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Sustainable Employment in the Age of Digitalisation:
challenges, obstacles, and opportunities

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The changing task composition of Belgian workers, 1995-2021

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1. Introduction

This paper empirically examines the task composition of Belgian workers over the past 25 years. The aims of the study are (1) to describe work tasks of workers and their relation with workers' characteristics and occupations, (2) to study the evolution of the task composition of workers and (3) to decompose the overall change in work tasks into a part that results from changing work tasks within occupations and another part that results from changes in the occupational structure. The analysis is based on data from the European Working Conditions Survey (EWCS) for the period 1995-2021 and the Survey of Adult Skills (PIAAC) for the period 2011-2018. To the best of our knowledge, this is the first study on changes of the task composition of workers for Belgium. Many labor markets, including the Belgian labor market, are characterized by substantial degrees of educational mismatch – i.e. a situation in which the skills of job seekers (labor supply) do not match the skills required in vacancies (labor demand). Because specific tasks require specific types of education and training, a better understanding of the evolution of work tasks, can help policy makers to implement educational and training policies that could reduce the degree of mismatch in the future.

The remainder of this chapter is organized as follows. The next section presents a brief overview of the literature on the effects of the digital revolution focusing on the changes in the task structure of employment. Section 3 presents the task framework that is used for the analysis and section 4 presents the results. Section 5 provides an overview of the literature on the consequences of technological change on skill requirements and discusses the implications of our empirical findings for skill requirements in the Belgian labor market. Section 6 contains a conclusion.

2. Literature review¹

Most of the recent literature on the effects of the digital revolution has focused on automation and its effect on the employment structure (Acemoglu & Restrepo, 2019; Autor, Levy, & Murnane, 2003; Arntz, Gregory, & Zierahn, 2016; Frey & Osborne, 2017). Automation refers to the substitution of human labor by machines in the production process (Deschacht, The digital revolution and the labour economics of automation: A review, 2021). Because of the progress in technology over the past years, computers and machines can now replace workers in different industries at a lower price. A historical example of this process is the development of agriculture over the 20th century. Between 1910 and 2010, the share of total employment in agriculture dropped by 84 percent in the US, by 77 percent in the UK and by 83 percent in Japan and this drop was largely due to technological advancements in agricultural machinery (Roser, 2013). Recently, we have also observed the disappearance of bank tellers as technology created more efficient ways for digital payments and ATM machines. In Belgium, the number of bank branches has fallen by 42 percent between 2000 and 2011 and the number of jobs in this sector by 20 percent over the same period (Trends-Tendances, 2012). Frey and Osborne (2017) empirically investigate the effect of automation and their results predict that 47 percent of all US jobs have a high probability of being automated in a decade or two. Based on these results, Bruegel, a European economic think tank, shows that a similar share of Belgian jobs is also at risk of automation in the next decades (Dolphin, 2015).

The above examples and the study of Frey and Osborne typically assume that all workers within an occupation that is at high risk of being automated will lose their jobs. However, any occupation is essentially a bundle of tasks and workers within a broad occupation may thus be very differently exposed to automation depending on the tasks they perform. Similarly to Frey and Osborne, Arntz et al. (2016) assess the potential

¹ This literature review draws heavily from Deschacht (2021)

of automation of the different occupations taking into account the heterogeneity of workers' tasks within occupations. Using PIAAC survey data, they concluded that, if it is assumed that machines displace certain tasks instead of whole occupations, on average 9 percent of jobs in the 21 OECD countries are automatable, an estimate far away from the one of Frey and Osborne. However, even if the number of jobs disappearing due to automation is limited, technological change also induces changes in the task composition within occupations (Autor, Levy, & Murnane, 2003; Arntz, Gregory, & Zierahn, 2016; Autor D. , 2014). An example of the changing task content is the occupation of office secretary work, in which the tasks have shifted away from essentially typewriting towards more management related tasks, while the occupation itself has not disappeared over the years (Khalid, Swift, & Cullingford, 2002).

Theories and research on the effects of technological change on the task composition of workers explain that there are two major types of tasks, routine tasks and non-routine tasks, and that while routine tasks can easily be automated, non-routine tasks are more complicated to automate (Autor, Levy, & Murnane, 2003; Autor D. , 2014). Indeed, *routine tasks* which are defined as tasks that follow an exhaustive set of rules can easily be specified in computer code and executed by machines. *Non-routine tasks* which refer to tasks that involve situational adaptability, visual and language recognition, problem solving, creativity or persuasion are tasks that do not follow clear rules and are thus more complicated to automatize. Consequently, this theory suggests that digitalization leads to a decline in labor demand for routine tasks and an increased demand for non-routine tasks. This is the *routine-biased technical change hypothesis*. This hypothesis is confirmed by many empirical studies that show a decrease in the demand for routine tasks over the past decades (Autor, Levy, & Murnane, 2003; Autor D. , 2014). In relation to the Belgian labor market, the authors of this report found that the percentage of Belgian workers in occupations that involve many routine tasks has declined from about 40 percent to 25 percent between 1986 and 2020 (Deschacht & Detilleux, 2022).

Other studies have attempted to differentiate task changes at the intensive margin (within occupations) from task changes at the extensive margin (between-occupations) (Autor, Levy, & Murnane, 2003; Spitz-Oener, 2006; Akçomak, Kok, & Rojas-Romagosa, 2016; Hardy, Keister, & Lewandowski, 2018). Changes at the intensive margin examine how the tasks of workers within the same job have changed over time. A recent example of such change is the shift to online teaching in higher education as a result of the Covid-19 crisis. Some of the teaching by university professors can be considered a routine task in the sense that the same lecture is taught every year. Video recordings of these lectures allow for a substantial automation of teaching, which is shifting the task content of university lecturers towards more non-routine tasks, such as responding to individual questions and evaluating students. Changes at the extensive margin have been more widely studied and they describe how the employment shares of jobs that are intensive in a particular task evolved over time. Akçomak et al. (2016) empirically analyzed task changes in the UK between 1997 and 2006 and found that the decline of routine tasks is due to both within and between occupations changes, that the increase in social tasks can be attributed mostly to changes in the occupational structure and that the increase in computerization is mostly due to within occupations changes.

3. Task framework

In this section we describe how the tasks of workers are measured in our empirical study. Our strategy relies on the work done by Fernández-Macía, Hurley, & Bisello (2016) who, based on a review of the literature, identified a number of task categories that best describe the recent developments of labor demand and structural change in employment. Chapters 5 and 6 in the Fernández-Macía, Hurley, & Bisello (2016) report gives detailed information on how the task framework is constructed.

Table 1 presents an overview of the task categories included in the task framework developed by Fernández-Macía, Hurley, & Bisello (2016). **Tasks** are classified based on two characteristics, the 'content' of work and the 'methods and tools' used at work. Broadly speaking, this approach divides tasks based on *what* workers do at their jobs and *how* they do their jobs. The content characterizes the skills required to perform a task and contains (1) physical tasks, which refer to tasks in which workers perform physical manipulations and transform material things, (2) intellectual tasks, which refer to tasks that involve the transformation of information and the active resolution of complex problems, and (3) social tasks, which refer to tasks in

which workers interact with other people. The methods and tools used at work describe how the work is organized and the type of physical objects that are used to perform the tasks. The methods characterize whether workers work in teams or autonomously and whether their jobs involve routine tasks. The tools describe whether workers need machines and/or information and communication technologies (ICT) to perform their jobs.

Table 1: Task framework

<p>Content</p> <p>1. Physical tasks: Tasks aimed at the physical manipulation and transformation of material things, which can be further differentiated into two subcategories:</p> <ul style="list-style-type: none">a. Strength: Tasks that primarily require the exertion of energy and strength.b. Dexterity: Tasks that primarily require a fine physical skill and coordination, particularly using hands. <p>2. Intellectual tasks: Tasks aimed at the manipulation and transformation of information and the active resolution of complex problems, which can be further differentiated into two sub categories:</p> <ul style="list-style-type: none">a. Information-processing: Manipulation and transformation of codified information, which can be further divided into:<ul style="list-style-type: none">i. Literacy: Manipulation and transformation of verbal information.ii. Numeracy: Manipulation and transformation of numeric information.b. Problem-solving: Tasks that involve finding solutions to complex problems, which can be further divided into:<ul style="list-style-type: none">i. Information-gathering and evaluation of complex information.ii. Creativity and resolution. <p>3. Social tasks: Tasks whose primary aim is the interaction with other people, which can be further differentiated into four subcategories:</p> <ul style="list-style-type: none">a. Serving/attending: Personally serving or attending customers, clients or patients.b. Teaching/training/coaching: Training and coaching others.c. Selling/influencing: Persuading and influencing others.d. Managing/coordinating: Supervising and coordinating others. <p>Methods and tools</p> <p>1. Methods: The forms of work organization used in performing the tasks, which can be further differentiated into three subcategories:</p> <ul style="list-style-type: none">a. Autonomy: The extent to which the worker is free to carry out the task as they need.
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Note: from Fernández-Macia, Hurley, & Bisello (2016) ("What do workers do at work?")

3.1 Construction of task indices

As explained by Fernández-Macía, Hurley, & Bisello (2016), there are two ways to measure the task composition of workers. Researchers either use surveys in which workers answer questions about their working conditions and the skills they use at work, or they rely on occupational databases in which experts assess the types of tasks workers perform in each occupation. Occupational databases (such as O*NET and SOC in the US or ESCO in Europe) may be more precise than surveys because, for example, new recruits may provide wrong or inaccurate answers about the tasks they perform at work or workers who dislike a certain task may exaggerate the intensity of this task in their jobs. Occupational databases are also better related to the task framework developed above. Nevertheless, it is harder to study changes in the task content of workers using occupational databases and we thus concentrate our analyses on worker surveys.

Our strategy to investigate the task composition of jobs is to create task indices for each of the different elements of the task framework shown in Table 1. In order to do so, we aggregate information from a set of survey questions drawn from the two micro-level datasets used in this study. Table A.1 (Appendix A) lists the survey questions that were used to compute each of the different task indices. For example, the task index “physical strength” was constructed by aggregating variables q30a, q30b and q30c (on whether a worker’s main paid job involves, respectively, tiring position, lifting or moving people and carrying heavy loads) in the EWCS. The selection of variables and the aggregations in Table A.1 were based on the work of Fernández-Macías, Bisello, Sarkar, & Torrejón (2016) who identified the variables that could be mapped together to get a measure of a task index. We performed a factor analysis to verify the consistency of the indicators.

To date, the PIAAC data have only been collected once in Belgium between August 2011 and March 2012 while the EWCS data have been collected every 5 years since 1991. The questionnaires of the EWCS have gone through several modifications over the years, especially in 2021, and some of the variables needed to construct the task index are not present in each wave. Table A.1 provides the survey waves in which each variable is observed. For the EWCS, our analysis focuses on 2021 (or evolutions until 2021) when possible. However, the task indices for creativity, team work, standardization and machines are based on 2015 data since the necessary information was missing in 2021. Similarly some of the variables present in 2015 and/or 2021 were not present in the 1995 wave of the survey, which imposes a problem to study evolutions over time. When looking at the evolution of the task composition of workers, we thus only used variables that are observed since 1995 to compute the task indices. For example, the task index “Physical strength” is only based on the two variables q30a and q30c when we study evolutions over time because variable q30b was not observed in 1995.

Because the variables were measured on different scales, we first normalized each of them into a normative scale that ranges from 0-100 indicating the intensity by which the task is performed. The normalization was done using the equation:

$$\text{norm}_x = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) * 100$$

where x_{\max} and x_{\min} represent the highest and the lowest value variable x can take. When necessary, we reversed the scales so that higher values correspond to higher intensity in performing the task.

4. Results

4.1 How do work tasks vary across Belgian workers?

The first objective is to study how tasks vary across workers in the Belgian labor market. Table 2 presents the mean task indices scores in the whole sample and separately by sex, age and education. Education

distinguishes between low (no secondary diploma), middle (secondary diploma) and high (more than a secondary diploma) educated workers.

Table 2: Task index scores

	All	Sex		Age				Education		
		Men	Women	<=30	(30-40]	(40-50]	>50	Low	Middle	High
<i>EWCS</i>										
Physical: Strength	25.8	23.6	28.0	27.1	25.2	25.6	25.7	34.0	31.2	20.9
Intellectual: Problem solving	65.5	65.9	65.1	67.9	67.6	65.6	61.8	57.7	61.7	69.6
Intellectual: Creativity ^a	77.9	78.0	77.8	74.0	78.5	78.0	80.3	65.6	75.9	84.1
Social	57.4	52.7	62.7	59.7	57.1	58.5	55.1	55.9	57.5	57.9
Method: Autonomy	62.3	63.5	61.2	61.9	62.5	62.2	62.5	57.4	60.2	64.4
Method: Team work ^a	45.7	48.1	43.0	43.9	48.1	49.7	40.6	36.0	44.8	50.3
Routine: Repetitiveness	60.1	60.0	59.9	58.6	61.0	59.5	60.8	72.0	67.1	53.4
Routine: Standardization ^a	59.9	65.5	53.5	61.7	57.8	61.0	59.5	56.1	62.5	59.1
Tools: Machines ^a	12.4	17.9	6.2	14.4	13.3	12.7	9.8	18.3	18.3	5.2
Tools: Technology	75.2	72.7	78.3	68.8	79.1	76.8	74.9	42.4	64.1	88.8
Number of obs.	2,736	1,397	1,301	530	639	697	842	269	861	1,593
<i>PIAAC</i>										
Intellectual: Business literacy	56.5	55.2	57.9	48.7	60.8	59.9	56.2	30.1	46.5	73.1
Intellectual: Technical literacy	45.7	49.5	41.6	41.7	47.9	47.9	45.2	31.7	41.6	53.5
Intellectual: Humanities literacy	23.7	24.8	22.4	18.5	25.7	25.3	25.1	9.4	15.5	35.0
Intellectual: Accounting numeracy	38.7	42.2	34.9	34.3	42.7	42.1	35.3	21.4	32.3	49.2
Intellectual: Analytical numeracy	18.3	22.3	14.0	16.7	21.1	20.4	14.7	5.9	11.5	27.7
Intellectual: Learning	55.1	56.4	53.7	61.7	56.6	52.1	50.4	45.0	52.3	60.1
Social: Selling	44.4	45.5	43.1	39.5	46.7	47.0	44.1	28.5	38.6	54.2
Social: Teaching	24.3	26.1	22.2	20.0	26.5	27.0	23.3	9.9	17.0	34.9
Social: Managing	22.4	26.3	18.3	16.1	25.8	25.6	21.2	12.1	19.1	28.0
Method: Autonomy	65.9	65.7	66.0	59.9	67.9	66.8	68.5	52.3	60.8	73.7
Tools: ICT	53.8	55.6	51.9	50.9	57.6	54.8	51.0	34.6	44.8	61.2
Number of obs.	2,617	1,340	1,277	592	676	759	590	176	900	1,442

The sample consists of Belgian workers in year 2021 (EWCS) and between years 2011 and 2012 (PIAAC). The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A. The numbers of observations give the lowest sample that is used to calculate the task indices.

^a Data not available for 2021 so indices are measured in year 2015.

In all the samples, the mean scores of the intellectual task indices are much higher than the means of the physical task index. The physical task index is higher for low-educated workers, while the intellectual tasks indices are higher for high-educated workers. There are also gender differences with women having a somewhat higher score for the physical task index (we return to this finding later in this report) and men having higher scores in all of intellectual tasks except for business literacy. The gender difference is especially large in the numeracy task indices. The social task index based on the EWCS data, which is more related to the general question “Are you directly dealing with people”, is higher in the female sample, while the social task indices for the PIAAC data, which measure more specific tasks such as selling, teaching or managing, are higher in the male sample. Looking at the methods of work, we find that high-educated workers more often work autonomously and that low-educated workers more often perform repetitive tasks. Finally, we find that male, young and low-educated workers more often use machines at work and that high-educated workers more often use computers.

In table 3, we present the mean task index scores broken down by occupation groups defined by the ISCO-08 classification at the 2 digits level. Appendix Table C.3 presents an overview of the occupations of the ISCO-08. To visualize the relationship between the tasks and occupations, we use a color scale in the table so that a darker color represent higher task intensity. That is, the darker the green color within a column, the higher is the task index in the occupation compared to the other occupations.

We find that the physical task index is particularly high in blue collar occupations (ISCO occupations 5, 7, 8 and 9 which represent, respectively, “Service, shops and market sales workers”, “Craft and related trades workers”, “Plant and machine workers” and “Elementary occupations”). The physical task index is also high in occupation 22 which represents health professionals and occupation 53 which represents personal care workers. Because women are highly represented in these occupations, we believe that health jobs are driving our finding of a higher physical score for female workers. Intellectual task indices, on the contrary, are higher in occupations 1 and 2 which represent, respectively, managers and professionals workers. The intellectual task indices related to numeracy are especially high in occupation 21 and 24 (“Science and engineering professionals” and “Business and administration professionals”), those related to humanities literacy in occupation 26 (“Legal, social and cultural professionals”) and those related to business and technical literacy in occupation 1 (“Managers”). The social task scores measured in the EWCS sample are high in occupations 22 (“Health professionals”), 23 (“Teaching professionals”) and 5 (“Services and sales workers”). The highest score for the selling and managing social tasks are in occupation 11 which represents chief executives, senior officials and legislators and the highest score for the teaching social task is in occupation 23 which represents teaching professionals. The mean routine task indices are high in the blue-collar occupations 7 (“Craft and related trades workers”) and 8 (“Plant and machine operators and assemblers”). Routine tasks related to repetitiveness are also concentrated in occupations 9 (“Elementary occupations”) and 44 (“Clerical support workers”). Occupation 9 includes cleaners, agricultural workers and laborers in mining, construction, manufacturing and transport among others. Finally, we find that the machine task index is very low in almost all occupations except for the blue collar occupations 7, 8 and 9.

On the other hand, the technology and ICT task index scores are large in almost all occupations but especially in the white-collar occupations 1, 2 and 3 (“Managers”, “Professionals” and “Technicians and associate professionals”).

Table 3: Task indices scores, by ISCO08 2-digits

ISCO	EWCS										PIAAC										
	Physical: Strength	Intellectual: Problem solving	Intellectual: Creativity ^a	Social	Method: Autonomy	Method: Team work ^a	Routine: Repetitiveness	Routine: Standardization ^a	Tools: Machines ^a	Tools: Technology	Intellectual: Business literacy	Intellectual: Technical literacy	Intellectual: Humanities literacy	Intellectual: Accounting numeracy	Intellectual: Analytical numeracy	Intellectual: Learning	Social: Selling	Social: Teaching	Social: Managing	Method: Autonomy	Tools: ICT
11	11.2	72.6	87.5	54.3	71.5	45.5	44.6	60.2	2.7	89.6	87.4	58.4	49.6	69.8	34.8	66	77.7	55	63.1	85.6	68.3
12	9.7	70.5	87.2	45	74.6	59.2	53.1	63.9	0.4	96	85.8	60.4	43.4	75.2	40.7	64.7	74.9	48.8	46.8	85.5	70.7
13	17.7	71.9	89.2	53.3	70	55.2	51.6	71.5	5	88.1	84.6	61.5	43.1	63.2	40.1	62.3	66.1	45.3	56.7	81.9	70
14	27.4	67.5	88.6	73.4	68.6	31	52.9	55.5	4.1	81.8	86.6	45.9	37.8	79.1	26.7	58.2	80.4	25.6	48.7	88.3	58.3
21	15.3	71	87.3	38	72.1	50.4	54.3	66.3	10.3	91.6	76.6	60.1	35.7	65.4	48.9	64.9	53.8	34.5	29.9	78.8	72.5
22	52.3	71.7	84.7	89.4	50	60.4	55.7	62.4	4.6	90.6	65.5	59.3	31.6	27.5	15.1	57.6	57.3	29.7	25.9	68.7	44.7
23	23.7	70.7	87.5	81.9	53.6	45.8	44.2	58.9	3.6	84.2	64.2	52.6	43.6	34.4	24.2	59.4	45.2	63.3	22.4	67.7	58.1
24	8.7	72	87.5	42.3	73.7	44.2	54	58.1	0.5	96.4	88.5	59.6	41.8	73.1	44.5	63.8	63.9	29	25.3	82.8	70.2
25	9.8	75.8	88.3	24.6	76	56.3	58.3	60.1	6.8	98.9	72.8	53.4	36.4	45.4	42.2	66.4	42.7	31.5	16.8	73.9	85.1
26	22.4	69.9	86.2	63.7	63.1	53.3	48.8	50.1	2.1	87.6	75.5	48.3	51.9	35.2	13.7	67.2	51.5	31.9	21.7	77.5	59.8
31	22.7	66.9	85.4	48.7	66.8	57.7	52.4	73.4	23.9	82.7	62.7	61.7	23.9	49.4	31.7	57.5	45.3	34.7	38.9	66	57.4
32	23.2	71.9	77.8	63.5	54.5	65.5	57.2	72	16.7	88.9	60.9	49.9	22.1	31.4	14.9	60.1	41	19	20.6	60	47
33	14.3	69.1	79.7	52.7	70.2	47.3	56.1	55.5	3.8	94.2	81.5	52.5	28.3	57.2	25.5	57.5	56.9	23.7	23.1	76.9	63.6
34	22.9	67.6	86.8	57.9	59.6	51.3	48.4	46.4	2.3	70.4	71.4	44.4	33.4	43	12.4	58.3	53.6	30.4	29.3	73.1	59.9
35	15.1	74.9	85.9	40.3	70.2	70.3	66.7	68.4	6.5	97.7	75.4	53.3	36.3	39.3	28.2	70.6	44.6	41.7	23.9	74	76.2
41	12.3	64.7	69.7	45.7	69.7	44.5	64.1	47.8	4.2	96.6	82.5	44.1	18.6	49.9	19.5	51.2	37.8	15.2	22.4	71.7	62.6
42	16.2	63.1	73.3	51.7	60.3	57.3	66.1	68.8	9	96.1	84.8	51.9	25.6	56.1	13.2	64.8	64	18.4	19.3	67.8	60.8
43	24.3	61.1	66.3	39.7	63.2	46	66.8	64.4	13.4	78.8	55.4	45.2	12.1	39.3	17.5	51.7	33.3	15.6	16.9	59.8	47.8
44	28.2	52.7	78.3	53.5	59	51.2	80.8	55.2	6.9	65.9	53.1	40.1	14.2	30.8	15	50	35.1	18.6	17.4	65.7	50.5
51	36.3	59.8	77.9	78.5	57.9	36.9	72	55.7	7	46	39.6	26.8	15.5	31.9	5	56.2	45.5	16.9	18.8	62.8	32.5
52	30	62.6	77.6	86.1	52.1	36.4	63.9	58.7	11	64.4	59.1	37.3	17	55.9	13.2	57.9	74.3	14.2	17.9	63.2	38.2
53	59.5	61.2	81.3	80.7	50.8	49.8	61.8	42.6	3.2	66.4	46.1	39.5	16	14	3.3	50	35.6	14.3	12.1	56.9	33.5
54	18.8	66.9	76.5	65.5	52	56.3	49.1	67.6	12.6	81	57.7	60.4	33.3	15.3	11	60.7	56	24.5	26.2	54.7	49.5
71	38.4	65.7	86.9	53.3	59.9	47.3	68.2	77.7	33.8	41.1	26.6	36.7	10.7	26.4	9.3	52.3	30.3	12.1	17.6	58.2	33.4
72	34.8	68.7	78.2	41.9	58.3	59.8	61.2	76.5	44.4	56.2	30.4	47.6	13.1	22.5	11	54	26.9	13.1	16.7	57.7	34.3
73	23.9	60.2	72.4	36.6	59.5	62.5	69	66.3	23.1	65.4	44.6	49.5	16.3	44.2	23.8	38.7	42.5	21.3	28.8	62.9	43.7
74	37.1	66.3	84.3	58.5	64	66.7	65.8	64.7	26.6	62.9	41.2	55.3	13.5	26	12.1	59	34.1	17.5	14.7	57.9	43.1
75	26.2	60.3	78.9	42.1	54.9	41.5	59.8	73.4	35	45.3	39.2	35.3	16.1	41.3	13.4	51.2	41	14.1	21.5	57.7	31.3
81	36.2	57.5	53	17.8	56.7	49.6	76.7	74	54.1	45.7	25	40.2	8.8	28.2	11.7	49	17.5	18	13.1	44.3	22.4
82	30.9	58.2	58.6	26.3	60.4	66	85.3	100	32.5	56.3	19.1	37.1	6.5	9.7	6.7	47.5	20.2	11.7	15.9	37.6	24.7
83	29.4	52.7	69.9	61	49.9	31	76	53.6	16.5	49.8	28.8	43.4	8	17.7	4.2	43.4	18.5	6.6	4.8	43.1	17.2
91	34.7	44.9	57.8	65	65.6	16.3	83.3	39.6	7.2	26.7	13.5	19.8	3.2	4.2	0.2	30.7	7.6	2.6	3.4	58.1	23.8
92	35.9	62.1	55.8	43.5	67.7	29.5	80.7	40.6	33.5	19.5	36.7	29	17.5	28.3	12.5	64.3	31.3	7.5	19.3	55.8	31.7
93	33.9	59.5	52.4	31.4	56.1	44.9	74.2	70.9	37.1	35	14.1	21.7	5.3	8.5	2.5	39.2	12.5	5.3	5.1	26.9	9.3
94	40.1	60	58.1	61.1	39.7	53.9	67.7	53.4	22.2	10.2	18.7	24	4.8	7.1	2	46.5	14.4	5.6	5.1	41.5	41.7
96	33.5	56	73.1	62.4	62.6	29.4	65.5	53.5	15.4	43.1	29.4	28.2	9.9	12	6	48.3	26.7	8.3	14.2	50.8	34

The sample consists of Belgian workers in year 2021 (EWCS) and between years 2011 and 2012 (PIAAC). The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A and Table C.3 gives the ISCO08 classification. The color scale highlight, for each task index, the occupation with the highest value.

^a Data not available for 2021 so indices are measured in year 2015.

Table 4 compares the mean task indices in growing occupations (occupations 33, 24, 22, 26, 25, 23, 21, 31, 53 and 34) and declining occupations (occupations 72, 75, 73 and 74). We selected the occupations that have grown and declined the most over the past 30 years based on a previous analysis of the Belgian Labor force survey (Deschacht & Detilleux, 2022). In this study, we ranked occupations based on changes in the absolute number of workers in each of these occupation between 1995 and 2020. The 10 occupations with the biggest positive changes represent the growing occupations and the 4 occupations with the biggest negative changes the declining occupations.

The results in table 4 indicate that intellectual and social mean task indices are higher in the growing occupations while the physical and machines tasks are higher in the declining occupations. We also find that routine jobs are concentrated in the declining occupations and that workers in the growing occupations use

computers much more intensively compared to those declining occupations. This goes in the same direction as the idea that new jobs working in complement of computers are appearing and that jobs in which workers perform more routine tasks are disappearing.

Table 4: Task index scores, by growing/declining occupations

	ISCO (2-digits)	
	Growing	Declining
<i>EWCS</i>		
Physical: Strength	25.7	32.6
Intellectual: Problem solving	69.5	65.5
Intellectual: Creativity ^a	84.7	78.9
Social	61.1	45.2
Method: Autonomy	63.2	58.6
Method: Team work ^a	50.6	53.7
Routine: Repetitiveness	53.4	62.3
Routine: Standardization ^a	58.0	73.2
Tools: Machines ^a	5.3	37.1
Tools: Technology	87.3	55.0
<i>PIAAC</i>		
Intellectual: Business literacy	69.2	36.0
Intellectual: Technical literacy	53.3	47.1
Intellectual: Humanities literacy	33.3	14.1
Intellectual: Accounting Numeracy	42.4	29.0
Intellectual: Analytical numeracy	24.2	12.8
Intellectual: Learning	58.7	53.5
Social: Selling	50.3	32.8
Social: Teaching	34.4	15.0
Social: Managing	24.1	18.1
Methods: Autonomy	70.9	58.2
Tools: ICT	58.9	37.0

The sample consists of Belgian workers in year 2021 (EWCS) and between years 2011 and 2012 (PIAAC). The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A and Table C.3 gives the ISCO08 classification. Growing occupations are ISCO08 groups 33, 24, 22, 26, 25, 23, 21, 31, 53 and 34 and declining occupations are ISCO08 groups 72, 75, 73 and 74.

^a Data not available for 2021 so indices are measured in year 2015

4.2 How did tasks change over time in the Belgian employed population?

Our second objective is to study the evolution of tasks over the period 1995-2021. Because the PIAAC data is not longitudinal, only the EWCS is used for the rest of the analysis. When information needed to measure a task index was not available in 2021, we restricted the analysis to the 1995-2015 period. As explained in

the appendix, the task index “team work” is no longer in our analysis since the variables needed to construct this task index are not available before 2000.

Table 5 gives the mean task indices in 1995 and 2021 and the absolute and percentage change between these two mean scores. The last column gives the linear trend coefficients obtained for each task index separately, which are estimates for the average annual increase in the task index (see Appendix C for more information).

Table 5: Aggregate changes in average scores of task indices, 1995-2015

	Mean		change	% change	Trend coefficients
	1995	2021			
Physical: Strength	24.1	31.4	7.3	30.4%	0.220***
Intellectual: Problem solving	65.0	66.1	1.1	1.7%	-0.130***
Intellectual: Creativity ^a	80.6	86.7	6.1	7.5%	0.078
Social	59.0	56.5	-2.4	-4.1%	-0.138***
Method: Autonomy ^a	76.2	74.4	-1.8	-2.3%	0.048
Routine: Repetitiveness	39.4	58.9	19.5	49.4%	0.703***
Routine: Standardization ^a	53.1	59.9	6.8	12.8%	0.510***
Tools: Machines ^a	11.8	9.3	-2.5	-21.1%	-0.111***
Tools: Technology	27.2	77.4	50.2	184.4%	1.905***

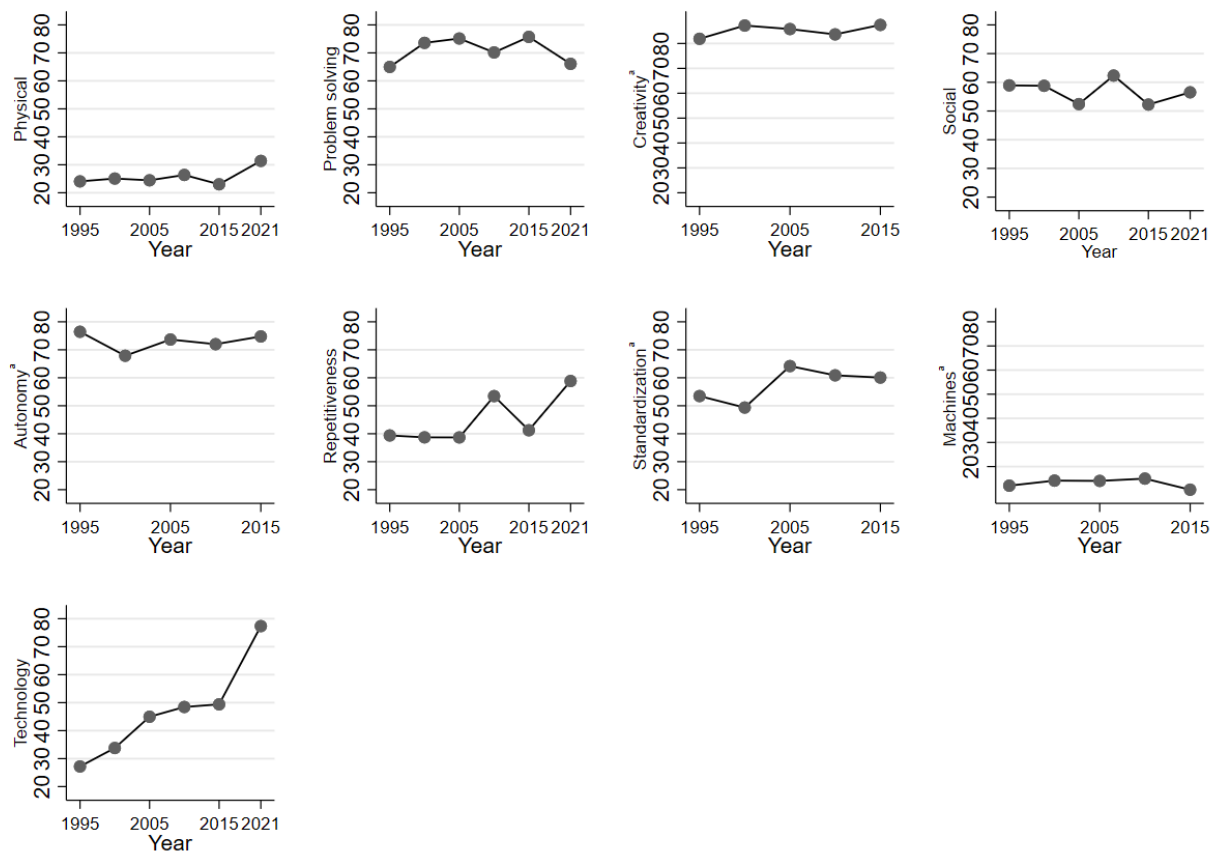
The sample consists of Belgian workers in 1995 and 2021. The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A. The trend coefficients represent the estimated coefficient of the variable year in the linear regression: $\text{task index}_i = \beta_{i,0} + \beta_{i,1}\text{year} + \epsilon_i$.

* $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$

^a Data not available for 2021 so indices and trend coefficients are measured over the period 1995-2015.

The estimates show that the two routine tasks average scores have consistently increased over the 1995-2021 period. The mean repetitiveness task index increased by almost 50% between 1995 and 2021 and the standardization task index increased by about 13% between 1995 and 2015. Regarding the tools used at work, we find that there is a decline in the use of machines at work while the use of computers at work has increased dramatically over the period. The mean technology score in 1995 was 27.5 and it more than doubled to 77.4 by 2021. In Figure 1, we see that the technology task index has increased over the full time period but the increase after 2015 is much steeper. Neither the index on creativity nor the one on autonomy show significant overall changes. More surprisingly, we find that the physical mean task index increased from 24.1 to 31.4 between 1995 and 2021 and that this increase is mainly driven by the increase between 2015 and 2021 (Figure 1). Additionally, we find that while the mean intellectual task index “problem solving” has slightly increased over that period, the estimated trend coefficient is negative and significant.

Figure 1: Task index evolution, EWCS 1995-2021



The sample consists of Belgian workers between 1995 and 2021. The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A.

Table 6 presents the linear trend coefficients for each task index separately by gender, age and education. We find that while the increase in the physical task index is true in all samples, it is concentrated in the middle- and high-educated samples with estimated trend coefficients close to 0.5 and 0.6, respectively. The trend coefficients for the problem solving task index are only significantly different from zero for male workers, workers aged more than 50 and high-educated workers. The coefficient is also much larger in magnitude in the high-educated sample suggesting that the overall decrease in problem solving is mainly due to the decrease among those workers. Again we find that there is no clear trend in the creativity and autonomy task indices since the trend coefficients for these two tasks are not significantly different from zero in any of the samples. The social task index has significantly decreased among female and high-educated workers. The two routine task scores have increased in all gender and age groups but while the trend coefficient for repetitiveness is positive and significant for high-educated workers, it is negative and significant for standardization in that sample. Finally, we find that the decrease in machinery is mainly concentrated among high-educated workers and that even if the increase in computers use is true in all samples, the trend coefficient is higher in magnitude for female workers, middle-educated workers and workers aged more than 50.

Table 6: Trend coefficients by sex, age and education

	Sex		Age				Education		
	Men	Women	<=30	(30-40]	(40-50]	>50	Low	Middle	High
Physical: Strength	0.177***	0.274***	0.215***	0.157***	0.294***	0.334***	0.209	0.509***	0.583***
Intellectual: Problem solving	-0.211***	-0.010	-0.095	0.007	-0.128	-0.247***	0.269	-0.088	-1.160***
Intellectual: Creativity ^a	0.060	0.222	-0.006	0.170	0.142	0.072	-0.217	0.667*	-0.004
Social	-0.022	-0.362***	-0.139*	-0.040	-0.040	-0.205**	-0.040	0.033	-0.514***
Method: Autonomy ^a	0.029	0.119	-0.026	0.112	-0.005	0.068	-0.293	0.462	-0.031
Routine: Repetitiveness	0.678***	0.710***	0.501***	0.782***	0.793***	0.971***	0.334	0.596***	1.090***
Routine: Standardization ^a	0.504***	0.536***	0.623***	0.331*	0.587***	0.397*	0.006	-0.156	-0.727**
Tools: Machines ^a	-0.068	-0.007	-0.113	-0.062	0.058	-0.252	-0.583	-0.444	-0.247*
Tools: Technology	1.762***	2.086***	1.565***	1.994***	1.960***	2.168***	1.628***	2.284***	1.896***

The sample consists of Belgian workers between 1995 and 2021. The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A. The trend coefficients represent the estimated coefficient of the variable year in the linear regression: $\text{task index}_i = \beta_{i,0} + \beta_{i,1}\text{year} + \epsilon_i$.

* $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$

^a Data not available for 2021 so trend coefficients are measured over the period 1995-2015.

Table 7 presents linear trend coefficients for each task index by occupation based on the ISCO-08 1 digit classification. Note that occupations in the EWCS were measured based on the ISCO-88 classification between years 1995 and 2015 and based on the ISCO-08 classification between years 2010 and 2021. There is thus no harmonized occupational classification over the full period 1995-2021. However, the ISCO-88 and ISCO-08 classifications are approximately the same at the 1-digit level and we thus only present the results at the 1-digit level here.

Our results suggest that the physical task index has significantly increased in all occupations except for occupation 1 (“Managers”) and 3 (“Technicians and associate professionals”) with the largest increase being in occupation 5 (“Service and sales workers”). Concerning the intellectual task index “Problem solving”, we find that the decrease in the task index score is concentrated among the white-collar occupations 1, 2 and 3. As shown before in Table 3, the intellectual task average score takes its highest value in these occupations but the results of Table 7 suggest that it has decreased in these occupations over the past 25 years. Interestingly, the social task index has been decreasing in the white-collar occupations 1, 2 and 3 and increasing in the blue collar occupations 7, 8 and 9. Finally, we find that the use of machines has been decreasing in many occupations but the trend coefficient is only significantly different from zero in occupation 9. The use of computers has been increasing in all occupations and the trend coefficients are larger in the white-collar occupations 1, 2 and 3.

Table 7: Trend coefficients by occupation

	1. Managers	2. Professionals	3. Technicians and associate professionals	4. Clerical support workers	5. Service and sales workers	7. Craft and related trades workers	8. Plant and machine operators	9. Elementary occupations
Physical: Strength	0.107	0.340***	0.100	0.367***	0.542***	0.344***	0.370**	0.298***
Intellectual: Problem solving	-0.231**	-0.758***	-0.526***	-0.142	0.151	-0.142	-0.087	-0.124
Intellectual: Creativity ^a	-0.065	0.124	-0.041	0.232	-0.180	0.244	0.326	0.065
Social	-0.879***	-0.539***	-0.592***	-0.450***	-0.087	0.330***	0.346*	0.741***
Methods: Autonomy ^a	-0.080	-0.216	0.113	-0.163	-0.237	0.250	0.359	0.582*
Routine: Repetitiveness	0.957***	1.018***	0.939***	1.104***	0.589***	0.425***	0.837***	0.615***
Routine: Standardization ^a	0.502*	0.970***	0.517*	0.626**	0.698**	0.222	0.169	-0.082
Tools: Machine ^a	0.001	-0.041	-0.071	0.143	-0.000	0.424	-0.272	-0.520**
Tools: Technology	2.241***	2.348***	2.192***	1.234***	1.740***	1.358***	1.482***	0.710***

The sample consists of Belgian workers between 1995 and 2021. The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A and Table C.3 gives the ISCO08 classification. The trend coefficients represent the estimated coefficient of the variable year in the linear regression: $\text{task index}_i = \beta_{i,0} + \beta_{i,1}\text{year} + \epsilon_i$.

* $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$

^a Data not available for 2021 so trend coefficients are measured over the period 1995-2015.

4.3 To what extent can the changing work tasks of the employed population be attributed to within occupation changes in tasks and to changes in the occupational distribution?

We perform a decomposition analysis to examine whether the overall changes in the task indices between 1995 and 2021 can be attributed to changes in the structure of employment (changes between occupations) or changes in the tasks within jobs (changes within occupations). The between occupations part refers to changes in a task that are due to a decline or an increase in the number of workers in an occupations where that particular task is performed a lot (for instance, the physical task index would decline if less workers are performing jobs that require physical tasks). The within occupations part refers to changes in a task that are due to changes over time in the type of tasks workers perform within a same occupation (for instance, the physical task index would decline if workers in a job that used to be intensive in physical tasks no longer perform physical tasks). We decompose the change of the index of a certain task j over the period 1995-2021 as follows:

$$\text{task}_{j,2021} - \text{task}_{j,1995} = \text{within}_j + \text{between}_j + \text{residual}_j$$

where $\text{task}_{j,2021}$ and $\text{task}_{j,1995}$ represent the average task index j in the overall employed population. The third term in the decomposition is a residual which includes possible interaction effects between within and between occupational changes. Appendix B contains a more detailed explanation of how each term in the decomposition is estimated.

The results of the decomposition analysis are presented in table 8. They suggest that the increase in the use of computers is mainly due to changes within occupations. The change in the problem solving task index is mainly due to changes between occupations while the change in the creativity task index can be attributed

to changes within occupations. The decline in machinery use is largely due to changes in the occupational structure and, finally, the increase in the routine task indices are due to changes within occupations.

Table 8: Decomposition analysis of task changes, 1995-2021

	Task		Change	Changes within occupations	Changes between occupations	Residual
	1995	2021				
Physical: Strength	24.1	31.5	7.4	11.7	-3.1	-1.1
Intellectual: Problem solving	64.9	66.1	1.2	-1.4	6.0	-3.4
Intellectual: Creativity ^a	81.9	87.4	5.5	5.4	0.8	-0.6
Social	58.9	56.5	-2.4	-2.0	3.7	-4.0
Methods: Autonomy ^a	76.4	74.8	-1.6	-2.7	1.1	-0.1
Routine: Repetitiveness	39.4	59.0	19.6	23.3	-4.8	1.1
Routine: Standardization ^a	53.3	60.0	6.7	7.6	-1.3	0.4
Tools: Machines ^a	12.1	10.4	-1.7	0.1	-1.2	-0.7
Tools: Technology	27.3	77.4	50.1	42.8	4.0	3.2

The sample consists of Belgian workers in 1995 and 2021. The task indices are measured on a scale from 0 to 100 indicating the intensity by which the task is performed (the higher the value, the more intensively the task is performed). The construction of the task indices is presented in the Appendix A. The first two columns give the mean task indices in 1995 and 2021, respectively, and the third column the change in the task indices. Columns 4 to 6 give the results of our decomposition. Changes within occupation changes in a task that are due to changes in the type of work workers perform within a same occupation and changes between occupations describe changes in a task that are due to changes in the occupational distribution.

^a Data not available for 2021 so trend coefficients are measured over the period 1995-2015.

5. Consequences for skills requirements

In this section we investigate the consequences of technological change and the resulting changes in the task composition of workers on skill requirements and we discuss the implications of our empirical findings for skill requirements in the Belgian labor market.

Because technologies change the type of tasks workers perform, technologies also affect labor demand and skill requirements. There are two major theories on the consequences of digitalization on skill requirements: ‘skill-biased technological change’ (SBTC) and ‘routine-biased technological change’ (RBTC). The SBTC theory explains that new technologies benefit workers with higher skills who see their labor demand increased, in detriment to lower skilled workers (Berman, Bound, & Griliches, 1994; Autor, Katz, & Krueger, 1998; Bresnahan, Brynjolfsson, & Hitt, 2002). The SBTC theory is built on the idea that new technologies complement more-skilled workers and substitute lower-skilled workers. The fact that educational levels have increased a lot over the past decades and that over this period the wages of higher educated workers have not fallen (on the contrary), supports the SBTC theory since the findings imply that the demand for higher educated workers must have increased over time with technological change (Autor, Katz, & Krueger, 1998). The RBTC theory predicts that digitalization leads to an increase in the demand for high-skilled and low-skilled workers and to a decrease in middle-skilled workers. This follows from the fact that the RBTC theory states that technological changes lead to an increase demand for workers performing non-routine tasks and to a decrease for workers performing routine tasks (Autor, Levy, & Murnane, 2003; Autor D. , 2014). Non-routine tasks which describe both tasks requiring problem-solving capabilities, intuition, creativity or persuasion (‘abstract non-routine tasks’) and tasks requiring situational adaptability, visual and language recognition or in-person interactions (‘manual non-routine tasks’), are particularly performed by both high-skilled and low-skilled workers (Autor, Levy, & Murnane, 2003). Routine tasks, on the contrary, are particularly performed by middle-skilled workers.

The RBTC hypothesis is thus consistent with the phenomenon of job polarization which is observed in many countries (e.g., Autor, Katz, & Kreaney (2006), Acemoglu & Autor (2011) and David & Dorn (2013) for the US; Goos and Manning (2007) for the UK; and Goos, M., Manning, A., & Salomons (2009; 2014) for Europe). Job polarization describes an increase in the employment shares in high-paid and low-paid jobs and a decrease in the employment shares in the middle-paid jobs. According to Jensen, Nielsen & Christiansen (2019), job polarization has been weak in Belgium compared to other European countries (such as France and Austria). Indeed, while there has been a clear increase in the share of workers in high-paying occupations and a clear drop in the share of workers in middle-paying occupations between 1997 and 2017,

the share of workers in low-paying occupations has remained relatively unchanged. Deschacht & Detilleux (2022), who used the Belgian Labor Force Survey to study sectoral and occupational evolutions, provide similar results. The phenomenon of job polarization is thus less pronounced in Belgium but we can still observe an increase in the percentage of workers in high skill occupations and a decrease in the percentage of worker in middle-skill occupations.

Some of the results reported in this paper are in line with the RBTC theory. First, we find that non-routine tasks are performed by both low- and high-skilled workers and routine tasks by middle-skilled workers. Indeed, table 3 shows that intellectual task indices, which can be considered as abstract non-routine tasks, are particularly high in high-skilled occupations (ISCO groups 1, 2 and 3) and that the physical task index, which is a manual non-routine task index, is particularly high in health occupations (ISCO groups 22 and 53) and in low-skilled elementary occupations (ISCO group 9). The mean routine task indices are, on the contrary, particularly high in occupations 7 (“Craft and related trades workers”), 8 (“Plant and machine operators and assemblers and 9 (“Elementary occupations”) but also in occupation 44 (“Clerical support workers”). Next, we find that non-routine task indices are higher in occupations that have been growing over time while routine task are higher in declining occupations. This suggest that the demand for non-routine tasks is increasing to the detriment of routine tasks as stated in the RBTC hypothesis.

The two main skills required to perform non-routine tasks are expert-thinking skills, i.e. “the collection of specific solution methods that vary according to the problem at hand” and complex communication skills (Levy, 2010). Computers still struggle to replace human input in solving unknown or unanticipated problems or tasks that do not follow clear rules. Solving new problems thus remain something for humans to do and expert-thinking skills such as adaptability, creativity, flexibility or problem-solving will still be required in the future (Levy, 2010; ILO, 2021; Manyika, et al., 2017; Autor, Levy, & Murnane, 2003; Goos M. , 2018). Computers also fail in replacing workers in tasks demanding complex communication and customer service skills (Levy, 2010; ILO, 2021; Manyika, et al., 2017). Communication can be very ambiguous since it does not only depend on the information given, but also on the context and the intonation used (Levy, 2010). By quickly replying to the questions, correcting misunderstanding and showing sympathy, humans can do a much better job in communicating information than machines. Because communication or complex thinking skills do not follow clear rules, they are quite complicated to teach. The literature shows that a strong foundation in reading and numeracy skills provides a strong basis for these more complex skills, because being able to formulate a problem or being able to identify important information is what will matter in future.

On top of the skills needed to perform non-routine tasks, digital skills are also likely to be required in all jobs in the future since digital technology is playing an increasingly important role and it now complements many workers in performing their work tasks. Our results support this idea since we find that computer use at work has increased dramatically over the past 25 years; the mean ICT task index more than doubled between 1995 and 2021. Together with expert-thinking and communication skills, digital skills are part of the *21st century skills* which define the knowledge and skills that are critically important for career success in today’s world (Van Laar, Van Deursen, Van Dijk, & De Haan, 2017). Digital skills range from generic skills which enables the use of digital technologies to access information or use software to more advanced skills such as programming, the development of applications or the management of networks (Kiss, 2018).

The tasks workers perform at their jobs are likely to change over the span of their employment. That is, even if the skills workers acquired before employment allows them to perform their tasks today, they are no guarantee for the future. Hanushek et al. (2017) argue that this is particularly true for workers with vocational education, since they acquired more specific skills that allows them less easily to adapt to changes in their work tasks. More general education may provide workers with broader knowledge and a solid foundation for further learning and adaptability to changes in work tasks (Hanushek, Schwerdt, Woessmann, & Zhang, 2017). In short, general education may teach workers how to learn and, hence, arm them for the challenges ahead in this digital era.

6. Discussion/Conclusion

Using the European Working Condition Survey (EWCS) and the Survey of Adult Skills (PIAAC), this chapter empirically examines the work task composition of Belgian workers over the past 25 years. We first describe the task composition of workers today and examine its relation with workers' characteristics. Then, we study how work tasks in the Belgian labor market have changed between 1995 and 2021 and we perform a decomposition analysis to study to what extent changes in the task composition of workers can be attributed to within occupation changes in tasks and changes in the occupational distribution. Finally, we investigate the consequences of technological change and the resulting changes in the task composition of workers for skill requirements.

We find that intellectual task indices are much higher than physical and social task indices. High-educated workers have higher intellectual task scores compared to low- and middle-educated workers and the opposite is true for the physical task index. We also find that physical and social task indices are higher for women compared to men. Looking at the method and tools used at work, we find that technology is much more intensively used than machines (not ICT) and that machines are more intensively used by low-educated workers. Low-educated workers also more often perform repetitive jobs and high-educated workers more often work autonomously. Next, we find that the physical, machine and routine task indices are concentrated in blue collar occupations. The physical task score is also high among health professionals and personal care workers. Because women are concentrated in these occupations, this could explain why the physical task index is higher for women. Intellectual and technology task indices are higher in white collar occupations. Since the growing occupations are mainly represented by white collar occupations and declining occupations by blue-collar occupations, we also find that intellectual and technology tasks are more common in growing occupation while physical, routine and machines tasks are more common in declining occupations.

Looking at the evolution of task indices, we find that there has been a large increase in the use of computers at work between 1995 and 2021, and that this trend accelerated between 2015 and 2021 which could be related to the Covid-19 pandemic. We also find that routine tasks have increased over the past 25 years and that the use of machines at work has decreased between 1995 and 2015. The increase in the routine tasks is concentrated in white-collar occupations and the decrease in machine tasks in elementary occupations. Our decomposition analysis suggests that the change in the routine and technology task indices are largely due to changes within occupations while the change in the machine task index is due to changes in the occupational distribution. There are no clear overall changes in intellectual, social and autonomy task indices. Intellectual tasks have been decreasing over time in white-collar occupations and we find that while the social task index has decreased in white-collar occupations, it has increased in blue-collar occupations. Somewhat surprisingly, we find that physical tasks have been increasing over the past 25 years and especially between 2015 and 2021. Our decomposition suggests that the changes in this task index are mainly due to changes within occupations.

Some results such as the increase in physical strength at work, the decline in problem solving, the average physical task index that is higher in the female sample compared to the male sample are somewhat unexpected. There are various possible explanations for this. The results might be explained by real trends such as the substantial increase in healthcare jobs, which often require physical work, or these results could be related to the quality of the survey. As explained before, the advantage of survey data compared occupational databases is that one can study the evolution of tasks over time. Yet, workers themselves answer the surveys and this may lead to imprecise estimates of the task composition when respondents find it hard to respond to questions about the intensity by which they perform a task. The 2021 data are quite exceptional because the questionnaires had gone through major modifications and the collection of the data was done during the Covid-19 pandemic. During the pandemic some sectors had been closed down (e.g. the HORECA) while the importance of other sectors had grown (e.g. the health sector) and these circumstances may be driving our results. Future data are required to tell whether the trends we observe are part of longer-term trends or not.

Our study on the consequences of the digital revolution for skill requirements suggests that skills required to perform non-routine tasks (expert thinking and complex communication skills, as well as digital skills) are likely to become more important in the future. We argue that because of the rapid pace of changes introduced by the digital revolution, the task of workers are expected to evolve and change over workers' careers. Workers will thus need to be capable to adapt themselves to changes and to be able to learn new skills. A stronger emphasis on general education, and basic numeracy and reading skills, may teach workers how to learn and, hence, arm them for the challenges ahead in this digital era.

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