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RESEARCH ARTICLE

Organisation, technological change and skills use over time: A longitudinal study on linked employee surveys

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Abstract

The impact of technological change on the content of jobs and accompanying skills is a central topic across disciplines. To date, ample research has directly linked the technological change to shifts in skills use; however, organisational change is rarely considered as an influencing factor. Based on a panel survey, this paper uses a Luhmannian approach to understand the relationship between technological change and organisational context. This theory is tested quantitatively and shows the importance of considering the working environment's nature when studying skills changes. The results show small effects by the technological change on changing skills use but larger effects by changes in the working environment. Recommendations for future research and practical implications are discussed.

KEYWORDS

automation, division of labour, longitudinal study, organisational change, skills, skills use, technological change, technology, working environment

INTRODUCTION

Debating the digitalisation of work, the relationship between technological change and future skills use comes to the fore once more. The expectations about future skills use are quite extensive, with a large number of observers insisting on a change towards more generic skills, and at the same time more specialised, technical knowledge. The highly anticipated 21st-century or digital skills are said to require a general need for workforce reskilling (Felstead et al., 2002; World Economic Forum, 2018).

Although skills use of the workforce claims to have large societal and economic effects for individuals, employers, regions and national economies, *there is no consensus among social scientists or policy-makers about the meaning of the skill concept* (Green, 2013). Following Green's advice to conceptually overarch economics, psychology and sociology, we distinguish three key features. First, skills have productive features: using skills at work helps workers be productive. Second, skills are expandable and training and development can enhance them. Third, skills are socially determined (Green, 2013). While the first two features gained much research attention (Goos et al., 2014), the last did not.

Consequently, the expectations about the future of work and skills use are underpinned with a lot of survey material, focusing on skills' economic and psychological features. Schlogl et al. (2021) discuss this policy-focused and grey literature and see a dominant narrative focused on placing the responsibility to deal with the future of work in the form of 'upskilling'. The analysis of the survey material itself used in this narrative needs to be considered too. An organisational sociological interpretation of the existing survey material used in this narrative unmasks the presence of a social framework, that is, the working environment's nature. Consequently, it teases the importance of the latter for skills use.

Elaborating on a longstanding tradition of skills use research, we focus in this article on the following question: 'What is the impact of technological change, a changing working environment and the interaction between technological change and the changing working environment over time on skills use?'.

This article contributes with an analysis of the influence over time of the change in the working environment on skills use: The skills use of people who have remained in their working environment is compared with that of people whose working environment has changed. For this analysis, a first alternative interpretation of skills from survey material is used. This alternative interpretation is framed in the systems thinking approach on organisations developed by Luhmann (2000). This article focuses on the transversal analysis of items from a linked panel data set from two data sources: the Netherlands Skills Survey (NSS) and the Lifelong Learning (LLL) Questionnaire (Akçomak et al., 2011; Kleruj, 2017; Oudejans, 2012; Ter Weel, 2014; Van den Berg et al., 2018).

In the next parts, this article first deals with the relationship between technological change and skills use. In line with Felstead et al. (2019), in this article, 'skills use' *refers to the level of skills required of workers to carry out their jobs, the extent to which workers use the skills and abilities they possess and the extent to which workers receive training that develops job-related skills*. Second, this article substantiates the working environment's role and the change in this environment for skills use. Working environments are classified as Tayloristic (incomplete) or complete working environments. Third, it critically dwells on the operationalisation of skills concepts, comparing the methodology of the British Skills and Employment Survey (SES), the Programme for the International Assessment of Adult Competencies survey (PIAAC) and the Netherlands Skill Survey (NSS). Fourth, our analyses on the linked panel data set show small effects of technological change on changing skills use, but larger ones by the changing working environment. Lastly, since the article reveals that research on technological change and skills use necessitates a thorough analysis of the working environment, we discuss future research and practical implications.

EXISTING LITERATURE AND HYPOTHESES

Technological change and skills use

The linkage between technological change and skills use has been highly debated in the past few decades (Gekara & Nguyen, 2018; Spencer, 2018; Wajcman, 2006). On the one hand, there is an extensive body of labour process writings, stating that corporate management perceives technological change as a lever to meet the pressing profit rationale. Raising the lever would then intendedly lead to increasing bureaucracies with rising task fragmentation. Deskilling strategies were being used to keep control in the workplace (Braverman, 1974; Noble, 1984).

On the other hand, there is ample literature focusing on upskilling theory. In tune with the gradually changing education levels, the ease of college graduates reaching the labour market improved (Adler, 2004). According to Acemoglu (2002), technological change over the post-war period had been skill-biased, referring to the trend that technological change in the working environment favours skills use at a college level or higher. Even with a large increase in college graduates' supply, the returns-to-college have increased (Acemoglu, 2002). The technological change would be skill-biased (SBTC). Goos et al. (2014) later noted the importance of global outsourcing strategies to keep wage increases at bay. They measured that both off-shoring and technological change can enhance routine-based tasks. Demand for middle-skilled occupations is decreased, favouring low- and high-skilled occupations (Autor et al., 2003; Goos et al., 2014). Hence, the technological change would also be routine-biased (RBTC). While debating the importance of SBTC and RBTC, recent studies insisted on changes in skills towards ever-higher levels due to robotics and artificial intelligence levels (Brynjolfsson & McAfee, 2011; Frey and Osborne, 2017).

Frey and Osborne (2017) addressed that another paradigm would be more fitting, stating that technological change does not merely affect routine tasks, as Autor et al. (2003) insist, but also the nonroutine ones. In their opinion, tasks should be split up into engineering bottlenecks, that is, tasks related to perception, manipulation, creativity and social intelligence (Frey & Osborne, 2017, p. 261). Integrating these into one measure, Frey and Osborne convincingly calculated that 47% of the US occupations, based on O*NET analysis, belong to the high probability category, risking to be fully automatable in a decade or two due to technological change. In Europe, similar analyses were conducted using PIAAC analysis, resulting in somewhat lower automation impacts (Arntz et al., 2016; Nedelkoska & Quintini, 2018). Towards the worker, the advice from these scholars is to prepare well. Acquiring more creative, social and technical skills will help them if they mean to win the race with technology (Brynjolfsson & McAfee, 2011; Frey & Osborne, 2017, p. 269; Gekara & Nguyen, 2018, p. 222).

The argument about the relationship between technological change and skills use has thus become somewhat complicated over time. However, what seems to connect the distinct theories over the past decades, is that these views have tended towards a unilinear and deterministic view of technological change. That is, directly moving from the availability of new technologies in the working environment to changes for skills use (Wajcman, 2006). Next to that, lately, workers are held responsible for aligning their skillset with the expected skill requirements due to technological change. In a study of the future-of-work literature, Schlogl et al. (2021) conclude that technology is seen as a prime cause of challenges in the labour market and requires individuals to start upskilling. Even though some scholars addressed the importance of the working environment—people's interaction with machines, and each other is highly dependent on the local context—(Bal et al., 2021; Cascio & Montealegre, 2016; Hodder, 2020), this aspect gained not so much attention.

Working environment and skills use

We are only aware of some empirical studies that focus on skills used in working environments that undergo technological change (Gale et al., 2002). The discussion about technology and skills in Frey and Osborne and Nedelskoska and Quintini, as main sources, reveals that most technology's information is actually not on the technology itself. The main assessment of the technological change in these studies is done by looking at employees' skills set. Changing skill levels indicate changing technology itself, in case the degree to which engineering bottlenecks can be identified in an occupation, meaning that skill levels are the outcome used to make statements about the organisation's input side. However, the exact relation from the technology to the outcome remains quite clouded.

Van Reenen (2011) summarises this previous approach as the 'design paradigm', which explains that a firm optimises the use of technology and management practices: 'Key is that the management practices we observe, are intended to maximise profit in far from perfectly competitive spot markets'. He sets the 'managerial technology paradigm' as an alternative explanation. Variations in management do not merely reflect variations in the firm's surroundings. Companies differ in management practices for many reasons, especially information constraints (Van Reenen, 2011). To survive in unpredictable markets, Bloom and Van Reenen (2010) stress that management needs to invest in monitoring, target setting and people management as the quintessential areas (Van Reenen, 2011). They acknowledge that these areas, based on the principles of continuous manufacturing, evaluation and improvement from lean manufacturing, will have positive trickle-down effects on the working environment (Bloom et al., 2019; Womack et al., 1990).

Bloom and Van Reenen summarise management practices on a one-dimensional scale. Consequently, only one parameter indicates how organically or chaotically working environments are organised (Bloom et al., 2019). In contrast with the performance-oriented economists, the sociological literature specifies distinct organisational structuring ways to shed light on the working environment's status and nature (Krzywdzinski, 2017, p. 263). For decades, there has been a growing consensus that a distinction can be drawn between organisation structures that centralise decision-making and structures in which decentralised decision-making is more important. Kuipers, Van Amelsvoort and Kramer (2020) distinguish between more Tayloristic and more integrated management structures. These more integrated management structures offer richer working environments, while the more Tayloristic structures are associated with fragmented working environments. The core of this theoretical perspective is a systems approach derived from Niklas Luhmann (Baecker, 2006; Luhmann, 2000; Nassehi, 2005). Organising allows us to reduce complexity. Organisations do this in different ways. Technology, processes and hierarchy are all instruments for dealing with demands from the environment. However, Luhmann's theory does not consider technology as a system alongside the social system, as is the case in the Sociotechnical Theory of Trist and Bamforth (1951). In Luhmann's view, technology and the social are aspects of the same system. This means that technology cannot have a separate logic to which the social system then responds. Organisations are systems of communication that respond to environmental demands. In which direction they develop themselves is difficult to predict. In this theory, organisations have several options for responding to their environmental demands and for 'surviving'. In addition to Taylorist models, organisations can therefore use non-Taylorist models to structure their internal organisation. For this article, this theoretical explanation is sufficient. We understand that the same technology can fit into both a Taylorist and a non-Taylorist context. The point is to find out what choice organisations make as 'decision machines' (Nassehi, 2005). In practice, we know that communication processes in Taylorist contexts are 'simpler', that is, hierarchical and more top-down. In non-Taylorist contexts, communication processes are more difficult to shape. Bottom-up processes require more internal attunement to realise decisions and goal alignment. Both forms of organisation have different economic effects. There is a preference for non-Taylorist models in the sociological literature because the expectation is that the communication processes are more in line with the human image we have in our modern society (Nassehi, 2005). The literature on high-performance work systems (HPWS) links organisational structure to the use of skills, arguing that more integrated management structures would simultaneously improve the use and development of skills (Appelbaum et al., 2000). Separately, Osterman (2018) discusses the evidence that in HPWS models, win–win employment practices benefit both firms and workers. However, according to various reviews, empirical evidence on the use of skills in context is scarce and far from overwhelming (Osterman, 2018) and difficult to collect (Dhondt et al., 2017). For this paper, it is important to note that skills should not simply be linked to technological change, but that changes in skills are best interpreted from the broader organisational context in which technology is an aspect (Kuipers et al., 2020).

Reclassifying skills use in surveys

Considering the previous sections' discussion, a different classification of skills use is needed, namely one that considers how work is organised. Annex S1 contains a comparison between the three focal surveys: the SES (Felstead et al., 2002, 2019, 2007), the PIAAC (OECD, 2013a), and the NSS (Van den Berg et al., 2018). The table in Annex S1 shows that skills cover very distinct skill realities in both jobs and personal features. Most of these skills attribute the ability to perform tasks to employed individuals. That is the conventional perception of skills. Relating to literacy and numerical (mathematical) skills, one must, for example, be literate to have communicative tasks. The more the tasks require these communicative skills, the more communicative skills will be developed. Physical strength requires individuals to have the strength or stamina. Yet, the more the working environment's tasks require physical skills, the more these skills will be developed. Even though these skills are regarded as an individual affair, they seem partially attributable to the working environment.

That is fully applicable for some other skills. Client communication, for example, is only possible if one's working environment allows working in relation with clients. Problem-solving skills, for example, are only relevant if the working environment gives the employee the responsibility to solve the problems encountered at work. The solely conventional perception of skills, being features that apply to individuals, collapses when realising the working environment's organisation's impact. In line with the fundamental attribution theory (Jones & Harris, 1967), skills use at work suffers from incorrectly over-emphasising individual features at the expense of situational explanation (i.e., the working environment).

Modern sociotechnical systems thinking endorses this reasoning and divides tasks into four categories: executive, preparation, supportive and regulating tasks (Kuipers et al., 2020; Van Amelsvoort, 2016). The executive tasks are covered in Annex S1 through the category-*specific skills*. These skills form the executive core of daily activities. However, even with a similar core, jobs can look quite different if compared to their generic skills, that is, preparation, supportive and regulating tasks. Regardless of the core of the job, one working environment may offer jobs more or less regulating tasks (e.g., decision power), supportive tasks (e.g., checking for errors), preparation tasks (e.g., knowledge about products and services), than another.

Having different sorts of tasks in a job might be a consequence of technological change (e.g., industry automation changes the operator's work from executive to supportive tasks). Yet, in much of the cases, jobs have sets of tasks because of a conscious organisational choice, willingly allocating tasks to jobs. The working environment thus allows conducting certain tasks. Jobs can be compared according to the degree to which these generic skills are assigned to them. Jobs containing these generic skills to fulfil preparation, supportive and regulating tasks are regarded as more ‘complete’ functions (Hacker, 1989; Vaas et al., 1995). Jobs without these tasks are regarded as ‘incomplete’ functions.

The SES, PIAAC and NSS surveys identify problem-solving skills in occupations. As indicated, we see these problem-solving skills covering the broader set of generic skills. Therefore, these problem-solving skills (tasks) should receive a more special assessment. These skills typically indicate the level of the existing task division within organisations. Different task divisions can be seen as different working environments. Working environments in which jobs do not have these generic skills can be seen as incomplete or Tayloristic working environments. Working environments in which jobs do have these generic skills are complete or non-Tayloristic working environments. Analysing problem-solving skills, with survey instruments, such as SES, PIAAC and NSS, offers an opportunity to assess the task division at individuals' level. There are several advantages to this approach. First, the association of generic skills to the division of tasks can be investigated. Second, the assignment of (nonproblem solving) skills is not seen as fixed, but as a function of the division of tasks. If the division of tasks changes, we may expect changes in the skills used. Third, the spread in skills used within one job can now be explained by the division of tasks. Fourth, technology's role in relation to generic skills can be understood and investigated across organisations. This framework provides us with the necessary means to analyse the impact of changing working environments on skills.

Hypotheses

The linked panel data set to be used (cf. next section) allows investigation of our research question: ‘What is the impact of technological change, a changing working environment and the interaction between technological change and the changing working environment over time on use of social skills, literacy and communication skills, and ICT and mathematics skills use?’. Whether an employee works in an incomplete or complete working environment, is seen as an indicator of the working environment being Tayloristic or non-Tayloristic. The central research question can be investigated with the following hypotheses in Table 1.

TABLE 1 Hypotheses (H) under study

H1	*Employees changing to a complete working environment, experience increased skills use.*
H2	*Employees experiencing technological change do not experience their skills use change over time.*
H3	*Employees experiencing both technological change and changes in the working environment (towards complete environments), do not experience an extra change in their skills use over time.*

DATA, ANALYTICAL APPROACH AND MEASURES

Data

The primary data source for this article is the NSS. This survey is built from components of the SES and PIAAC (Akçomak et al., 2011). The following will give insights into the composition and development of these three instruments.

As indicated earlier, the SES aims to measure our society's shift to a knowledge economy that would stress the greater use of generic skills. That is why the SES, created in the 1990s, identifies eleven generic skills to describe work transition in the British context. However, the list of generic skills is constructed by researchers somewhat inductively, building on the experience with previous surveys (Felstead et al., 2002). The authors indicate not to spend time investigating specific skills. PIAAC is a comparable skills survey. PIAAC survey has been developed with the help of a series of expert groups (OECD, 2013a). Integrating the set of skills is explained with the shift in information processing demands on workers. These changes need to be documented for sound policy advice on adult training and company support. Looking at both, the SES and the PIAAC share a significant number of items (see Annex S1). Yet, they do differ. The authors present the classifications of items in another fashion. The SES formulates the items describing generic skills in jobs, while the PIAAC categorises the items into information-processing and generic skills in jobs. Skills in the latter are seen as tools, for example, to help solve problems (Nedelkoska & Quintini, 2018; OECD, 2009). For the description of generic skills use in the workplace, the SES has been the main reference for other instruments (see Annex S1). Being administered by the OECD (2013a) OECD, the PIAAC-survey (PIAAC, 2009) unsurprisingly focuses on a similar list of skills (Felstead et al., 2007; OECD, 2013a, footnote 3).[1]

Although Green (2013) profoundly discussed the methodology and the operationalisation of skills use, the selection of skills and the actual composition of the SES and PIAAC have not been questioned over the past years. The existence of one skills framework next to the other seems commonly accepted and not so much prone to criticism: the surveys might differ, but whichever skills framework you use, it is the right one to make statements about individuals.

The NSS was developed in 2011 and leaned mainly on the SES (Akçomak et al., 2011; Van den Berg et al., 2018). So far, the NSS has been administered in 2012 and 2017. The list of skills used in the NSS is a translated copy of the SES list, with some new items added to describe the working and skills situation at the individual level over time. Apart from the main aim of measuring skills use, the NSS offers insight into how people appraise the importance of their daily work tasks and how effective they are in performing these tasks. The NSS shows where individuals learned to perform work tasks, investigates how working life can be prolonged and research how mobility in the labour market can increase (Akçomak et al., 2011; Kleruj, 2017; Oudejans, 2012; Ter Weel, 2014). The NSS is part of the Longitudinal Internet

Studies for the Social Sciences (LISS) panel administered by CentERdata (Tilburg University, The Netherlands), covering a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register (Scherpenzeel, 2011). Three surveys were fielded as supplements to the LISS.

The NSS2017, the second wave of the NSS, was conducted as a part of the LLL survey (Streefkerk, 2017; Van den Berg et al., 2018).[2] The LLL2017 provides insights into technological change and how it was experienced in the past few years at the individual level.[3] Using these data sources, linking the first wave of the NSS (i.e., NSS2012) to NSS2017 and LLL2017 enabled the authors to provide insight into how changes in the working environment and technological change relate to skills use. Because the NSS is part of the LISS-panel survey, another opportunity is to describe changes in work situations over time among the same individuals (Eisen, 1999). This longitudinal approach with the same individuals poses some intrasubject correlation issues and potential feedback on answers that will be controlled. The NSS does not contain a description of the technological environment employees are working in. However, as with the PIAAC, the NSS contains the same items to measure the presence of engineering bottlenecks as Frey and Osborne have listed. Akçomak et al. (2011) did not use their skill list in this way, but Van den Berg et al. (2018) did. The latter authors added the measure 'on major technological change in the past few years' to the LLL2017 to have an extra indication about technology. Figure 1 shows an overview of the surveys collected in 2012 and 2017, which help answer the research questions and test the hypotheses.

First, we selected those 1550 respondents who participated in all three surveys. From this group, we only included the individuals that were still in paid employment in 2017, resulting in 1155 employees. In this group, in 2017, 1149 respondents have been employed for at least 5 years at the same employer and holding the same job. By applying this selection criterion, we ensure that the respondent's answers to the questions on eventual changes in the working environment between 2012 and 2017, and eventual changes in the skills required between 2012 and 2017 are not due to career switches. Lastly, after listwise deletion of missing values on the study variables, 1126 employees were in the final sample, averaging 50 years of age in 2017 (SD = 10), while 55% were male. This longitudinal population study allows us to follow individuals that work in changing or stable working environments. The period that we are looking at, five years, is long enough to see an organisational change (OECD, 2013b). The OECD (2013b) estimated that the average estimated life of organisational capital is between 4.0

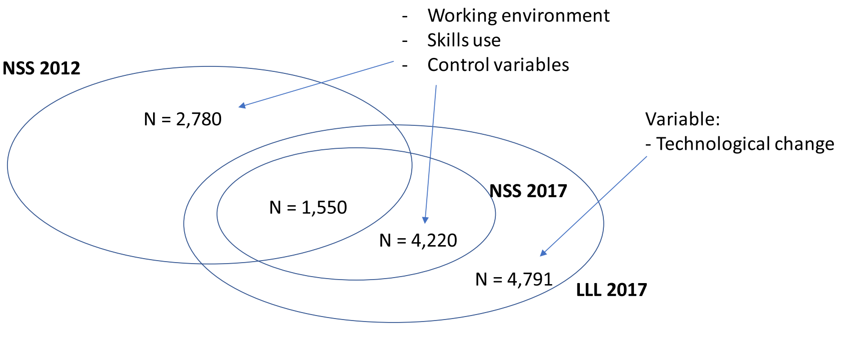

FIGURE 1 Overview of the surveys and number of participants (= N). NSS, Netherlands Skills Survey [Color figure can be viewed at wileyonlinelibrary.com]

and 5.4 years. Our data provides such a time horizon. This longitudinal design is the most advanced design available in this study field to analyse organisational practices and understand the impact of organisational and technological change (Dhondt et al., 2017; Osterman, 2018). Future research should investigate if the changes and impacts found remain stable.

Measures

The starting point for the working environment and the scales for skills use were the 24 tasks of the NSS (see Annex S1; Ter Weel & Kok, 2013). Participants had to indicate the relevance of these tasks in their current job on a Likert scale ranging from 1 = *not at all important/not applicable* to 5 = *crucial*.

Skills use

Three scales, each measuring different required skills, were calculated from this list. First, a three-item scale on required social skills was operationalised (Cronbach's $\alpha = 0.83$ in 2012; 0.84 in 2017—sample item '(please indicate how important this is for your current job): dealing with people during your work'). Second, we calculated a six-item scale on required communication skills ($\alpha = 0.91$ in 2012; $\alpha = 0.92$ in 2017—sample item '(.) reading and appraising lengthy reports, letters or memos'). And, lastly, a six-item scale on required mathematics and information communication technology (ICT) skills was operationalised ($\alpha = 0.85$ in 2012; $\alpha = 0.86$ in 2017—sample items '(.) performing calculations with decimals, percentages or fractions'; '(.) using a computer, for example, to draw up documents, work with spreadsheets, search for information on the internet or send emails').

Working environment

Three scale variables were calculated from the NSS: a three-item scale on regulating tasks ($\alpha = 0.72$ in 2012; $\alpha = 0.76$ in 2017—sample item '(.) persuading or influencing others'), a four-item scale on supporting tasks ($\alpha = 0.87$ in 2012; $\alpha = 0.88$ in 2017—sample item '(.) analysing problems'), and a two-item scale on preparatory tasks (inter-item correlation $r = 0.42$ in 2012, $r = 0.41$ in 2017—items '(.) planning your own activities'; '(.) planning other people's activities'). Next, we dichotomised these three scales to build a single measure called working environment. The working environment-score is a dummy variable of which 0 represents an environment where these three tasks are absent or present only moderately (incomplete working environment), and 1 represents an environment that requires all three tasks (the complete working environment, with all three scores above the neutral point of the Likert scales).

Technological change

As indicated above, the developers of the skills surveys interpret the changing skill levels as an indication of the changing technology itself (Nedelkoska & Quintini, 2018; Van den Berg et al., 2018). The latter authors, also the researchers responsible for the NSS 2017, found it necessary to add an item on technological change to their survey. The LLL2017 contains a question on technological change, which we conceive as an additional exogenous variable predicting skills change. The question asks the participant if, in the past few years, there have been technological changes in the working environment that have changed the content of the work. The five response options ranged from 1 = *no, not at all* to 5 = *to a very large extent*. Even though this variable is measured at the same time as the skills in the NSS 2017, the reality it measures is before 2017 (i.e., retrospective question). The question does not identify the technology itself that is changed but does record the person's perception of whether an impactful technological change occurred. Minor technological changes are therefore less likely to be contained in this answer. The answer allows seeing if the impactful change also leads to changes in *skills use*.

Analytical approach

Since the hypotheses are about changes in not only the dependent skills variable from T1 (NSS2012) to T2 (NSS2017) but also about changes in the main independent variable 'IC' (incomplete vs. complete working environment), the design involves repeated measures with varying covariates (with the 'covariate' even as a central independent variable). Hence, also the change in the central independent variable 'IC' has to be taken into account in the model. We, therefore, modelled:

$$(\mathrm{Skills}_{T2} - \mathrm{Skills}_{T1}) = \mathrm{Constant} + B \times (\mathrm{IC}_{T2} - \mathrm{IC}_{T1}),$$

which is similar to the multivariate analysis of variance or general linear model repeated measures approach.

Next, we computed '$\mathrm{Skills}_{T2} - \mathrm{Skills}_{T1}$' and estimated the equations by multiple linear regression analyses for each 'skills use' scale. Also, the influence of technological change was included in the models. Next, we performed subgroup analyses to assess whether a change in IC in an environment that has versus an environment that has not been affected by technology, does make a difference for the required skills.

To increase the robustness of the results, we adjusted the analyses for several socio-demographic background variables, which in earlier research have shown to be associated with both the predictor variables and skills variables: sex, age, and seven grouped occupations (first digit code of the International Standard Classification of Occupations).

TESTING THE HYPOTHESES

Descriptive analyses

Between 2012 and 2017, 79% of the employees worked within a stable working environment (68% in an incomplete working environment in both years, and 11% in a complete one). A total of 21% of the employees changed from the working environment: 12% moved from a complete working environment in 2012 towards an incomplete working environment in 2017; while 9% faced a change in the other direction—thus from incomplete to complete.

Table 2 presents the means, standard deviations and intercorrelations of the study variables. The relationships between changes towards complete working environments and changes in

TABLE 2 Means (*M*), standard deviations (SD) and Pearson correlations (*r*) ($N = 1126$)

	M	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Working environment (−1 = *from complete to incomplete*; 0 = *no change*; 1 from incomplete to complete)	−0.03	0.46	1												
2. Technological change (1 = *no, not at all*; 5 = *to a very large extent*)	3.00	1.30	−0.02	1											
3. Sex (0 = female;, 1 = male)	0.55	0.50	−0.02	0.13*	1										
4. Age	50	10	0.08*	0.02	0.02	1									
5. Managers and professionals (ISCO 1&2)	0.31	0.46	0.00	0.18*	0.08*	0.00	1								
6. Technicians and associate professionals (ISCO 3)	0.22	0.42	0.04	0.04	−0.06	0.04	−0.36*	1							
7. Clerical support workers (ISCO 4)	0.14	0.35	0.02	−0.10*	−0.11*	−0.02	−0.27*	−0.21*	1						
8. Services and sales workers (ISCO 5)	0.11	0.31	−0.02	−0.11*	−0.14*	−0.01	−0.23*	−0.18*	−0.14*	1*					
9. Craft and related trades, and Skilled agricultural workers (ISCO 6&7)	0.08	0.26	−0.02	−0.01	0.21*	0.00	−0.19*	−0.15*	−0.12*	−0.10*	1				
10. Plant and machine operators and assemblers, and elementary occupations (ISCO 8&9)	0.06	0.24	0.00	−0.11*	0.06*	−0.01	−0.17*	−0.14*	−0.10*	−0.09*	−0.07*	1			
11. Unknown ISCO	0.09	0.28	−0.02	−0.01	0.00	−0.02	−0.21*	−0.16*	−0.12*	−0.11*	−0.09*	−0.08*	1		
12. Changes (2017 minus 2012 score) in social skills	−0.04	0.79	0.21*	0.03	0.00	−0.06*	0.04	0.00	0.00	0.03	−0.05	−0.07*	0.00	1	
13. Changes (2017 minus 2012 score) in literacy and communication skills	0.01	0.96	0.22*	0.02	0.00	−0.05	0.02	0.00	0.03	−0.01	−0.02	−0.04	−0.01	0.27*	1
14. Changes (2017 minus 2012 score) in ICT and mathematics skills	−0.05	0.82	0.22*	−0.05	0.01	−0.04	0.00	0.00	−0.02	0.08*	−0.02	−0.05	0.00	0.20*	0.42*

Abbreviations: ICT, information communication technology; ISCO, International Standard Classification of Occupations.

*$p < 0.05$.

skills use between 2012 and 2017 are positive and significant for all three skills uses (r ranging from 0.21 to 0.22).

There is no significant relationship between, on the one hand, changes from incomplete to complete working environments (or vice versa) from 2012 to 2017; on the other, the degree of technological developments at work that changed job content is not significant. Hence, these variables are somewhat independent. Besides, technological change is also not related to changes in the three skills uses.

Besides, the changes in skills use are, to some extent, and positively related to one another (r ranging from 0.20 to 0.42), where changes in literacy and communication skills and changes in ICT and mathematics skills are related strongest. This correlation means that these skills tend to be demanded in the same contexts.

Multivariate analyses

Table 3 shows the outcomes of the regression analyses of the changes in the three used skills. First, the baseline skill levels in 2012 already predict the level of the outcome measures in 2017 to a high extent ($\beta = 0.22$ for the use of social skills; $\beta = 0.43$ for the use of literacy and communication; $\beta = 0.57$ for the use of ICT and mathematics; all significant at $p < 0.001$ level).

Next, the associations between job completeness in 2017 and the used skills are positive and significant (β ranging from 0.23 to 0.27; $p < 0.001$). Working in a complete job in 2017 is linked to higher skills use.

Changes in the completeness of the working environment affect changes in the used skills positive (β around 0.22; $p < 0.001$)— in casu, a change to working in a complete working environment in 2017 is linked to an increase in required skills use.

These results support Hypothesis 1.

Table 3 shows that technological developments at work that have changed job content, have no impact on social skills and literacy and communication skills, but might affect changes in ICT and mathematics skills negatively ($\beta = -0.05$; $p < 0.10$). Therefore, the results also support Hypothesis 2.

Next, as Table 4 shows, we assessed whether employees whose working environment changed between 2012 and 2017 or did not, and reported technological change or not (the two subgroups), experienced a change in required job skills.

Concerning two out of the three skills under study, there was no difference between the two technology subgroups in the effect of changes in working environment (these subgroup results were not included in Table 4, since the regression coefficients for the subgroups were similar). Hence, the results support Hypothesis 3 for two skills: social skills and literacy and communication skills. If working environment change was reported, the effect on change in these skills was not dependent on technological change. However, as Table 4 shows, the effects of change in the working environment on ICT and mathematics skills are different when considering the degree of technological change. The results imply that when technological change had been present to a (very) large extent, change in working environment affected ICT and mathematics skills less ($\beta = 0.17$, $p < 0.001$), than if there had been no or only to some extent technological change ($\beta = 0.27$, $p < 0.001$). This result is not in line with Hypothesis 3. Nevertheless, the results provide partial support for Hypothesis 3 (for two out of three job skills, the hypothesis was supported).

TABLE 3 Results of the linear multiple regression analyses of changes (2017 minus 2012 score) in social skills, literacy and communication skills, and ICT and mathematics skills (standardised regression coefficients [β]) ($N = 1126$)

	Social skills	Literacy and communication skills	ICT and mathematics skills
	β	β	β
Working environment (−1 = *from complete to incomplete*; 0 = *no change*; 1 from incomplete to complete)	0.22****	0.23****	0.22****
Technological change (1 = *no, not at all*; 5 = *to a very large extent*)	0.03	0.02	−0.05*
Sex (0 = female, 1 = male)	0.02	0.01	0.04
Age	−0.08***	−0.07**	−0.06
Occupation (managers, and professionals [ISCO 1&2] = reference category)			
Technicians and associate professionals (ISCO 3)	−0.03	−0.02	−0.00
Clerical support workers (ISCO 4)	−0.02	0.02	−0.03
Services and sales workers (ISCO 5)	0.02	−0.01	0.08*
Craft and related trades, and Skilled agricultural workers (ISCO 6&7)	−0.06	−0.02	−0.03
Plant and machine operators and assemblers, and Elementary occupations (ISCO 8&9)	−0.08**	−0.04	−0.06
Unknown ISCO	−0.01	−0.01	−0.00
R^2	6.1%	5.7%	6.5%

Abbreviations: ICT, information communication technology; ISCO, International Standard Classification of Occupations.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; ****$p < 0.001$.

DISCUSSION AND CONCLUSION

From the Luhmannian perspective, technology is an aspect of an organisation and not a separate subsystem. The impact of technology should be understood from the wider organisational context. This means that we cannot expect a direct impact of technology on skills. This perspective also means that companies do not restructure work and functions starting from engineering bottlenecks, as Frey and Osborne (2017) claim. Managers use broader contexts to decide about work. Costs assessments (Van Reenen, 2011), capital–labour relations (Braverman, 1974) and labour market situations (Autor, 2015) will weigh more heavily in decisions than the potential of technology to function autonomously. It is important to understand this organisational context in which employees are confronted with technology, how that context is changing, and what that means for those employees' required social skills, literacy and communication skills and ICT and mathematics skills. Our results show the following in figuring out the impact of technology change and the changing working environment on skills use. Employees changing to a complete working environment,

TABLE 4 Results of the linear multiple regression analyses of changes (2017 minus 2012 score) in ICT and mathematics skills in the two sub-samples, based on the extent of technological developments (standardised regression coefficients [β])

	No/to some extent technological developments ($N = 687$) β	To a (very) large extent technological developments ($N = 439$) β
Working environment (−1 = from complete to incomplete; 0 = no change; 1 from incomplete to complete)	0.27**	0.17**
Sex (0 = female, 1 = male)	0.04	0.05
Age	−0.06	−0.05
Occupation (managers, and professionals (ISCO 1&2) = reference category)		
Technicians and associate professionals (ISCO 3)	0.04	−0.06
Clerical support workers (ISCO 4)	0.01	−0.08
Services and sales workers (ISCO 5)	0.13*	0.02
Craft and related trades, and skilled agricultural workers (ISCO 6&7)	0.02	−0.07
Plant and machine operators and assemblers, and elementary occupations (ISCO 8&9)	−0.04	−0.06
Unknown ISCO	0.04	−0.05
R^2	9.2%	4.4%

Abbreviations: ICT, information communication technology; ISCO, International Standard Classification of Occupations.
*$p < 0.01$; **$p < 0.001$.

experience an increase in skills use and vice versa: Those employees who have confronted a change towards a more Tayloristic working environment experience a loss in skills use. Hypothesis 1 has been supported by our results. Hypothesis 2, stating that 'Employees experiencing technological change do not experience their skills use change over time', is also supported. Hypothesis 3, 'Employees experiencing both technological change and changes in working environment (towards complete environments) do not experience an extra change in their skills use over time', was partially supported. There was support for two out of three job skills under study here. However, the use of ICT and mathematical skills increases more strongly in an environment in which technological change is less present than in an environment in which technological change is more present.

In the current debate on changing skills use, the impact of the working environment tends to get overlooked. As Schlogl et al. (2021) have assessed, most of the (grey) literature on the future of work is biased towards technology having an upskilling effect. They indicate that this should not be seen as a positive result, mainly because the responsibility for this upskilling is put on the shoulders of the employee and not of management. This article contributes to the literature, clarifying that the working environment explains more in the change in generic skills use (operational or executive skills) than technological change does. The current debate

(McKinsey & Company, 2017; World Economic Forum, 2018) tends to overestimate the role technology plays in changing skills use. We clarify this with our Luhmannian approach to organisation. Organisations are systems with technology, working positions and recruiting systems as aspects of the functioning. The different aspects cannot be isolated from one another. Technological change may impact skills use, but this article shows that the working environment is needed to understand how. For companies and employees, it is essential to develop more understanding of how to create and implement more complete working environments (Gibbons & Henderson, 2013) and understand how this channels technological change. As Spencer indicates, there is a need to improve the quality of work itself and the organisation offers this possibility (Spencer, 2018, p. 9).

Specific skills will undoubtedly change if the technological change increases, but the current literature focuses on generic skills. The discussion about 21st-century skills (Van Laar et al., 2017) is only relevant if researchers consider the type of working environment workers need to conduct their tasks. This result confirms prior research on organisational and managerial practices (Bloom et al., 2019; Boxall & Mackie, 2014).

Another implication of this study is the connection between a complete working environment and technological change. The results do not provide a full answer to what this relationship likely looks. Is it because a more complete working environment is a prerequisite for more technological change? Or is it because more technological change leads to more complete work? The interaction effect, which underlies the results in Table 4, shows that technological change in ICT skills actually results in a lower increase in those skills in a complete environment and a higher increase in an incomplete environment. So it seems that technological change ‘dampens’ the impact of the environment on skills. This dampening effect might indicate that the working environment is more important than technology to understand skills use changes. Case study research may be needed to clarify what we have found. More detailed information is needed on how technological change actually plays out. Can we see differences between different kinds of technology?

Although the three generic skill sets in the study are interlinked, the change in the working environment and technology are intertwined with other skills used in the final results. Change in the working environment affects communication skills. The combination of changing working environment and technology mainly affects ICT and mathematical skills. In the first situation, employers have a greater need for writing and reading by employees in a complete working environment. These skills are less needed in more incomplete, Tayloristic working environments. With the second situation, more questions arise. More technology would go hand in hand with higher requirements for ICT and mathematical skills. We can understand that dealing with important technological changes leads to more use of those skills. However, if the employee works in a complete environment, the increase in demand for these skills is less than expected. Even if an employee works in an incomplete environment, and technological change takes place, those skills' requirements increase relatively speaking. All kinds of new requirements arise in the incomplete environment, which can only be tackled with the employee's skills. The tight organisation does not provide everything.

The study shows that we need to be careful measuring skills use. The current instruments (SES, PIAAC, NSS) have been developed from different practical perspectives. These surveys measure skill sets by looking at tasks. However, several tasks reflect organisational practices, rather than individual skill sets. Connecting all tasks to individual skills supports a bias towards technology-based arguments. Seeing the tasks as an indication of these organisational practices, offers more options to management and workers to discuss the organisational options for skills development.

The longitudinal setup of the current research allows investigating changes in the working environment. It provides a strong methodological improvement compared to most of the cross-sectional research used in this study domain. It allows for a (partial) check of causality since changes in working environments and perceived technological change can be checked over time. The same persons reporting changes can be analysed in their skills demands. The article supports developing more of this kind of research rather than limiting the analysis to cross-sectional approaches.

This approach has several limitations. We relied on measurements conducted with a survey that was built with the same purpose as the SES survey. We only have a general, one-item assessment by the employee that something on the technology side significantly changed for technological development. We do not know which technology has changed, nor precisely how long ago. The conceptualisation of technological change may, therefore, not be sufficiently precise. For future research, more attention should be given to measuring technological change more extensively and precisely. As indicated, case study research is needed.

The different skills use items have been measured in one survey setting, leading to common method bias. This bias should be unproblematic because the NSS developers have applied systems to randomise the way questions have been put to respondents. The fact that we follow individuals over time may lead to feedback and intrasubject correlation. We have controlled for such effects in the regression. To ensure the impact we have described, more stability after more measurements should be recorded (Eisen, 1999).

In our future societies, employees will have to focus more on developing their skills. Merely focusing on upskilling and pointing out their own responsibility is insufficient. Developing stronger skills to deal with technology requires a more radical change of direction from employees and managers than advising employees to focus on social, communicative and creative skills themselves (Frey & Osborne, 2017). In many (Taylorist) work environments, this choice will do nothing for an employee. The discussion is not so much that technology requires different skills from the employee, but rather how employees participate in their work and the functioning of their organisation. This study shows that in those contexts where employees have more control over what they do, technology actually helps to strengthen employees' skills.

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CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

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ENDNOTES

[1]The list of skills is somewhat biased towards information activities (communication skills, social skills, numerical skills, problem-solving skills) and the importance of technology (ICT skills). The idea is that all skills, and surely problem-solving skills, reflect the rising importance of information processing in jobs. This kind of information-solving is seen as a function of technology (OECD/PIAAC Expert Group in Problem Solving in Technology-Rich Environments, 2009): 'Because digital technologies are primarily aimed at storing, processing, representing and communicating symbolic information, the types of problems that will be used in the PIAAC problem-solving assessment clearly belong in the first category (p. 8)'. The rising use of technology would entail the use of these problem-solving skills. Once more, technology determinism manifests/emanates when the expert group discusses the direct influence of technology-rich environments on problem-solving competencies (OECD/PIAAC Expert Group in Problem Solving in Technology-Rich Environments, 2009). The PIAAC-working group sees the problem-solving skills relying on much of the 'core' cognitive processes as literacy and numeracy (p. 14). This is certainly the case, but then the cognitive processes in problem solving should be broken down to the numeracy and literacy (and possibly other) cognitive processes.

[2]The LLL2017 was funded by Researchcentrum Onderwijs en Arbeidsmarkt (University of Maastricht). The NSS2017 was funded by the Dutch Ministry of Social Affairs and Employment (Kleruj, 2017).

[3]Question: 'Have there been technological developments at your work that have changed the content of your work? (Answer scale: 1 = *Not at all* to 5 = *To a great extent*)'.

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