE.

this article. The BQ asked about the respondent's computer experience. The assessment was paper-and-pencil-delivered to respondents with no computer experience, while the remaining respondents were routed to the ICT Core test. This consisted of six tasks which required the respondent to perform basic actions on a computer: mouse-clicking, typing on a keyboard, selecting an option from a drop-down menu, scrolling, selecting a piece of text, and using the drag & drop feature. Depending on their performance, they received a score ranging from 0 to 6. The respondents with a score above 3 passed the ICT core test and were routed to CBA. Those who failed the test or refused to take it on the computer were routed to PBA. In the PIAAC design, the ICT core test was thus an instrument serving to determine whether a given respondent was able to use a computer as a mode of assessment administration. In this article, however, we use this test to assess basic digital skills. More information about the assessment design and other technical aspects of the PIAAC survey can be found in the PIAAC Technical Report (OECD, 2019).

Three years after the PIAAC survey, from October 2014 to February 2015, field data collection for postPIAAC was conducted. Interviews were administered to 5224 PIAAC respondents who were reached and did not refuse to take part in the follow-up study. As during the original PIAAC survey, a BQ was administered, containing both some questions repeated from PIAAC and new questions. A test of basic digital skills was administered to respondents who claimed to have some computer experience, based on the ICT Core Test but containing three additional items, related to copying a file, using copy and paste tools within a document, and using basic arithmetic formulas in a spreadsheet. The postPIAAC study also included other questions and tests, but no repeated assessment of literacy, numeracy or PSTRE.

The postPIAAC study followed the PIAAC approach, providing a main sampling weight and 80 replicate weights to properly estimate standard errors.

3.2 Study group

The analysis presented in this article was conducted on a group of postPIAAC respondents between 19 and 56 years old who did not possess basic digital skills when the PIAAC interview was administered. These were respondents who claimed to have no computer experience or who failed the ICT core test. Refusals to take the test on the computer were interpreted as missing data because the respondent's actual proficiency was uncertain, although available evidence suggests that most refusing respondents have very low levels of digital skills (Non et al., 2021; Rynko, 2013).

This group was further divided into two subgroups: those who acquired basic digital skills between PIAAC and postPIAAC ('acquisition group') and all others ('non-acquisition group'). The former group included respondents who received a score above 3 for the basic ICT tasks which were repeated in postPIAAC (i.e. when the newly added tasks were not considered). The latter group included respondents who received a lower score and those who declared no computer experience, and for this reason the tasks were not administered to them.

Some small categories of respondents were excluded from the analysis. One of these categories consisted of 13 people who had retired from the labor market before PIAAC. Another comprised nine respondents with missing data on the 'ready to learn' index, which is considered an important control variable. Since the identification strategy in this work is based on the comparability of the acquisition and non-acquisition groups, it was also necessary to exclude categories that would distort this comparability due to their absence (or near absence) in only one of these groups:

- respondents having a job that required a high qualification (ISCED 5 or higher) – 25 such respondents in the acquisition group but only one in the non-acquisition group;
- respondents with a high qualification (ISCED 5 or higher) – 37 in the acquisition group but only two in the non-acquisition group;
- one respondent from the non-acquisition group whose area of study was 'Teacher training and education science' – there were no such respondents in the acquisition group.

After all these exclusions, the acquisition and non-acquisition groups ultimately included in the analysis consisted of 277 and 297 respondents, respectively. The statistical description of both groups can be found in Table A.5 in the appendix.

3.3 Causal identification strategy

The purpose of this article was to test whether basic digital skills help in professional life by comparing the acquisition group to the non-acquisition group. The basic identification problem is that, as seen in Table A.5 in the appendix, the acquisition group is very different from the non-acquisition group. One of the most striking examples is their age composition. People aged from 19 to 26 when the PIAAC interview was administered constituted 61% of the acquisition group but only 5% of the non-acquisition group (or 21% and 1%, respectively, after applying the postPIAAC sampling weight). Hence, the simple difference in labor market outcomes between the two groups may easily have been caused by the difference in age composition rather than the acquisition of basic digital skills. In other words, there is a substantial selection bias which precludes causal inference from a simple comparison of the two groups.

To make the two groups comparable, the propensity score weighting technique (PSW, also known as inverse probability weighting) with regression adjustment was used. This can be described as weighting both groups in such a way that their weighted compositions in terms of the control variables are similar to one another and also to the composition of the weighted group resulting from combining the two groups and then running a weighted regression on the joint groups. This means that the average treatment effect (ATE) was estimated, i.e. the average causal effect of the acquisition of basic digital skills by a person from the target population who did not have these skills before (Guo and Fraser, 2010; Hirano and Imbens, 2001; Murnane and Willett, 2011). Ten preparatory propensity score weights were calculated, one for each of the ten literacy and numeracy plausible values (PVs), using the covariate-balancing propensity score (CBPS) method developed by Imai and Ratkovic (2014). This package accepts sampling weights, so the propensity score weights were combined with the postPIAAC sample weights in order to make inferences about the whole target population. The final propensity score weight was calculated as the mean of the ten preparatory weights. When probit or logistic regression was used instead of the CBPS method to estimate the propensity score, very similar results were obtained (not shown).

As demonstrated in the methodological literature (Imbens, 2024), PSW with regression adjustment yields unbiased estimators of the causal effect of basic digital skills acquisition if the following assumptions are met:

1) The professional situation of any individual who had no basic digital skills when the PIAAC interview was administered was not subsequently affected by the acquisition or non-acquisition of basic digital skills by other individuals (stable unit treatment value assumption, SUTVA).

2) The propensity score for all individuals included in the analysis must be strictly greater than 0 and strictly less than 1 (overlap assumption).

3) All factors that affect both the acquisition of basic ICT skills and labor market outcomes are accounted for by the set of control variables used (unconfoundedness or CIA, or selection-on-observables assumption).

Assumption 1 would have been violated if the acquisition of basic digital skills had conferred a labor market advantage at the expense of other low-skilled individuals or if the application of newly acquired basic digital skills had increased co-worker productivity. While these scenarios cannot be excluded a priori, the empirical results presented below suggest that such violations did not materialize. The obtained estimates do not exhibit the biases expected under a SUTVA violation, suggesting that the findings remain unaffected by such concerns.

Assumption 2 was made plausible by excluding categories which were absent in either the acquisition or the non-acquisition group (as described in the 'Study group' section).

Assumption 3 underscores the necessity of controlling for factors relevant to both skills acquisition and labor market outcomes. The risk of omitted variables bias is demonstrated in a much-cited paper by DiNardo and Pischke (1997), who used a regression model to show that the wage differentials associated with the use of computers and with the use of pencils look similar, suggesting that in both cases they reflect unobserved heterogeneity among workers and jobs, such as differences in unobserved skills correlated with computer knowledge, rather than true returns to computer (or pencil) use. To avoid this risk, a large set of control variables was used in the present study. Importantly, this set included values of outcome variables as measured in PIAAC. For example, the state of being employed in 2011/2012 was used as a control variable when the impact of basic digital skills acquisition on employment in 2014/2015 was estimated. This was a particularly strong control variable, as it can be assumed to have accounted for all factors which affected employment status, to the extent to which their effects did not change between 2011/2012 and 2014/2015.

3.4 Control variables and bias reduction

All the control variables were taken from the PIAAC dataset, so they were measured before any individual acquired (or failed to acquire) basic digital skills. There were two sets of control variables: those used to estimate the propensity score and those used in the regression (along with the main regressor of interest – the dummy variable which takes on the value 1 for members of the acquisition group) to estimate the causal effect. The difference between these two sets was that the latter contained scale variables for literacy, numeracy, and readiness-to-learn index, whereas in the former set these variables were replaced with dummy variables corresponding to proficiency levels or index-bases quartiles. Table A.5 in the appendix presents the former set, consisting of 64 variables, including two redundant dummy variables which were removed from the regression model to avoid collinearity. The control variables describe respondents' education and work history, skills, readiness to learn, experience with computers, job characteristics, family, and basic demographics. For literacy and numeracy, only variables based on the first PV were shown in the table, to avoid cumbersomeness. For each variable, the bias, i.e. the difference in mean (equal to the share of a given category) between the acquisition and non-acquisition group was given – before PSW, after PSW, and after additional regression adjustment. The last bias statistic was obtained from a regression with the given control variable as the dependent variable, the acquisition of basic digital skills as the regressor of interest, and the other non-redundant control variables as the remaining independent variables. Obviously, the same control variable could not be included as both the dependent variable and an independent variable. This means that the statistics given do not reveal the entire bias reduction, as they do not take into account the additional bias reduction that resulted from including a given control variable as a regressor in the regression adjustment model. Nonetheless, they show that PSW brought about a considerable bias reduction, and that the regression adjustment reduced this bias further. There are only four categories for which PSW and regression on other control variables did not decrease the bias, but increased it:

public sector workers, those in the second quartile of readiness to learn, and those at proficiency level 1 in numeracy and in literacy. Before PSW, the difference between the acquisition and non-acquisition groups exceeded 5 percentage points for 39 of the 64 variables (the greatest difference was 55 p.p. for respondents without computer experience before PIAAC). After PSW and regression on other control variables, only seven such variables remained (the greatest difference, amounting to 7 p.p., was obtained for respondents at proficiency level 1 and those below this level in literacy). It can be concluded that PSW did not entirely remove observable bias, but that in combination with regression adjustment it accounted for most of the effect of the differences in group composition and thus made causal inferences about the consequences of basic digital skills acquisition much more plausible. Other attempted methods of bias reduction (such as PSM and alternative weighting) produced poorer results.

3.5 Estimating standard errors

PIAAC is a complex survey which requires special techniques to estimate standard errors of any estimates. This is due to two important features, beyond the usual sampling error, that add to the inherent uncertainty of statistical estimation. Firstly, a complex and country-specific survey design requires the use of replication techniques. Secondly, the skills assessedwere estimated using IRT scaling, and 10 PVs were generated to account for the uncertainty of this estimation. The recommended approach is to use replicate weights and repeat every analysis 10 times, taking each PV in turn, and then to average over results to obtain the correct point estimate and use a special formula to calculate the standard error. All these features were continued in postPIAAC. The propensity score weighting adds an additional layer of complexity, because the propensity score estimation may also introduce a random error. To account for all these potential sources of error, the standard PIAAC replication approach was adopted in conjunction with PVs, but 80 postPIAAC replicate weights were combined with 80 propensity score weights, and the resulting 80 combined weights were used instead of the ordinary postPIAAC weights. Each propensity score weight was calculated using a different postPIAAC replicate weight and one of the PVs.

As will be seen from the results of the analysis, the estimated standard errors are very large. To determine the reason for this, a forward stepwise procedure of including different error sources (propensity score estimation, PV imputation, and complex sample design) to estimate standard error was used. It turned out that the standard errors largely increased once the variation of propensity score estimated in different replicate samples was taken into account. Standard errors derived from a regression-only estimation (omitting PSW) were substantially smaller. However, it should be noted that the regression-only estimation does not consistently identify the average effect of basic digital skills if this effect is heterogeneous, i.e. different across individuals (Angrist and Pischke, 2009; Morgan and Winship, 2007). Moreover, the regression-only approach is more sensitive to model misspecification than the doubly robust PSW with regression adjustment (Słoczyński and Wooldridge, 2014). Hence, drawing causal inference from the two divergent groups of modest size, i.e. the purpose of PSW, seems to be a major cause of the large standard errors.

3.6 Minimum detectable effect

In order to get some insight into how the large standard errors affect the statistical power of the analysis, a simulation was conducted. This procedure involved generating artificial outcomes which depended on the acquisition of basic digital skills and the control variables in a predetermined way. The artificial outcomes were binary variables derived from a probit regression model[3]. Each of these variables corresponded to a different ATE size. This approach allowed for a determination of the minimum ATE required to achieve statistical significance using the estimation methods employed in this study.

[3] The artifical outcome variable was set to 1 if the following condition was met (and to 0 otherwise): -δ* (1 - acq) + (0.419 * age19_26) + (0.525 * age27_40) + (-0.173 * age51_56) + (-0.384 * female) + (0.162 * partner) + (0.134 * children) + (-0.348 * edlevel3_23) + (-0.112 * vetY) + (0.988 * b_q01b_1) + (-0.424 * b_q01b_3) + (0.282 * b_q01b_4) + (0.594 * b_q01b_5) + (0.588 * b_q01b_6) + (0.971 * b_q01b_7) + (0.171 * b_q01b_8) + (0.751 * b_q01b_9) + (0.302 * edu12m) + (0.226 * employed) + (-0.029 * outlf) + (0.202 * student) + (-0.58 * nopaidworkever) + (-1.033 * nowork12m) + (0.307 * isco_cat1) + (0.371 * isco_cat2) + (0.062 * isco_cat3) + (0.035 * isco_cat4) + (-0.157 * sector1) + (0.099 * sector2) + (-0.231 * public) + (0.077 * selfemployed) + (0.35 * headcount1_10) + (0.376 * headcount11_50) + (-0.103 * headcount51_250) + (0.792 * headcount251_more) + (0.112 * supervisor) + (0.187 * indefinite) + (-0.576 * satisfied) + (-0.615 * verysatisfied) + (0.126 * earn1800) + (-0.298 * earn3000) + (-0.764 * earnmiss) + (-0.322 * req_medium) + (-0.2 * learn_oth) + (-0.169 * learn_do) + (-0.063 * learn_upd) + (0.132 * no_skills_more) + (-0.145 * need_training) + (-0.154 * computerexperienceN) + (-0.122 * readytolearn) + (0.004 * pvlit3) + (-0.002 * pvnum3) - 0.582 + los > 0 where acq is binary variable corresponding to the acquistion of basic digital skills, los ~ N(0,1) is a random error term, the regression coefficients are actual estimates from a probit regression of the ‛any improvement since PIAAC‛ outcome variable on the control variables and δ is the parameter which determines the ATE size. By replacing the first term -δ * (1-acq) with -δ the (counterfactual) outcome for a given respondent in case of no basic digital skills acquisition was generated. By removing this term from the regression the (counterfactual) outcome for a given respondent in case of basic digital skills acquisition was generated. The comparison between these two (Counterfactual) outcomes allowed for the calculation of the ATE for a given δ value.

The simulation revealed that PSW with regression adjustment yielded significant estimates once ATE exceeded 13 p.p., while the regression-only technique yielded significant estimates once ATE exceeded 14 p.p. These results suggest that smaller effects may remain undetectable given the sample size and methodology.

3.7 Outcome variables

All the outcome variables were binary, so the estimated effects are given as the difference in the share of people for whom a given outcome was observed. The outcome variables can be divided in three groups.

The first group includes variables which inform us whether a certain positive aspect of an individual's professional situation was reported in postPIAAC: being in employment, having a permanent contract, supervising employees, declaring oneself to be satisfied or very satisfied with the job, and declaring oneself to be very satisfied with the job.

The second group includes variables based on a comparison between PIAAC and postPIAAC results, indicating whether a given respondent became employed, earned a permanent contract, became a supervisor or supervised many more employees than before[4], found a satisfying job or became more satisfied with the job, had higher nominal earnings than before, experienced any of the aforementioned improvements, or had lower nominal earnings than before.

The third and final group includes variables which inform us whether a given respondent declared in the postPIAAC study having been promoted in the current job or having experienced a change in earnings since the previous year. In the case of promotion, two variables were created, corresponding to the promotion taking place in the preceding 12 months or at any time. Three outcome variables indicate whether the individual's earnings increased, increased by more than 10% (roughly corresponding to the cumulative inflation rate between PIAAC and postPIAAC), or decreased.

4. RESULTS AND DISCUSSION

Table 1 presents the estimated effects of acquisition of basic digital skills. Both estimates from standalone regression model (omitting PSW) and from PSW with regression adjustment are given. The latter are less precise, as larger estimated standard errors show, but have the advantage of consistent and robust estimation of the average causal effects. The majority of estimated effects are small, below 3 p.p. in absolute terms, and insignificant. The remaining effects exceed 3 p.p., but, in case of PSW with regression adjustment, they are not as large as the corresponding standard errors, so they are also far from being statistically significant. The standalone regression approach yields smaller standard errors, but neither in this case is any of the estimates statistically significant.

[4] In practice, only one respondent was found to supervise many more employees (1-5 employees in PIAAC, 11-24 employees in postPIAAC).

Table 1 ***Effect estimates***

Variable label	Unadjusted difference	Regression only effect	R.o.e. S.E.	ATE	ATE S.E.
In employment	+ 16.0	-1.5	6.8	+ 0.9	14.6
Became employed	+ 5.7	-2.1	4.2	+ 1.5	14.5
Permanent contract	+ 14.1	+7.8	5.1	+ 9.0	13.3
Earned a permanent contract	+ 6.0	+5.1	3.4	+ 8.0	15.7
Supervising employees	+ 5.1	+4.3	4.3	- 0.0	12.2
Became a supervisor or supervises many more employees	+ 3.7	+4.3	3.9	- 0.5	11.6
Has a satisfying job	+ 10.1	-4.4	7.6	- 8.4	24.5
Has a very satisfying job	- 0.6	-3.7	4.0	- 3.1	9.8
Found a satisfying job or became more satisfied with the job	+ 1.3	-8.0	5.3	- 5.1	17.7
Increased earnings	+ 19.3	-0.2	7.2	+ 1.4	16.5
Decreased earnings	- 8.2	+0.1	6.2	+ 0.5	13.8
Any improvement listed above since PIAAC	+ 17.9	-3.4	6.8	- 3.9	16.2
Promoted in the current job	+ 6.0	+2.6	3.3	+ 2.5	9.3
Promoted in the current job in the last 12 months	+ 1.9	+0.8	1.5	+ 0.9	12.7
Increased earnings since the previous year	+ 12.6	+10.3	6.6	+10.2	12.5
Incr. earnings by more than 10% since the previous year	+ 3.9	+0.7	2.9	+ 1.4	3.7
Decreased earnings since the previous year	- 2.3	-1.5	4.6	+ 1.2	12.7

Note. All values are in p.p.. Unadjusted difference is the difference between those who have acquired ICT skills and those who still do not possess them after applying the sampling weight but before any correction for selection bias. R.o.e. S.E. = standard error of the regression-only estimate (i.e., without propensity score weighting). ATE = average treatment effect. ATE S.E. = standard error of ATE.

Although the share of people who experienced any improvement in their professional situation between PIAAC and postPIAAC is much larger among those who acquired basic digital skills (54.4%) than among those who did not (36.5%), this difference disappears completely after controlling for selection bias. In fact, this difference even turns into a negative estimated average effect of skills acquisition (−3.9 p.p.); however, this should not be interpreted causally, given that it is much smaller than the estimated standard error and that it would no longer be negative if increase in earnings was not taken into account.

Similarly, the wide difference in the percentage of respondents whose earnings increased between PIAAC and postPIAAC (48.3% in the acquisition group vs. 28.9% in the non-acquisition group) shrinks to 1.4 p.p. after controlling for selection bias. Intriguingly, a substantively large and positive effect of 10.2 p.p. remains if a self-reported increase in earnings in the year preceding postPIAAC administration is considered instead. But since the standard error of this estimate is even larger (12.5 p.p.), there is no convincing evidence that the acquisition of basic digital skills affected the respondents' wages.

The only other aspect of the respondents' professional situation with a sizeable positive effect is the probability of earning a permanent contract (+ 8.0 p.p., or + 9.0 when the outcome variable is simply having a permanent contract when post-PIAAC was administered). But neither is this effect statistically significant. Additionally, none of the potential mechanisms described in hypotheses 1-5 seems to explain why the acquisition of basic digital skills should only affect the probability of obtaining a permanent contract without affecting earnings or the probability of being in employment. This suggests that a causal interpretation should not be given to these estimates.

A sizeable negative effect (−8.4 p.p.) on having a satisfying job can be observed as well. One could hypothesize that this is a sign of frustration in some respondents who put effort into acquiring digital skills but did not experience an expected improvement in their professional situation. A more detailed analysis, however, shows that the acquisition of basic digital skills had no negative effects on satisfaction with such aspects of their professional situation as earnings, job stability, or opportunities to use skills at work. Hence, it seems more probable that the negative effect observed is merely a random deviation from zero explained by large standard errors.

Summarizing the results, the large standard errors make it difficult to draw conclusions on causal effects in the Polish working-age population. When we focus on our subsample instead, the fact that after controlling for initial circumstances and many individual characteristics, the estimated effects of basic digital skills acquisition on employment, earnings and promotion are close to zero suggests that these skills usually did not help the respondents improve their professional situation. This conclusion calls for an explanation of why none of the mechanisms described by hypotheses 1-5 worked. In this regard, three possible explanations are presented and tested below.

The first explanation could be that basic digital skills 'are rarely the missing link that miraculously transforms employment prospects. Lower wage, lower skill workers typically face multiple barriers' (Garrido et al., 2009: iv). Hypothetically, the acquisition of basic digital skills did not help the respondents because they still faced other skill deficits that impeded their professional progress. The PIAAC study measured respondents' proficiency in literacy and numeracy[5]. If the estimated effect of basic digital skills acquisition was close to zero, but the estimated effect of the interaction between basic digital skills acquisition and at least medium proficiency in literacy and numeracy was positive, it would suggest that basic digital skills only help when they are accompanied by sufficient literacy and numeracy skills. However, this is not the case. In fact, when the abovementioned interaction term is included in the model, the corresponding effect turns out to be negative and insignificant for many outcome variables, such as transition into employment, an increase in earnings, or satisfaction with one's job (see Table A.2 in the appendix). Hence, the first explanation is not consistent with the data, at least as far as complementarity between basic digital skills and literacy and numeracy is concerned.

There is yet another sense in which acquiring basic digital skills alone may not be enough to provide an advantage in the labor market. The PIAAC ICT Core test only contained very basic computer-related tasks, such as typing on a keyboard or using the drag & drop feature. It may be that the labor market does not reward such basic skills, but does reward somewhat more advanced skills, such as the ability to use widespread office software. This could reconcile our findings with those of previous research, which has usually detected a positive impact of digital skills on labor market outcomes, but took into account the whole range (or the upper levels) of digital skills, rather than only basic skills. In fact, the authors of a discussion paper conclude that a 'modest increase in skills is not likely to lead to higher wages or better jobs for those with no skills at the outset' (Non et al., 2021). The few other studies which suggest that basic skills were advantageous in the labor market, except for (Lane and Conlon, 2016), were actually based on data pertaining to internet or software use at work and for this reason are not comparable with the present article, which focuses on people who initially had no basic digital skills but acquired these skills before a follow-up study.

Additional tasks administered under postPIAAC, requiring the respondent to use copy-and-paste tools within a document or use basic arithmetic formulas in a spreadsheet, allowed us to test this second explanatory hypothesis. To this end, an additional binary variable was added to the outcome regression models. This variable took the value of 1 if a given respondent correctly solved at least 7 of 8 postPIAAC ICT Core tasks. For such outcomes as employment, type of contract, and supervision of employees, the estimated effects of this variable do not support the hypothesis, as they are negative and insignificant. Only in the case of high job satisfaction and reported change in earnings in the year preceding postPIAAC are the estimated effects consistent with the hypothesis, as they are positive for high satisfaction and an increase in earnings, negative for a decrease in earnings, and substantively large, albeit smaller than the associated standard errors (see Table A.3 in the Appendix).

Another source of information about the respondents' more advanced digital skills is their responses to postPIAAC questions regarding whether they have ever created computer programs or webpages or used a spreadsheet or a word processor, either at or outside of work. An interaction between an affirmative answer to at least one of these questions and the acquisition of basic ICT skills was introduced as an alternative additional variable in the regression models. This time, the results are consistent with the hypothesis for many types of change between PIAAC and postPIAAC, such as becoming employed, earning a permanent contract, and an increase in earnings. In these three cases, the estimated effect of the additional variable exceeds 10 p.p., while the main effect of digital skills acquisition is small and sometimes negative (see Table A.4 in the Appendix). Again, however, no effect is statistically significant. It is worth noting that an employer who hires new employees is more likely to know their declared experience with software than their actual performance. This, in line with hypothesis 3, may explain why the former seems to have a positive impact on labor market outcomes while the latter does not. If there was a reverse causality issue (those who had become employed were more likely to use an office suite), it should be reflected in the performance as well.

The PIAAC question asking the respondents whether they have the computer skills needed to do their job well was repeated in the postPIAAC questionnaire. When we use an affirmative response to this postPIAAC question (or a change from non-affirmative to affirmative between PIAAC and postPIAAC) as the outcome variable in our model, the estimated

[5] A person was assumed to have at least medium proficiency in literacy and numeracy if his or her average plausible value exceeded 226 in both the literacy and numeracy domains.

effect of basic digital skills acquisition is +0.143 (or +0.080). A slightly larger effect (+0.171) is estimated when the outcome variable is using a computer at work at the time of the postPIAAC study (but not PIAAC). Although these coefficients are not significant, they suggest that the acquisition of digital skills did help some respondents to perform their duties better.

The third possible explanation is that acquiring basic digital skills did not improve respondents' professional situation because their jobs did not require such skills. And in such jobs, returns to ICT skills are negligible (Falck et al., 2016; OECD, 2015). In fact, 25% of the acquisition group declared during the postPIAAC interview that they use a computer at work, and 12% stated that at least a medium level of digital skills (e.g. using spreadsheets) was required to perform their jobs. This is much more than in the PIAAC interview (10% and 4%, respectively) and in the non-acquisition group (postPIAAC 4% and 3%, PIAAC 3% and 1%). But this also means that a large majority of the acquisition group did not use digital skills at work, so it is not surprising that these skills did not affect their professional situation.

5. CONCLUSIONS

As stated above, the impediment to drawing well-grounded conclusions from the analysis presented here is the large size of standard errors, which results from propensity score estimation using two small and divergent groups. However, among all the techniques tried, the one adopted was the most efficient at removing selection bias. Refraining from PSW and using only a regression model does not seem to be a better solution, firstly because regression does not identify the average causal effect (Angrist and Pischke, 2009; Morgan and Winship, 2007), secondly because it is more vulnerable to model misspecification than the doubly robust PSW with regression adjustment model (Słoczyński and Wooldridge, 2014) and thirdly because it does not seem to provide advantages in terms of statistical power. An instrumental variable which would offer another way to remove the selection bias was not available. The large standard errors can thus be considered a price to pay for more credible causal inference.

After removing, to a great extent, the selection bias, most of the estimated effects become close to zero. Although masking of an existing causal effect by unobserved confounders cannot be excluded, low estimates suggest that basic digital skills did not improve the professional situation of most respondents who developed them in the period between PIAAC and postPIAAC. This would mean that none of the mechanisms described by the initial hypotheses worked. Additional strands of analysis indicate two probable reasons. First, most of these adults did not obtain jobs requiring digital skills. Second, what seems to be rewarded in the labor market is experience using work-relevant software, rather than possessing basic digital skills. From a policy perspective, this suggests that equipping people with basic digital skills (which in this study are understood as ability to perform simple computer-related tasks, such as typing on a keyboard or using the drag & drop feature) is not enough to increase their employability. It may be recommendable to develop basic digital skills to achieve other policy objectives, such as combatting social exclusion or improving access to public services. But as far as the labor market is concerned, education and training should go beyond basic digital skills and provide individuals with somewhat more advanced digital skills and documentable experience in using work-relevant software.

The generalizability of these findings may be limited regarding highly qualified individuals or those in high-skilled occupations (ISCED 5 or higher), as this group was excluded from the current analysis. Another limitation of this article is that it is based on data from a single country, collected between 2011 and 2015. The returns to digital skills presumably change over time and depend on the labor market context, e.g. labor market flexibility, industrial and occupational structure, share of temporary contracts, union density, and other characteristics of the economy and education system (Cutuli and Tomelleri, 2023; Dolton et al., 2007; Walton et al., 2009; Zamberlan et al., 2024). It can be argued that only skills that are scarce in a given labor market should be rewarded (DiNardo and Pischke, 1997). This raises the question of whether the conclusions drawn from the present analysis apply to other countries and to the current period. Since the share of digitally literate individuals in Poland has probably increased since 2015, one might expect labor market returns to basic digital skills to have stagnated or declined rather than increased. Consequently, the finding of negligible returns likely remains valid. Rather than suggesting a diminished focus on foundational digital skills, this underscores the necessity for Polish education and training system to move beyond basic proficiency and prioritize more advances skills. Another part of the question is whether the conclusions apply to other countries. The analysis presented by Lane and Conlon (2016) does not suggest any uncommon patterns in returns to ICT skills in Poland. However, among the 13 EU countries that participated in the 1st cycle of PIAAC, Poland had a particularly low level of digital skills, as evidenced by the second highest share of respondents not taking the ICT module, the lowest mean PSTRE score, and the highest share of low PSTRE scores. On the demand side, the declared levels of computer skills needed to perform jobs and the use of ICT at work in Poland were close to the EU average. Poland also had the second largest ICT skills mismatch and the highest share of respondents who claimed that their chances of being hired or getting a promotion or pay raise was affected by their lack of computer skills, but this prominence was driven by high-qualified adults, while the share of low-qualified respondents who believed they had the computer skills needed in their job was the second highest in the EU (Pellizzari et al., 2015). These data suggest that Polish employers should value digital skills highly because of their relative scarcity, but on the other hand, there were a considerable number of jobs not requiring digital skills for low qualified workers. This highlights the specificity of the Polish labor market. It is possible that in a different national cultural, educational and economic context basic digital skills are more appreciated by employers. Establishing precisely what level and type of digital skills are rewarded by employers in Poland and other countries remains an important objective for future research.

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https://drive.google.com/file/d/1pdCiG4ylWu1MIgw3nCZ8TtsWMy7VWzIA/view?usp=sharing

SUPPLEMENTARY MATERIAL

Supplementary data for this article can be found online.

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