DOMINANT TECHNOLOGY AND ORGANIZATION: IMPACTS OF DIGITAL TECHNOLOGY ON SKILLS

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Abstract

This paper describes a new approach to investigating, unraveling and explaining the implications of digital technologies for skills. To do so, the paper develops an approach to assess technology in companies in a more precise way, building on three main arguments. Firstly, current approaches to the subject treat all (new and emerging) technologies as equal. A more specific approach to technology is needed. Secondly, instead of starting from the potential of digital technologies, the focus should be on how technology investment decisions of companies are actually taken. Companies do not automatically reason from the available technology potential, but rather build on their current technology and capital stock and competitive position (the potential of technology). Thirdly, the organizational context should be considered. The actual use of skills in companies is strongly related to the organizational context. This is identified as the dominant organizational context. Based on these three main arguments, a new framework for work and skills technology impact research is suggested. Subsequently, the framework is applied to two professions in Dutch industry.

Key words

Skill Development, Future of Manufacturing, Industry 4.0, Work Design, Digital Skills

1 Introduction

The increasing use of advanced digital technologies is transforming innovation and production activities (Alcacer et al. 2016). This also changes the requirements for skills within and between organizations, sectors and countries, and may even render existing skills redundant or outdated (Autor 2015; Autor et al. 2015; Silva/Lima 2017; Zysman/Kenney 2018). The new digital paradigms include a wide range of enabling technologies, such as the Internet of Things, additive production, big data, Artificial Intelligence, cloud computing and augmented and virtual reality (Rindfleisch et al. 2017). However, although substantial research is being conducted into the relationship between digital innovation and skills, especially also in relation to ICT-acceptance (e. g. Autor et al. 1998), the impact of new digital paradigms for innovation, production and skills needs to be further explored (Consoli et al. 2016).

The existing research on the impact of new (digital) technologies on labor and skills is mainly focused on the impact of (digital) technology on the number and type of jobs (e. g. Atkinson/Wu 2017; Frey/Osborne 2013; 2017; Van Roy et al. 2018). Yet, the predictions in these studies are rather mixed. Some studies predict that between 40 and 90 percent of jobs may be lost (Frey/Osborne 2017), while in other studies, these percentages are around 10 percent (Arntz et al. 2016). This often gives too static an interpretation of what professions are. Little or no account is taken of mitigating effects such as the job content changes because of technology. New technology creates new types of jobs and new technology can lead to more work if the demand for products increases (Arntz et al. 2016). In fact, the introduction of these types of technologies is also much slower than expected (Van Helmond et al. 2018). In practice, the range of tasks in professions appears to be much broader and more adaptable than expected – which means that professions continue to exist, even if many tasks are computerized (Atkinson/Wu 2017). In general, the research has also mainly been approached from a macro and policy perspective (e. g. McKinsey 2018), and based on existing but limitative datasets (Frey/Osborne 2013; 2017). To the best of our knowledge, no new data or monitors have been developed to assess the impact of new technology.

Another important criticism of existing research is that technology has only been operationalized in a limited fashion (see for example Arntz et al. 2016; Frey/Osborne 2013; 2017; Kim et al. 2017). Frey and Osborne (2017), for example, only look at the possibilities of Artificial Intelligence (AI) and robots to overcome bottlenecks in professions. The most contentious point in their approach, however, is that computerization risk is measured by looking at the degree jobs contain certain skills: social, communicative, mathematical, problem solving and ICT skills. The degree that current jobs contain these skills predicts the degree that they will be computerized. It should be clear that predicting future skill needs with such an approach will lead to tautological reasoning. Graetz and Michaels (2015) and Acemoglu and Restrepo (2017a; 2017b; 2018) look at robot technology present in a region. Bessen et al. (2019) only focus on investments in technology. Brynjolfsson et al. (2014) also focus on a limited number of digital technologies, in particular AI, but do not empirically investigate this.

And finally, an important point of criticism is that the organizational context must be considered but is generally ignored in the analysis (Agnew et al. 1997). There is a lack of specific insights into how specific digital technologies are implemented and developed in organizations. In most research, this organizational dimension is a black box, as it is completely absent (including Frey/Osborne 2017; Kim et al. 2017; Arntz et al. 2016). However, these insights into the relationship between technology and organization are crucial to understanding and explaining the real impact of digital technologies on labor, organizations, tasks and skills.

Therefore, the understanding of the impact of digital technology needs further development. Technology must better be operationalized, and the organizational context and aspects of work, as well as technology investment factors, should be included in future research as well. This paper introduces two core concepts for research into the impact of digital technologies on work in companies and sectors that address the above issues and can bring the discussion further: the dominant technological context and the dominant organizational context. These concepts will be operationalized and the benefits of using these concepts in research will be shown. An example of changes in skill demand within and between jobs in the Dutch manufacturing industry shows the strength of this approach.

2 Dominant technology

To examine the impact of new digital technologies on skills and organizations it is important to determine what the dominant technologies will be for organizations. We believe three elements are important for this: first, specify the focus technologies; second, understand the heterogeneity of technology in organizations, i. e. vintage and investments in technology; third, the measurement of technology. These elements are explained below. The ideas are applied to the example of Dutch industry.

2.1 Five technology types

In the current research into digital technology, the implicit assumption is that it does not matter which manifestations technology takes. In the recent World Economic Forum report 2018 (WEF 2018), technology was conceived as the degree of adoption of nineteen specific technologies (from big data analytics to drones). The technology adoption rate is the percentage of companies that have implemented the technology. Bessen et al. (2019) see automation as the cost of automation. They make the distinction between automation costs and computer investments. However, they mainly gain insight into technology investments rather than the existing technological situation in a company. Also, the Internet of Things, additive manufacturing, big data, Artificial Intelligence, cloud computing, augmented and virtual reality, cobots, etc. are all assumed to have the same impact on the scope and quality of the work. In other examples of this approach, digital technology is sometimes measured using proxy variables, such as the percentage of robots in a country (Graetz/Michaels 2015) or calculated at the level of a region (Acemoglu/Restrepo 2017a, 2017b, 2018; Dauth et al. 2017). Some authors make more distinctions between types of technology. Acemoglu and Restropu (2017a, 2017b, 2018) distinguish between two types of capital: low-skilled automation and highly-skilled automation. They link these differences in automation to examples such as "industrial robots" and "AI". The Acemoglu and Restropu-model does not consider other types of technology.

From an organizational point of view, not all technologies are the same and they not only influence the complexity of tasks, but also the way in which organizations are managed. New technology thus influences various aspects of organizing that determine productivity. Bloom et al. (2014) have proposed another classification. They assert that ICT should not be viewed as a whole, but that information technology and communication technology in particular have different organizational consequences. Information technology (e. g. ERP, CAD/CAM) helps to strengthen the ability of middle managers to search for solutions, so that they can be expected to broaden their jobs and grow in autonomy and decentralization ("data access": Trantopoulos et al. 2017). Communication technology, on the other hand (e. g. email and communication networks), ensures that decision-making and coordination can take place more quickly. This allows middle managers to specialize more in what they are strong at and allows central managers to more quickly ensure alignment between middle managers. Communication technology therefore leads to task specialization and centralization of decisions. In fact, their distinction can also be used for the relationship between (all) management levels and the first-line workers. Communication technology affects the relationships from top to bottom in an organization; information technology allows for task enlargement at all levels. Ter Weel (2015) adds to this distinction that technologies can be aimed at automating tasks, or at increasing the capacities of employees (in line with information technology). We would like to add that innovations are also possible in management systems or organizational measures (Kuipers et al. 2018; Maenen 2018; Oeij et al. 2017). These different technologies can be more or less aligned in their implementation in organizational settings. Innovations in other dimensions of technology can be in line with impacts of information and communication technology.

With these distinctions, the complex technological developments can be reduced to the five categories information technology, communication technology, management systems, "hard" automation and human enhancement technology. These technologies have distinct predicted impacts on employment dimensions. Table 1 provides an overview of these five types of technology, with their process impact and expected labor impacts.

Type of technology	Process impact	Employment impact
Hard automation	Technology can automate human labor. This usually involves "hard automation" in which technology takes over the actions and tasks of employees completely. Examples are robots or automatic welding machines. Other examples in logistics are self-driving cars and trains, autonomous ships. It is important in hard automation that it does not always involve equipment. Sometimes it is possible to have customers do more work so that work can disappear. Think of supermarkets where cashiers become redundant when customers do self-scanning.	Disappearing tasks and occupations.
Human enhancement (supporting) technology	Technology can support employees in the execution of their tasks. This usually involves mechanical tools, but it can also involve automated tools such as exoskeletons (in construction and assembly) or digital tools such as vision picking (in logistics).	Enlargement of operator capabilities. Increased productivity.
Communication technology	This technology focuses on the communication processes between employees or between employees and managers. Communication with the outside world (e. g. customers, suppliers) can also be structured differently using this technology. Communication technology has contributed to the strong rise of global value chains. This technology fits in with the management processes in organizations. Communication technology does not always have to be mobile technology. A conveyor belt can also be seen as communication technology. Such a conveyor belt helps employees to specialize and centralizes decisions about the production process.	Strengthening of hierarchy, narrowing of tasks/specialization.
Information technology	This is a separate technological change that fits in with the way in which employees gain access to information. Data access technology is mentioned in the literature: information technology helps to speed up access to information.	Decentralization, broadening of tasks.
Management systems	With this technology, activities in organizations are to a large extent standardized and uniformed. Other technologies can play a role in such systems, but not necessarily. An example is the Lean Production system.	Quality improvement, productivity improvement, integration and specialization.

Table 1: Five technology types and their impact

2.2 The process of technology implementation: vintage and investments

In addition to the distinction between types of technology, the process aspect in technology needs to be considered. As was indicated, the potential of technology, the investment strategy and the available technology differ by nature. The process perspective helps us to understand the heterogeneity of the technology situation in organizations.

A starting point to understanding the technological situation in organizations is to find out what the current technology base of a company is. Porter (1985) saw technology as part of the core competence(s) of a company. The success of the application of new digital technologies depends on the current technological knowledge in the company. In the 1980s, a great deal of attention was given to the composition of the capital stock of companies. In calculations of total factor productivity, an estimate of the capital stock is needed. In this context, much research has been done into the calculation and composition of (company) capital. The reasoning is that the strength of a company depends on the extent to which the capital consists of new "vintages" of technology. Old vintages of capital must be replaced by new ones in order to cope with rising wages (Vergeer et al. 2015). During the 1980s, the importance of vintage effects of capital was long discussed by Dutch economists (Meijers 1994). The opinion was that the low wage policy followed by Dutch governments removed an incentive to invest in new technology, with the result that productivity fell due to outdated technology ("old vintages"). A criticism of this view is that vintage only "looks back", i. e. determines what existing technology is. However, recent investments in new technology can be an obstacle to investing in the most recent disruptive technologies. And new technologies may not always be the most efficient. "The results show that in some circumstances older vintages might appear on the efficiency frontier, unlike some newer vintages that are found to be inefficient, despite benefiting from the advancement of the technology." (Belu 2015).

There are few data sources available for the operationalization of "vintage". Calculating the impact of vintage is usually fairly complicated and the results only apply when all kinds of problematic assumptions are met. A recent German study, the IAB company panel survey (TNS Infratest 2014), measures vintage in a qualitative way: companies indicate to what extent their technology is "out of date" or "state of the art". What is important about the vintage discussion is that new technology needs time to be implemented. It can take time before a new technology has a positive influence on production/service provision (Nilutpal et al. 2009).

Secondly, it is also about the investments that companies make. What do companies want to change in their current capital? If the market offers a lot of "potential" of new technology, what exactly is the potential selected? If we take the results of Table 1 into account, can we then gauge what is being invested in? Traditionally, investments in "hard technology" are considered in order to show the capital investments of a country. For example, EU-KLEMS data[1] indicates how much was invested in tangible assets in the last year. Much is known about these investments at an aggregated level. Acemoglu and Restrepo (2018) focus precisely on these investments. Two questions are important here. The first question is what exactly is it that you want to know about this tech_nology. The EU-KLEMS study is mainly concerned with estimating the differences in the distance to the technological frontier. This frontier is a measure of technological advantage, and traditionally the country that generates the highest Total Factor Productivity with a technology is seen as the frontier. The EU-KLEMS data provides information on the differences in technology. The changes in investments indicate how countries want to make up for their shortfall (or lead) (CBS 2018, S. 106).

But it is not just about "hard technology". Various studies, sponsored by the OECD, have clarified that companies also invest money in less "hard" technologies to increase their

1 www.euklems.net/

productivity (Corrado et al. 2012; OECD 2015). This concerns "knowledge-based capital (KBC)" that consists of investments in ICT, R&D, management training, organizational capital, etc. (Gomez/Vargaz 2012; OECD 2013a). According to research by Corrado et al. (2012), investments in KBC contribute about 7 percent to 8 percent to the annual growth in labor productivity, which is slightly more than the contribution of investments in "hard capital". However, the research on KBC is progressing slowly. The main reason is that only register data is considered, only what is available about investments in companies. In the KBC, investments in management quality and company-related R&D account for the largest share (Elbourne/Grabska 2016; Andrews/Westmore 2014). For management quality, several measures are used. In Saia et al. (2015), this quality is related to PIAAC scores. Andrews and Westmore (2014) look at the extent to which professionals are supported for management positions. Earlier KBC studies looked at the size of the management consultancy sector. The importance of KBC is that it is seen as an important factor in promoting the diffusion of new technology (Elbourne/Grabska 2016).

The research into "intangibles" is also relevant to this paper because it provides us with insight into the scale of ICT investments. The main objective of the research by the EU-KLEMS network is to establish why all investments in technology and ICT do not yet lead to a productivity leap in economies (Byrne/Corrado 2016). Byrne and Corrado identify several reasons why the expected productivity leap is not visible, such as the fact that ICT costs are falling very sharply. More work is needed here because it remains difficult to determine the impact of ICT investments on growth. Various elements of ICT appear to be difficult to grasp in growth statistics. For many aspects of the investments, it will actually be necessary to look at the company level to determine what companies pay attention to technology and capital stock development (see Bessen et al. 2019).

2.3 The potential of technology

Most analyses of technology are about the potential of technology, what technology can do and how that potential will have consequences for work. Most consultants focus on this potential (WEF 2018; McKinsey 2018). In addition to the fact that no coherence is seen/differentiation is made between all these technologies, there is also no weighing of which technology will have the most impact. The OECD (2015) has proposed the "technology burst" imagery to determine differences in the potential of new technology. A "burst" exists when the number of patents in a technology field increases sharply at a given moment. In that case you can expect that new applications will flood the markets in the short term. Patents may not be the best indicator of the potential of technology. It is important to bear in mind that only half of the patents are used for a variety of reasons (CBS 2018). Despite this complication, a patent does give some indication of the development of the knowledge intensity of a sector and specialization of knowledge.

To illustrate this, we indicate what this "technology burst" reasoning yields if we use the distinction of five types of technology in the manufacturing industry. Using the Espacenet patent database, we made an inventory of patents related to the five technology-types. Espacenet is a tool of the European Patent Office (EPO) and gives free access to more than 100 million patents from all over the world. For the purpose of our analysis, specific technology categories were investigated, the date on which the first patent could be found, and the percentage of new patents for each category in the past five years. Figure 1 presents an overview of this analysis.

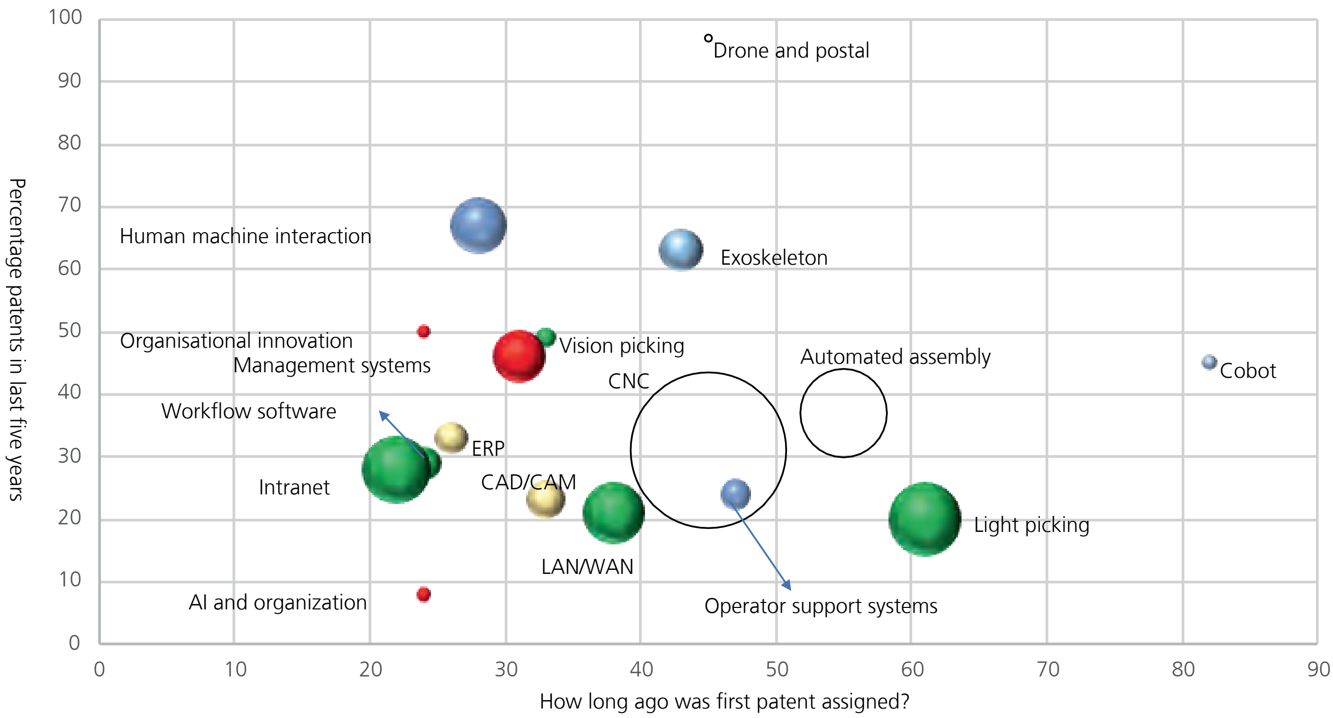

Figure 1: Overview of history of patent category, size of number of patents (size of bulb) and importance of number of patents in the past five years (Espacenet, download 10-8-2018) | Black circle: technology that automates human labor ("hard technology") | Blue circle: technology to support employees | Green circle: communication technology or technology that allows control from above | Orangelyellow circle: information technology that gives employees more access to information | Red circle: management systems or organizational innovation

2.4 Measuring dominant technology

How can these ideas relating to type of technology, vintage, investments and potential of technology be integrated to assess the technology situation in an organization sector or country? This is where the concept of "dominant technology" becomes useful. It is appropriate to distinguish between type of technology and phase in the investment process, but how can one weigh the dominant technological position of a company? There are no approaches to this in the literature. We propose to develop a composite index to determine which technology is dominant. Figure 2 clarifies what we have in mind.

The figure shows three phases in which a technology for a company, sector or country is situated: the actual use, the investment phase and the development or potential phase. The size of the bulb in the figure indicates how the technology in a phase relates to other technologies: the larger the bulb, the greater the importance of a technology in that phase. The colors of the bulbs indicate the growth of the technology in a specific time context: dark green indicates strong growth in a technology, light green limited growth, and orange a decline in growth. The figures in the bulbs mean the following:

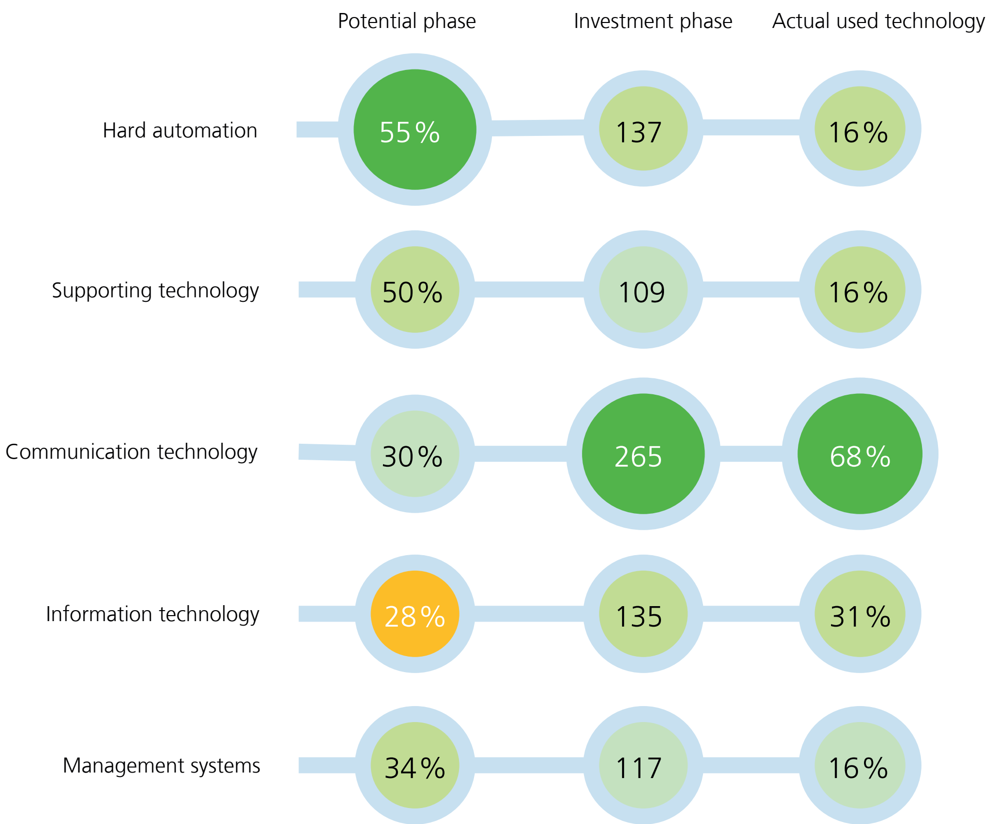

Figure 2: Visualization of dominant technology in the Dutch manufacturing industry

- Actual technology use ("reality") is the percentage of companies that have implemented a specific technology.
- Investments ("strategy") are an index figure (with an index = 100 for a comparable reference year) showing the growth compared to a reference year.
- Development ("potential") is the percentage of patents that have been approved in the past five years compared to the total number of patents in a technology.

Dominance is then determined as the technology that comes out strongest in the comparison between the three phases. The assumption is that the current reality must first be weighed, then the investments and only then the potential phase. In order to determine which technology will have the most influence on skills and work, we need to look not only at each phase, but also at all phases at the same time. This means that many combinations are possible, i.e. in the "vintage", for example, communication technology can be dominant, and in the investment phase attention shifts to information technology. In the longer term, it may be that the development in hard technology will weigh most heavily. Figure 3 shows three possible alternative technology situations.

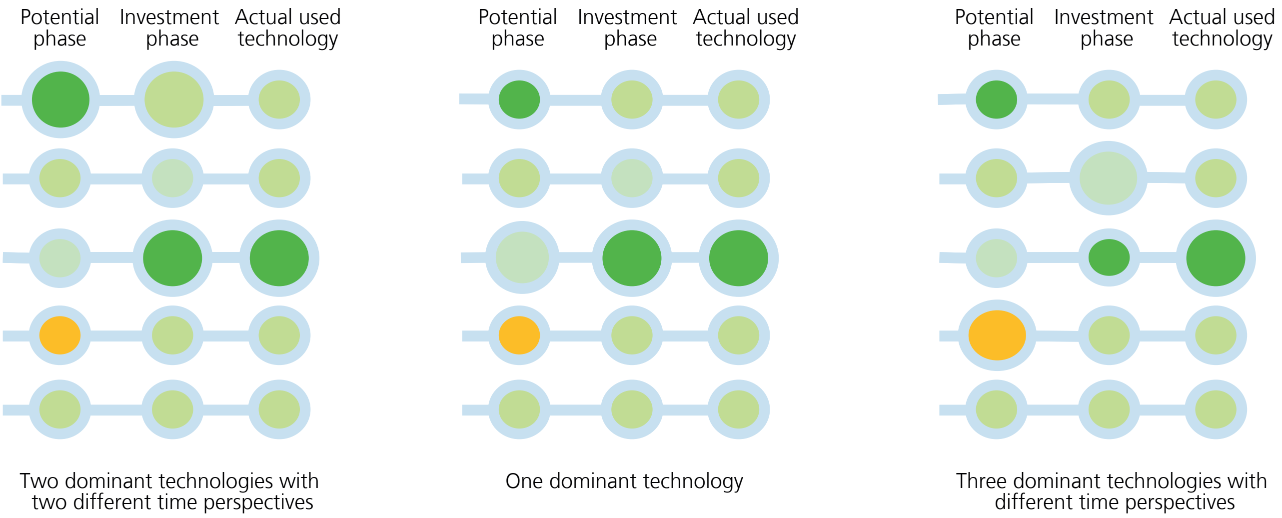

Figure 3: Examples of three alternative technology situations

In the first figure in Figure 3, two technologies are dominant, but in different phases: hard automation is a future given while currently communication technology dominates the installed base of technology and the investments. The second figure only shows one dominant technology: communication technology. Figure three shows a very dispersed picture: information technology promises a lot of changes in the future, supporting technologies are most important in the investment phase, and communication technology dominates the installed base. The dominant technology situations may therefore sometimes be very clear, sometimes more heterogeneous.

This perspective means that the supply of technology itself is not enough to grasp what will happen in companies. First it is important to examine what technology is present in the companies and then in which technologies investments are made. Only then is it useful to look at the supply of new technology.

2.4 Dominant technology in the Dutch manufacturing industry

To illustrate the power of this approach, an example of the dominant technology in the Dutch manufacturing industry was developed. In order to determine the dominant technology, a combination of several information sources was used (see for full information: Dhondt/Kraan 2019). For the existing technology, an analysis was made of the Dutch Statistics data on ICT (Statline data on ICT use by companies) and the Netherlands Employers Surveys (Van Emmerik et al. 2017). To calculate the investments in knowledge-based capital in Dutch industry, some of the necessary data is available. The EU-KLEMS data indicates how much was invested in tangible and intangible assets in the past years. However, the intangible assets are not complete, as described by Corrado et al. (2012) and the OECD (2015). Costs incurred for HRM, e. g. organizational investments, are not included in the figures for EU-KLEMS. Corrado et al. limit themselves to R&D and software investments. In the Dutch manufacturing industry, the ratio between tangibles and intangibles has shifted in favor of intangibles in the short term. In recent years, companies have again started to invest more in "hard technology", but intangible investments appear to have received even more attention in the manufacturing industry in the past few years. If one looks at at the whole of the Dutch industry, the same increase can be seen in intangibles, thanks to the fact that hard investments still weigh more heavily.

Figure 2 shows the outcome of our analysis for the dominant technology in Dutch manufacturing. The development in a technology is reflected in the series of three bubbles. The numbers in the bubbles represent the proportions between the bubbles at one particular moment:

- Potential: to assess the potential of technologies we use the percentage of patents in the last five years of total patents in a technology category in a given industry (for example 55 percent = 55 percent of patents for hard automation have been issued in the last five years);
- Strategy: the investment index for 2011–2015 has been calculated, which reflects the growth in investment in a technology (2011=100) (for example, investments in hard technology have increased by 37 percent during this period);
- Reality: the percentage of companies that have applied a technology from that category (e. g. 16 percent of companies have robots).

The size of a bubble indicates in which development perspective (potential, strategy, reality) a technology has the most weight. The largest bubble in a phase carries the greatest weight. The colors represent the situation in 2011–2017: dark green shows that there is strong growth in a technology; light green indicates that growth is limited; orange indicates that there is decline. In the Dutch manufacturing industry, this means that communication technology can be expected to have the most important influence now and in the short term. This means that network technology, e-mail systems and mobile technology will have the strongest impact on organizational processes and occupations. This technology strengthens the communication flows in the companies and, according to Bloom et al. (2014), should result in a stronger centralization of decisions towards top management and a narrowing of occupations on the shop floor. In the longer term, "hard automation" in Dutch industry seems to be bringing about major changes.

3 Dominant organizational context

3.1 Distinct organizational concepts

A second major determinant when looking at the impact of technologies on jobs and skills is the organizational context in companies and organizations. There is a general lack of insights into how specific digital technologies are implemented and developed in organizations. With management systems as the 5th technology type, we already introduced at the dominant technology level an aspect of how work is organized. However, we need to clearly distinguish management systems from organizational concepts, even though in practice there may be overlap between the two. Management systems are defined here as rules on how to work and the information systems that contain those rules. This means that these systems mainly include parts of the control system in an organization. Organizational concepts are broader and include the control, but also the views on how the work should be carried out, i. e. the division of labor. Organizational systems that are aimed at visualizing all aspects of the work are aimed at control. TQM, lean production and other concepts try to operationalize quality and performance of production systems. Other concepts such as workplace innovation (see Oeij et al. 2017) or employee-driven innovation (Aasen et al. 2013) are aimed at maximizing employee involvement in order to optimize innovation.

3.2 Measuring organizational concepts at different levels

The way in which technology is shaped within companies is also related to the organizational form. This presents a chicken-egg problem. According to economists (Bloom et al. 2014; Ter Weel et al. 2010) organizational form is seen as an effect of the technology, whereas organizational sociologists indicate that the choice for the technology is an effect of targeted choices (Child 1972; Kuipers et al. 2018; Maenen 2018). Changes in the organizational concept are regarded as an innovation instrument for companies. In the previous section, it has been indicated how companies have in recent years invested more in their organizational capital than in hard technology (see also OECD 2013a). The question is how the organizational concept itself can be operationalized. Different perspectives are discussed here. When looking at the organizational level, control and production processes should be considered. Control processes concern differences in the relationship between controlling, preparatory (planning) and supporting (maintenance) tasks. Decisions in these tasks can be centralized or concentrated. Centralization is about decisions in the execution of tasks in production or services, i.e. the distinction between managing and operational tasks. Concentration refers to bringing together preparatory and supporting tasks in production or service provision, i.e. creating complete or incomplete functions (job enrichment or the reverse) (Huys 2001). Companies can have all kinds of considerations to centralize or concentrate decisions. As the example of the Netherlands illustrates, in recent years companies appear to have increasingly centralized their control systems, supported (or driven) by communication technology (Borghans and Ter Weel 2006).

The introduction of this paper indicated that insight can be gained into the organization of work at the individual level of a worker. The task analysis advocated in the British Skill Survey (Felstaed et al. 2007), the PIAAC (OECD 2013b) and recently in the Netherlands Skill Survey (Oudejans 2012; Kleruj 2017) provides overviews of tasks related to preparation, support and management within organizations. Occupations without such tasks seem to indicate a focus on operational tasks. Occupations that do contain such tasks operate in contexts in which employees themselves must control their environment and the content of the work. Lorenz and Valeyre (2005) used the European Working Conditions Survey (Eurofound) to successfully distinguish, at the country level, the application of four organizational concepts: learning organizations, lean organizations, Taylorized organizations and simple organizational forms. The "learning" model is characterized by a high degree of autonomy and task complexity, learning and problem solving and a low degree of individual responsibility for quality management. The "lean" model is characterized by the presence of teamwork and job rotation, the variables for quality management and the various factors that limit the pace of work. Job autonomy is relatively low and strict quantitative production standards are used to control employees' efforts. The "Taylorist" model shows minimal learning dynamics, low complexity, low autonomy and an overrepresentation of the variables that measure the limitations of work pace. The "simple" model groups simple forms of work organization, where the methods are for the most part informal and uncoded. Advances in research into the impacts of technology will also have to take dominant organizational concepts into account in the research design.

3.3 Dominant organizational context in the Dutch manufacturing industry

What is then the current situation in the Dutch manufacturing industry? Dhondt et al. (2019) investigated seven major occupational jobs using the Netherlands Skill Survey (Ter Weel/Kok 2013). As explained above, the degree to which organizational tasks are included in a job explains the degree of labor division in an occupation[2]. From the study, 33 percent of middle managers operate in highly Taylorized work organizations. For packaging personnel, this percentage rises to 52 percent. The

2 For more information on operationalization, see Dhondt et al. 2019. A further elaboration of the results of the Netherlands Skill Survey is taken up in a follow-up article to this publication.

organizational concept used in a company is an important explanation of differences in occupational profiles. It is striking that in most occupational positions in Dutch manufacturing, the degree of Taylorization plays an important role. The reported percentages have not changed in both groups in past years, but the expectation is that Taylorization in both occupations will increase. One explanation is that the dominant communication technology logic plays a role, because this technology ensures a stronger centralization of regulating tasks in organizations. Occupations will tend to specialize.

4 Predicting impact of dominant technology and organization on skills

4.1 Future impacts

The analyses in sections 2.4 and 3.3 indicate that communication technology and Taylorization will be the dominant technology and organization in the coming years. If this context remains dominant in Dutch manufacturing, then further specialization at the occupational level and centralization of decision-making (with less autonomy for individuals) are the consequence. To illustrate this, results of the analysis of job profiles for middle managers and packaging jobs in the Dutch manufacturing industry are shown here. Both occupations are common in the manufacturing industry.

This paper focuses on improving the discussion about the relationship between new technology and work. The core debate is about the relationship between technology and skills. Other dimensions (quality of work, wages, etc.) are equally important, but receive less attention in the debate. Acemoglu and Restrepo (2018) and Bessen et al. (2019) for example focus exclusively on skills development. Frey and Osborne (2013) are interested in the size of employment in a job. Most of these studies assume a direct link between technology and labor aspects. Yet as indicated earlier, the organizational context must also be considered as a co-determinant of what kind of skills are needed. The skill debate revolves around two topics: the requested qualifications of individual workers and the issue of skills polarization at the workplace. The focus here is what impacts we can expect for the future of skills in the Dutch manufacturing industry, given the dominant technology and organization.

For estimating short-term impacts (three to five years), extrapolating trends still seems to be the most appropriate method. Other methods such as econometric estimations (Frey/Osborne 2017) or Markov Chain analysis (Kim et al. 2017) are only fruitful for long-term forecasts. The extrapolation method involves assessing the development in a dimension of work and then estimating how the dominant technology and organization will influence the development in that dimension. Trend information in itself is insufficient. It is important to estimate which factors will have more weight on the trend than others. That is why it is important to consider "expert judgement" in order to weigh the development in the trend. If possible, the information should be enriched with calculated information (e. g. extrapolation of time series). The full prediction requires (a) the current trend development in an occupational dimension and (b) the trend extrapolation for that dimension to the short-term future. Other extrapolations are possible but make calculations unnecessarily complex. The advantage of the presented approach is that any deviation from the trend should be made explicit. We only speak of a trend if there is a statistically significant change (or continuity) in a dimension. This approach is illustrated below.

4.2 Impact on skills within jobs

The following two figures below show the differences in required qualifications in two occupations in the Dutch manufacturing industry – for middle managers and packaging jobs – considering different organizational contexts. Organizational context is operationalized at the individual level as described above.

Figures 4 and 5 show that both middle managers and packaging workers in a "full job function" are asked for significantly more social, communicative, STEM and ICT competenci-

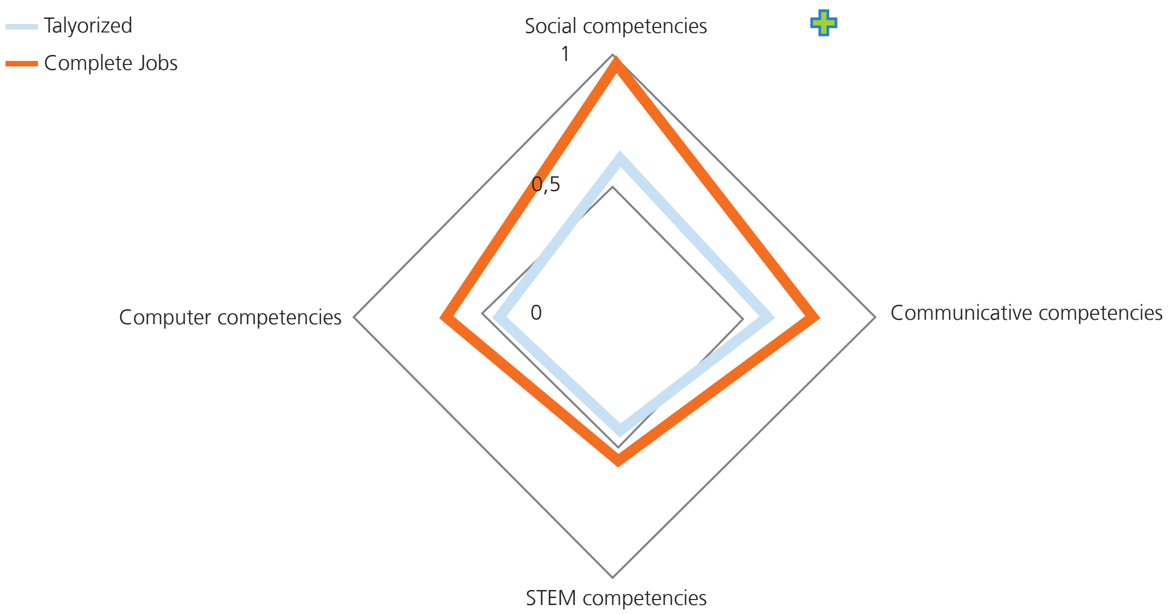

Figure 4: Middle managers: Overview of social, communication, STEM and computer competencies present. Comparison between available competencies according to Tayloristic or complete working context. Differences have been tested for significance (+: p<0.05).

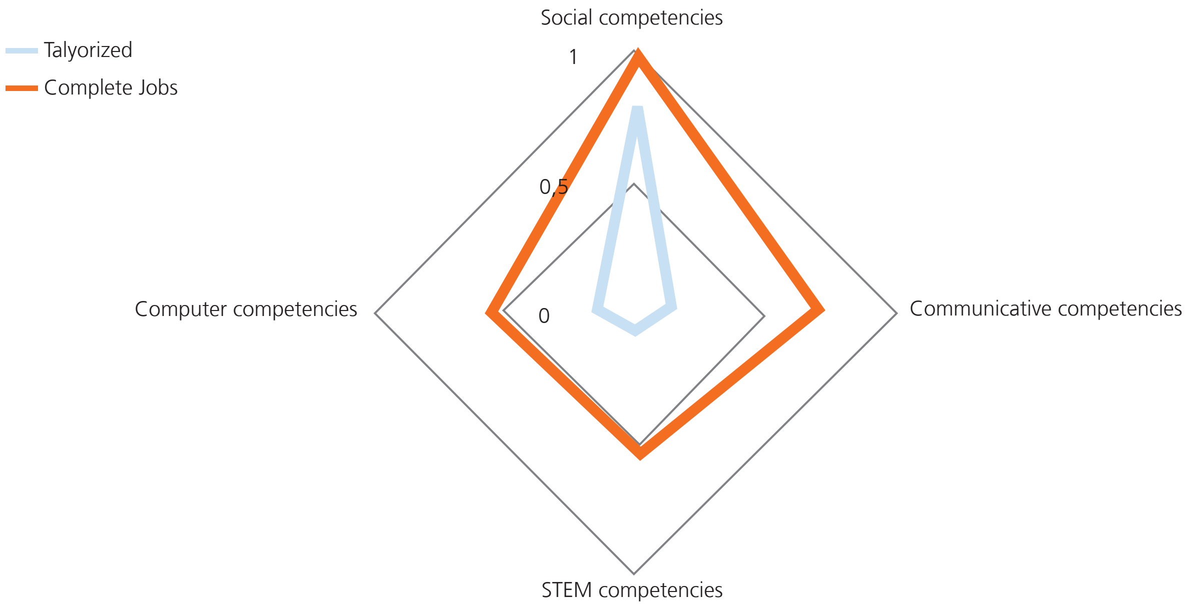

Figure 5: Packaging jobs: Overview of social, communication, STEM and computer competencies present. Comparison between available competencies according to Tayloristic or complete working context. Differences have been tested for significance (+: p<0.05).

es than in a "Taylorized function". If we know that the future degree of Taylorization in the function will increase, then it is clear that in the long term, fewer social competencies will be required for middle managers and fewer requirements will be set for packaging workers at all skill demands. Tayloristic concepts always lead to less reliance on these skills than in organizational concepts with more complete occupations, regardless of the technology used. Probably the type of technology can help strengthen the choice for an organizational context and in that way influence certain impacts.

4.3 Impact on skills distribution between jobs

The second discussion is about polarization of skills at the workplace. Impacts of dominant technology and organization may not be visible within an occupation, but in the relationships between occupations. Therefore, at least a sector view of occupations is required. The changing relationships between jobs can be described as polarization. When looking at skills, the access to and the development of skills may be very different between job categories. To illustrate the polarization effects, we look at the skill distance of the middle managers from the packers. To measure the distance, the level of higher skilled employees in a job is taken as an indicator: the percentage with a bachelor or master's degree. In packaging jobs, this percentage is 7 percent. In the period 2014–17, however, this percentage has significantly risen. In the middle manager jobs, there are 2.4 times more highly educated persons. The expectation is that the dominant technology and organization will not increase this skill polarization. The explanation is that the number of people with a bachelor degree or academic diploma among middle managers has hit a limit: a higher percentage of high-skilled managers seems improbable. If the degree of Taylorization increases, this will further reduce the skills required in both positions: figures 4 and 5 show that more Taylorized positions make less use of the social, communicative, STEM and computer skills. The polarization (i. e. the skill distance) may therefore decrease even more.

5 Conclusion and discussion

This paper proposes an alternative approach to analyzing the impact of digital technology on work in companies and sectors. In the literature, predictions about employment impacts are quite disperse. The main reason why predictions are still unreliable stems from the way in which technology, organization and aspects of work are currently conceptualized. The example of the Dutch manufacturing industry shows that one can arrive at predictions that differ substantially from those by Frey and Osborne (2013). The example of the skill changes within and between jobs was used to illustrate the importance of a new approach to understanding technological and organizational change. The estimations for the Dutch manufacturing industry show that the skill requirements for jobs are very high in non-Taylorized environments, and quite low in Taylorized working environments. The expectation is that dominant technology, the stress on more communication technology, will lead to more Taylorized jobs, reducing the needs for the so-called 21st Century skills. A second result is that there are polarized skill differences between job categories. These differences seem to become less in the future, because of the Taylorization. This is not itself a positive development for jobs, because the overall requirements are lower. Certain jobs will profit more of these changes than the ones covered in this paper.

New to this approach and monitoring system is the conceptualization of technology itself. In contrast to other approaches, a more "contained" approach to technology has been chosen in line with and following the process impact of technology: the impact is different when we talk about the potential of technology, the technology investment strategy and the current technology stock. Five technologies have been mapped and described. The concept allows us to formulate theoretically substantiated conclusions about possible impact. Based on these conclusions, professions in sectors were examined. The model provides a broad impact framework, broader than currently used in the analysis of technological development.

This paper has limited itself to skill differences within jobs and between jobs. In Dhondt et al. (2019), more work dimensions are used, also looking at the extent of employment in occupations, development in the quality of work, consequences for polarization in sectors, and perception of work dimensions. The model allows us to make predictions for the impact of technology on labor.

The task we have set ourselves is ambitious. More work is needed to elaborate and further operationalize the concepts developed in this paper. Most work will be needed on the three technology horizons proposed in this paper. For the research strategy, a combined data collection approach at the company and employee levels will be required. The bottom-line of the paper is that the work on the future of technology and its impact is only starting. Better methods need to be developed. This paper provides the first steps.

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