

A woman with long, wavy blonde hair is looking down at a white tablet computer she is holding. She is wearing a black top with intricate gold and white patterns. The background is a blurred city street scene seen through a window, with various lights and buildings. The overall lighting is soft and natural, suggesting an indoor setting near a large window.

The tectonics of skills:

Measuring the evolution  
of our skills landscape



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# 1. Foreword

A Frey and Osborne study about the likelihood of jobs being automated published in 2013 predicted that nearly half of all workers might lose their jobs. Many people interpreted this research as an alarming scenario. Many other studies followed, adding their data to the discussions. As Frey and Osborne later stated, their research was merely an indication of the advanced state of artificial intelligence, robotics and digitalisation.<sup>1</sup> Several studies since then show that, on a macro-economic level, technology complements labour rather than replacing it, thus increasing overall prosperity, rather than destroying it – a comforting message.<sup>2, 3, 4, 5, 6, 7</sup> Having a meaningful job is one of the most important factors of personal well-being and happiness, according to empirical research.<sup>8</sup>

However, the Frey and Osborne study did attract attention to the fact that Dutch jobs are changing, slowly but surely. Brynjolfsson, Mitchell and Rock found that most occupations in most industries include at least some tasks – both manual and cognitive ones – that can be automated with machine learning. They also found that few occupations can be entirely automated. Current research focuses on job augmentation rather than job replacement: smart automation and digitalisation changes the tasks people perform and how they perform them. Workers' knowledge, skills and abilities enable them to adapt to job augmentation. For example, technology substitutes for some skills, rebalancing the tasks performed by human workers and smart automation.<sup>9</sup> This job augmentation is likely to affect the majority of Dutch workers.<sup>10</sup>

Businesses will look for employees who are good at the tasks that smart automation and digitalisation struggles to do and which add value to the use of smart automation. The question is which knowledge, skills and abilities – in short which competences – will become more important over the next 15 years.

Previous qualitative research indicated that creativity and social skills will be the most important skills in the future.<sup>11</sup> In this report, we will use data analytics and machine learning to quantify which knowledge, skills and abilities are most important in the Netherlands now and which ones will be in the future.

To determine current and future skills needs, we will use a macroeconomic perspective. Skills needs are derived from the composition of the economy and its sectors, the jobs within those sectors and the knowledge, skills and abilities needed for these jobs. We will establish which knowledge, skills and abilities are important in the current economy. We will define which competences are future-proof, which are not and which ones people need to develop to be able to perform their future jobs. We will explore the importance of social skills and if they will really be crucial to the future. We will also debunk the myths that everybody should have programming skills and that all workers need to be reskilled.

Our analysis provides the cornerstones for a realistic outlook: similar to tectonic plates, our knowledge, skills and abilities as a whole need to slowly adjust and adapt to future job requirements. Shifts in competences are impactful, but occur very slowly for society as a whole. This will, however, require that individual workers need to increase their creativity skills, learning skills and above all social skills. When people become better at these things, they are better able to work together with smart automation and digitalisation and benefit from the opportunities that they provide.

Marc Borggreven  
Member of PwC Netherlands Board of Management, responsible for Human Capital

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- 1 Frey, M. and Osborne, C. (2018). Automation and the future of work – understanding the numbers
  - 2 Acemoglu, D. and Restrepo, P. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment
  - 3 Bessen, J. (2018). AI and Jobs: The Role of Demand
  - 4 Autor, D. and Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share
  - 5 ZEW (2016). Racing with or Against the Machine? Evidence from Europe
  - 6 CPB, Utrecht University and Boston University (2019). Automatic Reaction – What Happens to Workers at Firms that Automate?
  - 7 Cirillo, V. et al. (2019). Digitalization, routineness and employment: An exploration on Italian task-based data
  - 8 C.D. Fisher (2010). Happiness at work
  - 9 MacCrory, F. et al. (2014). Racing with and against the Machine: Changes in Occupational Skill Composition in an Era of Rapid Technological Advance
  - 10 Brynjolfsson, E., Mitchell, T. and Rock, D. (2018). What Can Machines Learn and What Does It Mean for Occupations and the Economy?
  - 11 WEF (2015). New visions for education

## 2. How real is the disruption?

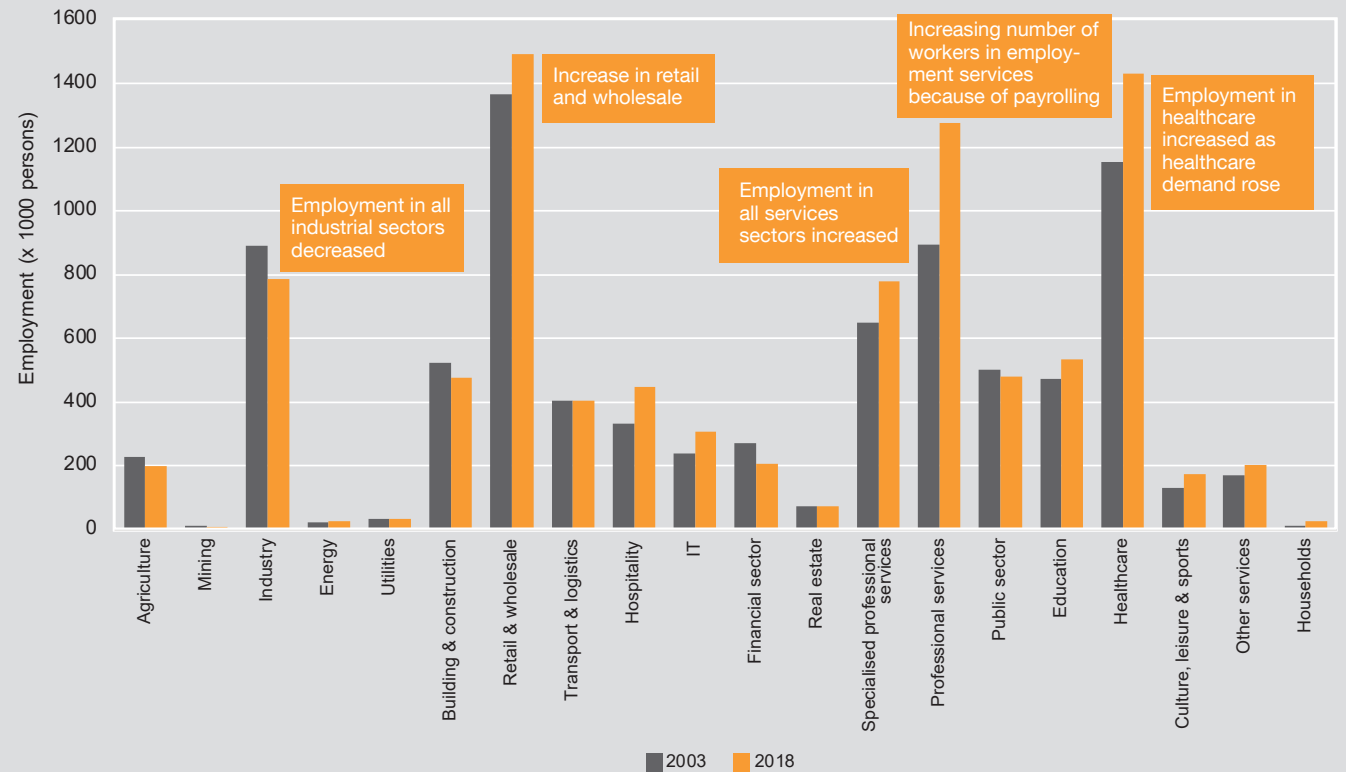
The skills we need to do our future job well is a product of three developments. Firstly, of the sector composition, as industries require specific knowledge, skills and abilities, and some industries outgrow others. Secondly, the sectoral job markets, as some industries need more workers in a specific profession than others. And lastly, the job content, as jobs require different skills.

### 2.1 The structure of Dutch industries is changing

Figure 1 shows that the economy has undergone major changes over the past 15 years. The ageing population for example is increasing the demand for healthcare services and thus the demand for healthcare workers. Technological advancements and the economic crisis seriously affected on the financial sector, and the latter also had a major impact on the building and construction industry. During the same period, the service and healthcare sectors – already major components in Holland’s economy – grew in importance, while others, such as the agricultural and industrial sectors, shrank.

These shifts have affected the demand for people with certain professions and in response to technological change, globalisation and other trends, these shifts will continue.

Figure 1. Shifts in employment per sector in the Netherlands



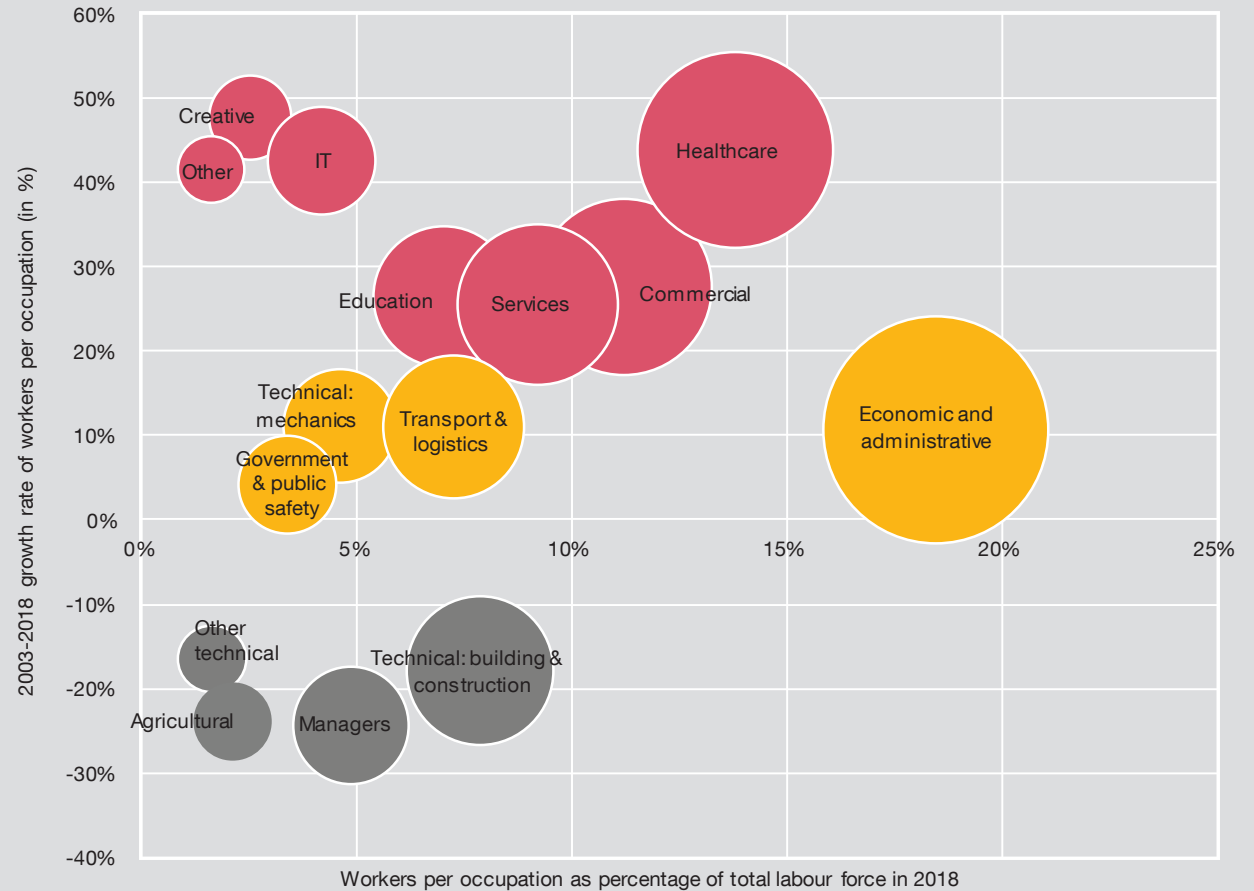
Source: Statistics Netherlands, PwC analysis

## 2.2 The rise and fall of professions

Next to shifts in the country's economic structure, Dutch workers now work in different professions than they did 15 years ago. For example, the number of managers and agricultural workers dropped, while the number of healthcare professionals and people working in commercial and services-related professions rose. We also see shifts within sectors. For example, the number of client-facing staff and administrative workers in the financial sector has shrunk considerably, while the number of IT professionals and data analysts increased. Creative occupations – such as graphic designers, translators and authors – are the fastest-growing group of professions in the Netherlands (see figure 2). The number of IT professionals saw spectacular growth as well – increasing 43% in 15 years – highlighting them as a rising star in the Dutch labour market. Job growth was especially strong for software developers, data analysts, telecom technicians and IT support staff. However, despite the high growth rates, we need to remember that IT professionals are still a relatively small group, both in absolute terms and as a percentage of the total labour market. The majority of Dutch workers are still employed as administrative, healthcare or technical professionals.



Figure 2. Growing professions in the Netherlands, between 2003 and 2018



Source: PwC analysis

## 2.3 Job components are changing

In 2018, over one third of Dutch employees reported that the technology – whether machinery or IT – they used the year before had changed.<sup>12</sup> Some professions were more highly affected than others: for example, well over 45% of security officers, doctors, therapists and IT specialists reported changes in the technology they used in their job (see figure 3). Security officers and IT specialists are also the most likely to report that they lack the latest knowledge and skills, and that some of their knowledge and skills are outdated.<sup>13</sup>

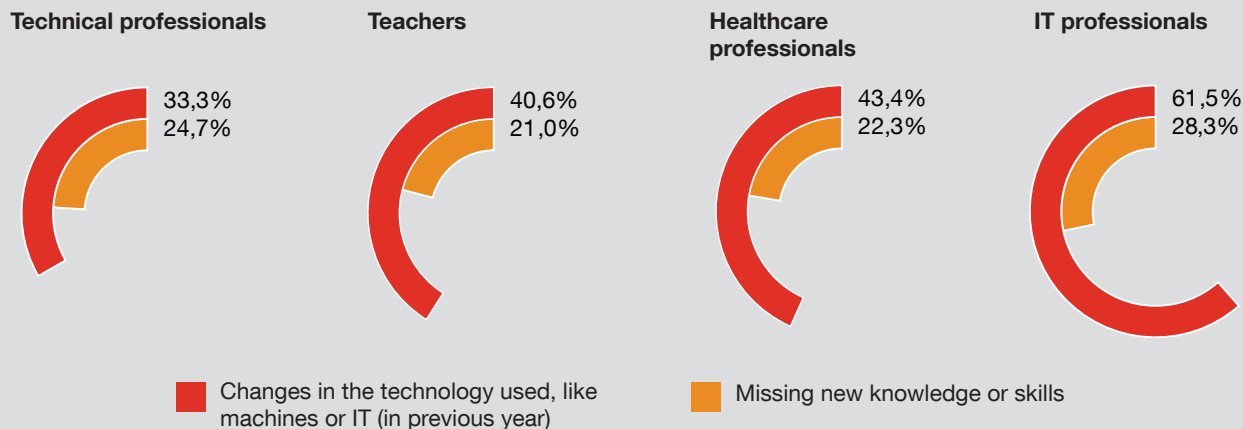
A CPB study shows that the impact of automation on job compositions is relatively slow and tends to be distributed over several years.<sup>14</sup> This reflects a process of learning and selection: workers have time to learn how to use the new technology and find out if they enjoy it, and employers learn which workers have the skills required to adapt to the new technology. The majority of jobs with tasks that are automated end up being adapted and taking on new roles or responsibilities.<sup>15</sup>

## 2.4 Competences are changing

Technology affects more than just the people who work directly with it. For example, robotic surgery is changing the way surgeons work, while also affecting the tasks theatre nurses and anaesthesiologists perform and the skills they use. Research shows that in robotic surgery, where most members of a team cannot see each other, everything needs to be said out loud. Robotic surgery team members communicated verbally more often, giving verbal instructions and verbally confirming them. Non-robotic surgery teams relied much more on non-verbal communication.<sup>16</sup>

Smart automation and digitalisation gradually takes over some tasks and adds others, such as monitoring and interpreting data. As real-time information becomes more readily available, supervisory and managerial skills to convert this data into effective actions become more important. More coordination, critical thinking and resources management are required in non-managerial roles, such as those of nurses and teachers.<sup>17</sup>

Figure 3. Dutch workers report changes in technology used and lack of new knowledge and skills, in 2018



12 TNO (2019). NEA Benchmarktool 2018: Arbeidsomstandigheden/Mentale belasting/Veranderingen in het werk

13 TNO (2019). NEA Benchmarktool 2018: Gezondheid en inzetbaarheid/Inzetbaarheid en functioneren/Aansluiten kennis en vaardigheden bij huidig werk

14 CPB, Utrecht University and Boston University (2019). Automatic Reaction – What Happens to Workers at Firms that Automate?

15 Dahlin, E. (2019). Are Robots Stealing Our Jobs? In: Socius: Sociological Research for a Dynamic World. Volume 5: 1–14

16 Cornell Chronicle (2018). Study Explores how Robots in the Operating Room Impact Teamwork

17 MacCrory, F. et al. (2014). Racing with and against the Machine: Changes in Occupational Skill Composition in an Era of Rapid Technological Advance

# 3. The good old competences will keep on ruling

The competences of Dutch workers have been relatively stable over time. What is important in the labour force today will remain so tomorrow. Dutch workers do need to improve these skills further, if we want to remain productive and competitive.

## 3.1 Calculating demand in competences

As smart automation and digitalisation change the tasks workers perform, the general opinion is that they will likely need new knowledge and skills to perform well in current and, more importantly, future jobs. The million-dollar question is: Which competences are already becoming more important and which ones are future-proof?

We analysed the composition of the Dutch labour market in 2011 and 2018 and established how many people work in which jobs. We then cross-referenced the O\*NET database with our data to assess the knowledge, skills and abilities Dutch workers currently should have and how skilled they should be in them.<sup>18</sup> We used data from both Statistics Netherlands and O\*NET from 2011 and 2018 to find out if competences themselves have evolved (i.e. have become more important in specific professions) and if professions now require different competences.

Based on the current situation in the Dutch labour market, we can also predict which competences will become more important. We replicated the Frey and Osborne study for the Netherlands to find out for each job how likely that job can be automated. We found that the average likelihood of a Dutch job being automated in 2035 is 12%.<sup>19 200</sup>

We then applied the automation probability for each job to the data of our analysis to predict how the composition of the Dutch workforce would change over time due to smart automation and digitalisation. Next, we analysed which knowledge, skills and abilities will become more important and to what extent.

We then ordered these competences in clusters so to analyse whether or not specific groups of skills and abilities will become more important. Additionally, we analysed job-postings data of USG People published between 2010 and 2017 to verify our assumptions and predictions. See the appendix for more details about the methodology used.

## 3.2 Overlapping competences in related professions

Our data analysis identifies the most important types of knowledge, skills and abilities for each profession. One of our key findings is that different professions often require similar competences. The competences required in related professions, such as certified nursing assistants and licensed practical nurses, are rather similar, but the levels vary. For example, customer and personal service, critical thinking and sensitivity to problems are very important in both professions. The required proficiency in biology and healthcare – knowledge and skills related specifically to these professions – vary between these professions, distinguishing them from each other.

Our analysis shows that workers in other professions also require high levels of customer and personal service, critical thinking and sensitivity to problems (see figure 4). Sports instructors and police inspectors need similar competences and competence levels as licensed practical nurses, apart from medical knowledge. As staff shortages in the healthcare – and other – sectors are high, identifying potential workers with the right skills and abilities and retraining them to increase specific knowledge could be highly beneficial for workers and healthcare institutions alike.

### What are competences?

A competence is the combination of practical and theoretical knowledge, cognitive skills, and abilities that enable, and improve the efficiency of, the performance of a job.

Knowledge is internalised theoretical information.

A skill is a capability or proficiency developed through training or hands-on experience. Skills are the practical application of theoretical knowledge.

An ability is a physical or mental attribute – innate or acquired by training – that influences performance.

18 A proficiency level of 3 out of 5 indicates high proficiency in a specific competence.

19 Ingwersen, M. (2019). Estimating the Effects of Technological Progress – A Data-Analytic and Agent-Based Approach.

20 The original Frey and Osborne study found that automation was likely for 47% of jobs in the United States. The gap between the Dutch and US labour markets is due to differences in the sectors within each economy.





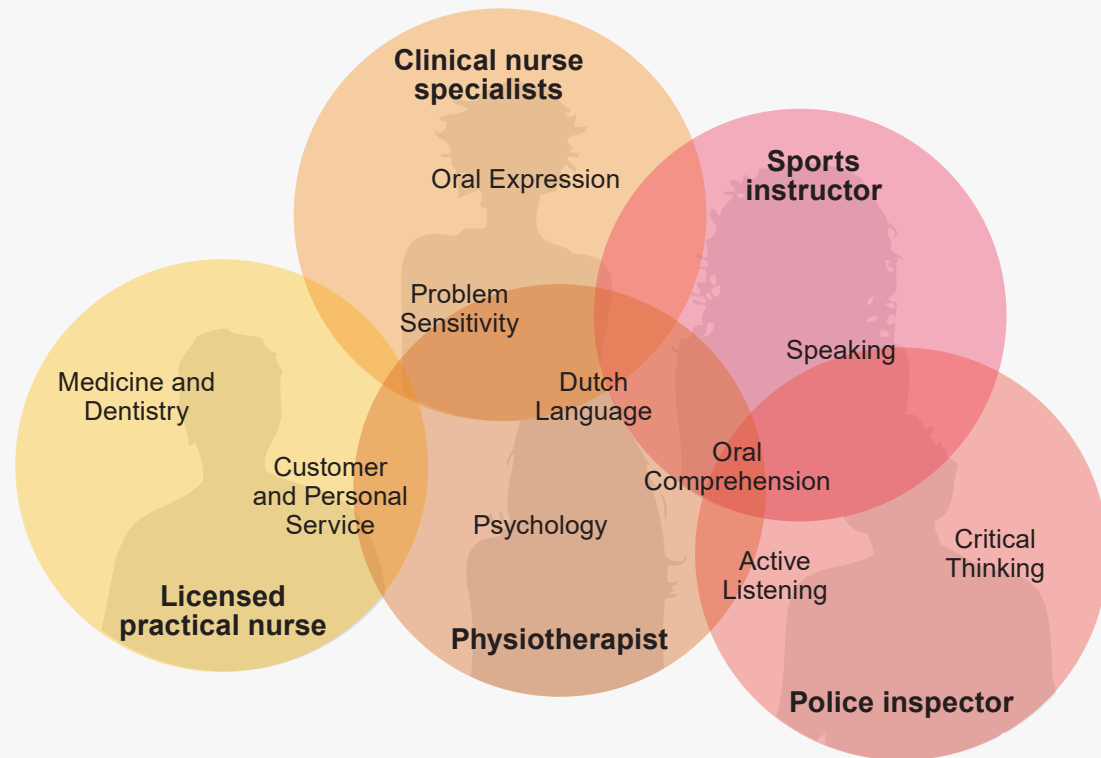
Similarly, in case of staff surpluses – of administrative workers, for instance – identifying employees' competence levels could potentially lead to new career opportunities. For example, there is overlap between the jobs of an administrative clerical worker and a quality controller.

While the overlap is not 100% in the top 5 types of knowledge, skills and abilities, there is enough to enable a clerk to take up

a job as a quality controller with some overseeable additional training.

People tend to only look for jobs in professions similar to what they are used to.<sup>21</sup> Our analysis shows that many professions require similar competences, and that means more career opportunities.

**Figure 4. Different professions have overlapping competences**



<sup>21</sup> RTL Z (2019). Al lang werkloos? Je bent geschikt voor meer banen dan je dacht (article).



### 3.3 Future-proof competences

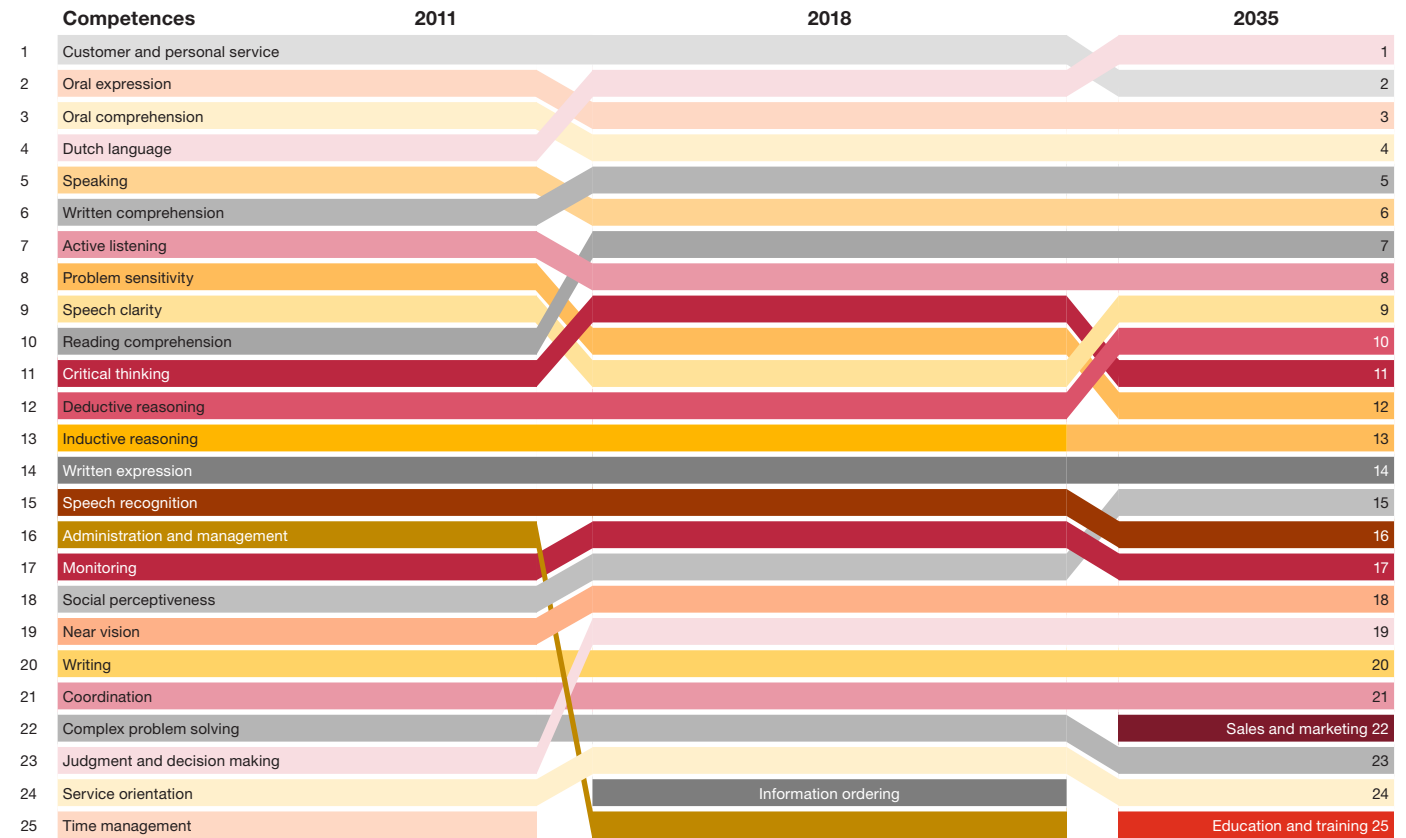
Based on the competences of each profession, we created a ranking of the types of knowledge, skills and abilities Dutch workers typically need, and the required proficiency level they display in each of these competences.<sup>22</sup> Figure 5 shows the top 25 competences required in 2011, 2018 and 2035. It is immediately apparent that the top 25 are relatively stable. The competences most important for the labour force will only slightly change as tasks and jobs change because of automation. Our most important competences are rather like tectonic plates, repositioning themselves very slowly. Our analysis proved that the main competences Dutch workers need – the knowledge, skills and abilities that are most commonly needed in the majority of jobs – are relatively future-proof.

When we look at the ranking in more detail, we notice that Dutch workers' competences reflect the fact that the country is a service economy. They have excellent knowledge of customer and personal service, which is important in 25% percent of Dutch jobs.<sup>23</sup> Bartenders, retail employees and receptionists, as well as teachers, nurses, personal assistants and police officers, need considerable knowledge levels related to customer service.

Among the top 25 most common competences in the Netherlands (see figure 5), 11 are related to listening, speaking, writing and reading the Dutch language, which is necessary for communication in every working environment. The majority of Dutch workers need to have a high proficiency in this field. There are very few jobs in which only a basic level of proficiency in reading, writing or speaking is sufficient, which stresses the importance of literacy in the Dutch economy.<sup>24</sup>

Critical thinking, complex problem solving and social perceptiveness are often mentioned as prerequisites for success in the society and workplaces of the future.<sup>25</sup> Our findings confirm the importance of these skills and identify them as skills that Dutch workers generally require to perform well in their current and future jobs.

Figure 5. Top 25 competences in the Netherlands, in 2011, 2018 and 2035



Source: PwC analysis

22 Appendix 2 lists the competences ranking and the proficiency level per competence in 2011, 2018 and 2035.

23 25% of Dutch workers need a proficiency level in customer & personal services higher than 4 (out of 5).

24 PwC (2018). Maatschappelijke kosten laaggeletterdheid.

25 WEF (2016). New Vision for Education. 21st-Century Skills.

### 3.4 Verbal skills and creativity trump social skills

First, we looked at the knowledge, skills and abilities individually. Then we organised them into clusters so as to identify which categories of competences are becoming more important.<sup>26</sup> Our analysis shows that verbal abilities, content skills (the skills people learn at elementary school, such as reading, writing and maths), idea generation (or creativity), processing (or learning) skills and social skills are already the most important competences for workers today. In 2035, they will require an even higher proficiency level.<sup>27</sup> Figure 6 shows that creativity and the ability to communicate verbally are particularly important.

Based on other studies, we expected social skills – such as negotiation, instructing, persuasiveness, service orientation, coordination and social perceptiveness – to rise in our ranking.<sup>28</sup> After all, social tasks are difficult to automate. Although their position in the top 5 is not expected to change, their importance is rising at a faster pace than that of any other cluster of skills and abilities. Social skills reduce coordination costs, allowing workers to specialise and work together more efficiently.<sup>29</sup> This makes them very important at a time when organisations are focusing on reducing coordination costs and on improving collaboration in a multicultural and globalised economy.<sup>30</sup> People need to increase their proficiency in these fields.

26 We applied the existing O\*NET clustering to our data. As the knowledge clusters sometimes contain only one knowledge item, we focus on skills and abilities. For more details, see: <https://www.onetonline.org/find/descriptor/browse>

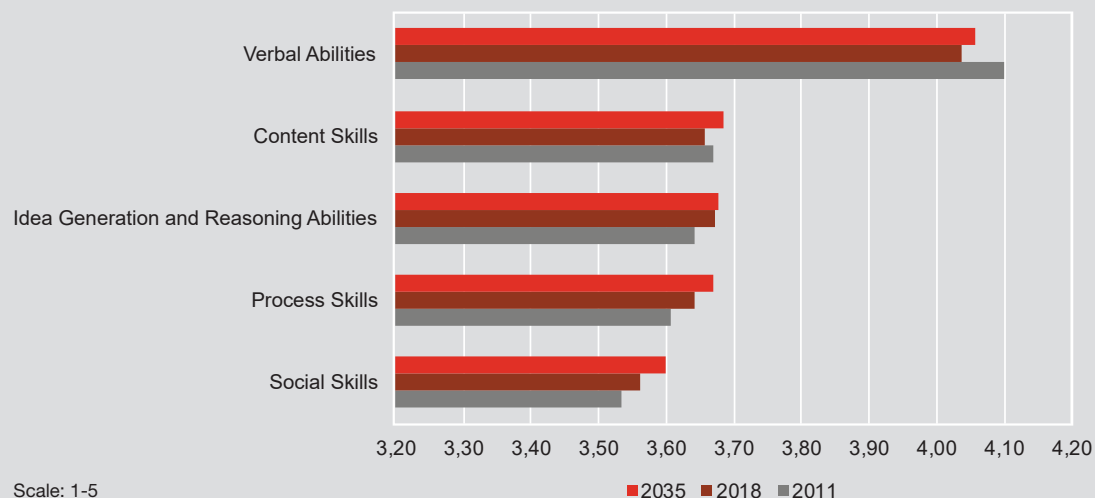
27 At a glance, the gap between current and future skills requirements seems relatively small. However, this is similar to structurally increasing the average CITO score from 535 to 536. It doesn't seem like much, but it means that nine million people will have to improve their score.

28 WEF (2016). 21st-Century Skills

29 Deming (2017). The Growing Importance of Social Skills in the Labor Market

30 Nesta (2018). Skills of the Future

Figure 6. Most important skills and abilities of the future



Scale: 1-5

Source: PwC analysis



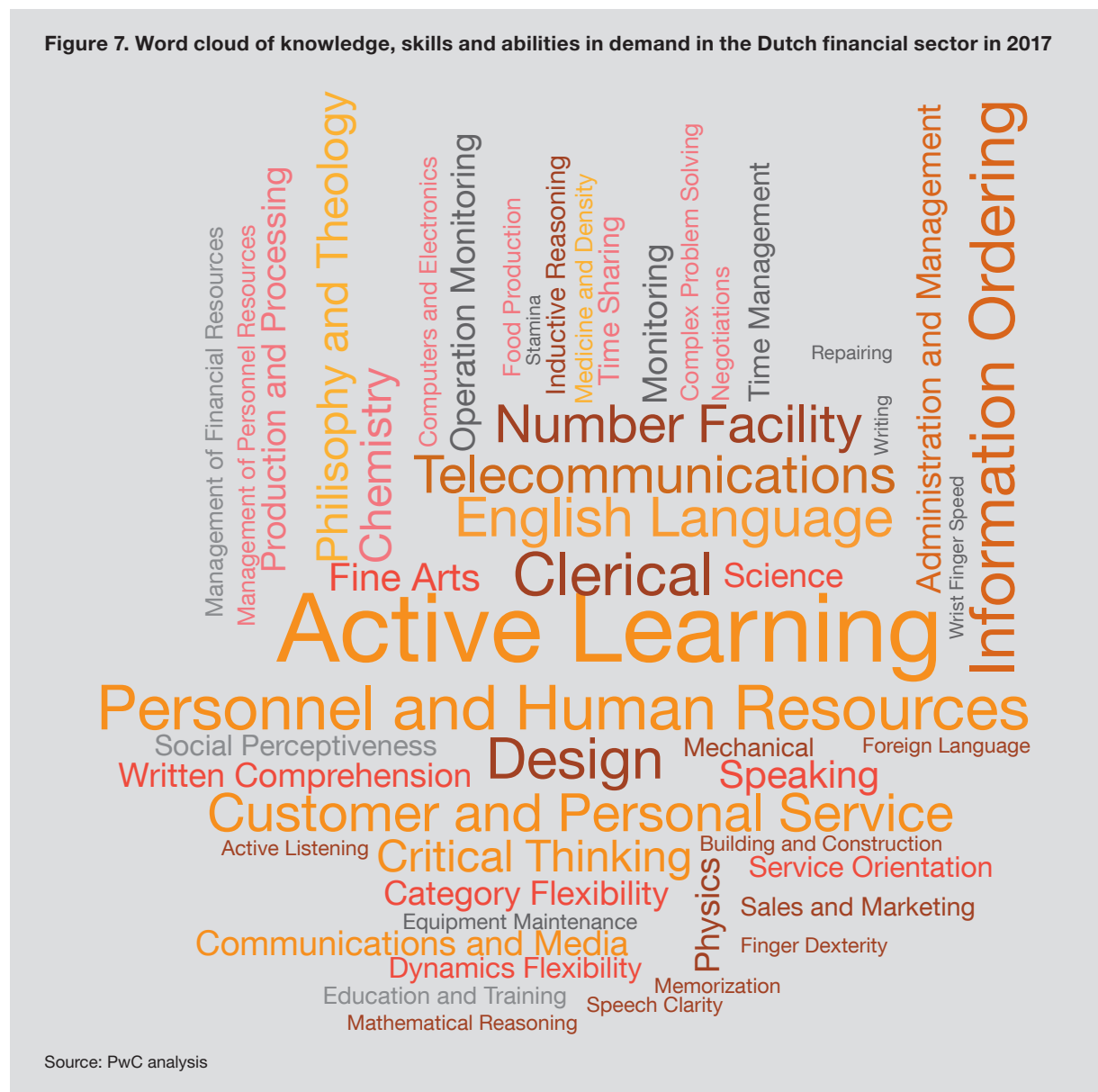
### 3.5 The fundamental importance of education and training skills

Our study shows that competences related to teaching and learning are also gaining in importance. Workers need to become better at process skills, including active learning, learning strategies, critical thinking and monitoring. Knowledge about how to effectively educate and train people is expected to rise in our ranking from the 35th place in 2011 to the 25th in 2035.

Our analysis of the USG job postings data supports this key finding. In the USG data, we found that active learning – the capacity to learn and apply new knowledge – has become one of the most sought-after competences in every sector in the past eight years (see figure 7). Knowledge about the best way to educate and train people and the skill required to select and use the instructional methods appropriate for specific individuals are extremely important for the teaching of children and young adults as well as the training of the many workers whose tasks and jobs are changing – they will have to be agile and adopt learning strategies quickly to be able to adapt in the digital age.



Figure 7. Word cloud of knowledge, skills and abilities in demand in the Dutch financial sector in 2017



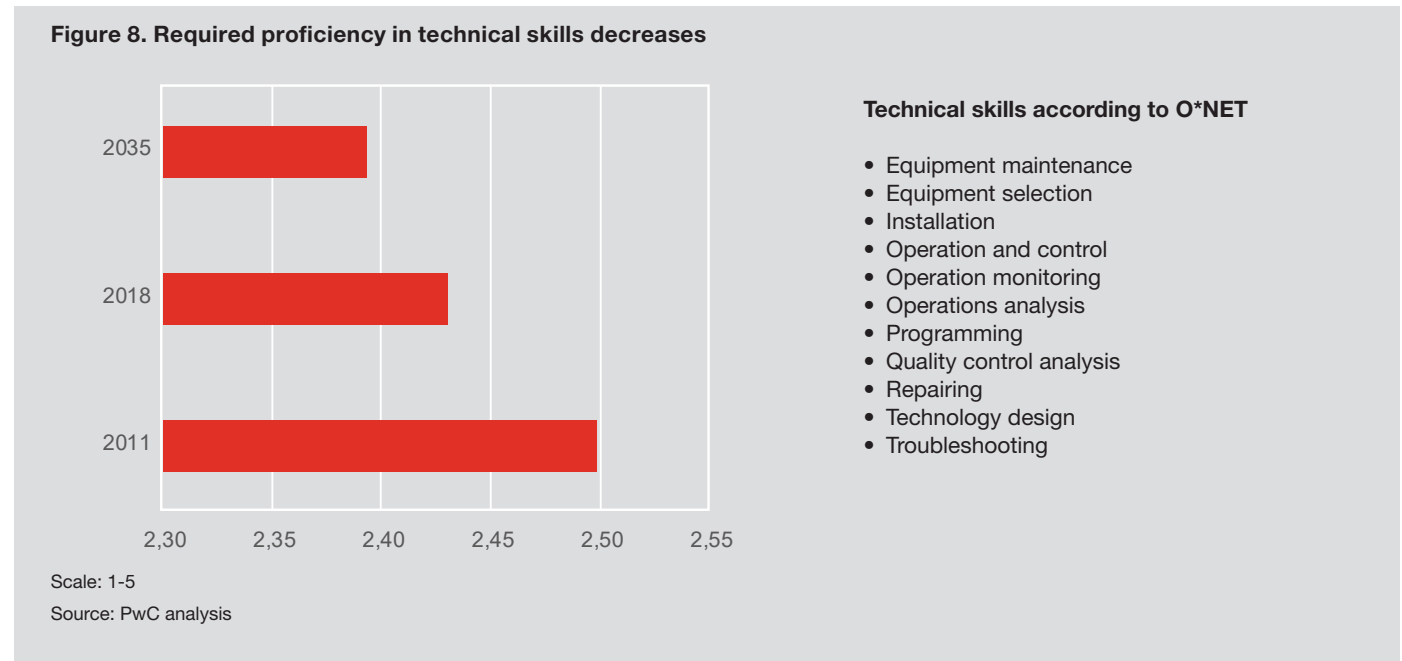
### 3.6 The need for tech skills: Fact or fiction?

Many studies advocate the importance of mathematical, technical and IT skills. It is often said that people will all need programming skills to be able to perform tasks in their future jobs.<sup>31 32</sup> The number of IT and data specialists is growing, but the base is relatively small compared to workers in healthcare, administration and services. The same goes for programming skills: there is only a small minority of workers who are highly skilled in programming and data analytics, and these skills are still relatively rare from a macroeconomic perspective. Even if the number of IT workers grew by 50% – approximately the growth rate of IT workers in the past 15 years – this knowledge and skills would remain relatively rare on a macroeconomic level.<sup>33</sup>

Contrary to popular belief, our analysis shows that technical skills such as equipment maintenance, technology design, operations analysis and programming skills, will become less important in the future (see figure 8). This is consistent with other studies.<sup>34</sup> Certain user interfaces and building blocks for programming languages already require less IT skills. Thirty years ago, an econometrician had to program his own models and can now use very user-friendly apps. So on the one hand, many workers in professions can perform better than they could in the past with less technical skills. On the other hand, we need more people with more advanced technical skills, who can write code and design apps and interfaces. The point is that the former group is a magnitude larger on the macroeconomic scale compared to the latter.

As smart automation, artificial intelligence, sensors and machine learning progress further, computers will be able to perform more and more tasks simultaneously. Moreover, they will increasingly perform complex tasks, such as complex decision-making and reacting to semi-routine incidents. Tasks that were once seen as too complex to be automated are increasingly becoming routine

thanks to increases in processing speed. As machine learning progresses, it is not unlikely that these applications will learn to adapt and improve themselves and the tasks they perform.



31 Fast Company (2016). Why coding is the job skills of the future for everyone (article)

32 The Guardian (2018). Rise of the machines: why coding is the skill you have to learn (article)

33 As our analysis is based on the current job situation in the Netherlands, we can't predict which – or how many – new jobs will be created in the next 15 years or which competences and skill levels will be required for these new jobs. To minimise the bias caused by the current status quo, we assumed that the number of people working in IT professions would increase by 50% by 2035, comparable with the growth rate of people working in IT professions over the past 15 years. The output of this analysis did not significantly alter our initial findings.

34 MacCrory, F. et al. (2014). Racing with and against the Machine: Changes in Occupational Skill Composition in an Era of Rapid Technological Advance

# 4. The competences effect

Businesses and workers should nurture the ability of workers to actively improve their current competences, especially creative, learning and social skills, which are relevant to almost all jobs.

## 4.1 What does this mean for society?

Where previous reports indicated that specific competences would become more important in future jobs, our data analysis quantifies which competences Dutch workers need in their future job and how proficient they need to be. Our analysis also shows that the competences required of the Dutch workforce remain relatively stable. These competences – the knowledge, skills and abilities Dutch workers need to perform their current and future jobs well – are comparable to tectonic plates. Similar to tectonic plates, the competences landscape consists of massive, general clusters of knowledge, skills and abilities, that as a whole need to slowly adjust and adapt to future job requirements. Shifts in competences are impactful, but occur very slowly. Even in 2035, the majority of workers in the Netherlands will not need to have acquired completely different competences to be able to perform well in their jobs.

Our analysis does show that the Netherlands needs to focus on helping its workers become more proficient in the competences that add value to smart automation and digitalisation. This upgrading should focus on two priorities.

## 4.2 Developing digital skills

The first priority for the Netherlands is to upgrade workers' understanding of and capability to work with new technologies. This involves assessing workers' digital skills: how well-equipped workers currently are for working with and deploying new technologies. Almost everybody in the Dutch labour force will ultimately have to work with smart automation, digitalisation or new technologies. Digital skills – being able to work with several new technologies – become a must to be able to work. We need to see them as being an integral part of a skillset for the 21st century professionals.

Dutch workers should all be able to use new technologies – as end users, not hardcore IT specialists. People working in all professions, from cleaners and welders to teachers and architects, should become familiar with new technologies. It's important to know how these technologies can best be applied in current and future jobs, how they change tasks, and how they support processes and change business models within different industries.

It's important to learn how best to use these technologies and interpret their outcomes so as to reap the benefits. Organisations of all sizes and in all sectors must make sure that they enable all current and future workers to use new technologies.

### Skills Bridging Programme in Luxembourg

In 2018, the Government of Luxembourg decided to develop a programme to provide technical and financial assistance to upskilling employees in companies facing major technological disruption. Their aim was to proactively develop the competences of workers so that businesses could better anticipate and adapt to emerging technologies.

Businesses participating in the Skills Bridging Programme first conduct a workforce-planning exercise to identify the jobs that will likely change due to automation and to identify the competences relevant to future jobs.

They then construct a skills-development plan to bridge the skills gap to tomorrow's jobs. After assessing the competences and the interests of the workers in participating companies, the programme identifies which jobs would fit a given employee and which additional training they would require to perform well in the job.

Based on the knowledge, skills and abilities their employees have at a given moment, companies offer them different types of upskilling training. These vary from awareness-creating courses to job-specific digital training and courses to develop social and soft skills. The training courses are company-specific and developed by each company itself.

The effect of the Skills Bridging Programme is threefold. First, it is a structural way to support the digital transformation of businesses in Luxembourg. Second, the programme increases internal mobility, which has a positive effect on workers' commitment and enthusiasm. Workers transferring to new jobs within the same company encourage performance improvements within it. Lastly, the programme increases the employability of Luxembourg's workforce and reduces the risks of job loss, unemployment and people needing social benefits.

### 4.3 Become better at what you do

Secondly, our analysis clearly shows that Dutch workers do not have to develop completely new competences, but rather need to upskill the competences they already have (see figure 9). People's ability to communicate with and relate to co-workers, customers and other stakeholders will remain their most important competence. In the digital age, businesses need their employees to have the social skills required to collaborate and connect effectively with co-workers and customers, understand their deepest needs and create trust in the relationship. Creativity and the ability to learn and apply new knowledge makes people

uniquely adaptable for the new tasks their future job demands. Data analytics or AI may show declining market shares, but service orientation helps identify client needs that are not yet met. Creativity makes it possible to come up with new ideas and product innovations. And the ability to learn and adapt helps workers adopt new technologies and use them to their full potential.

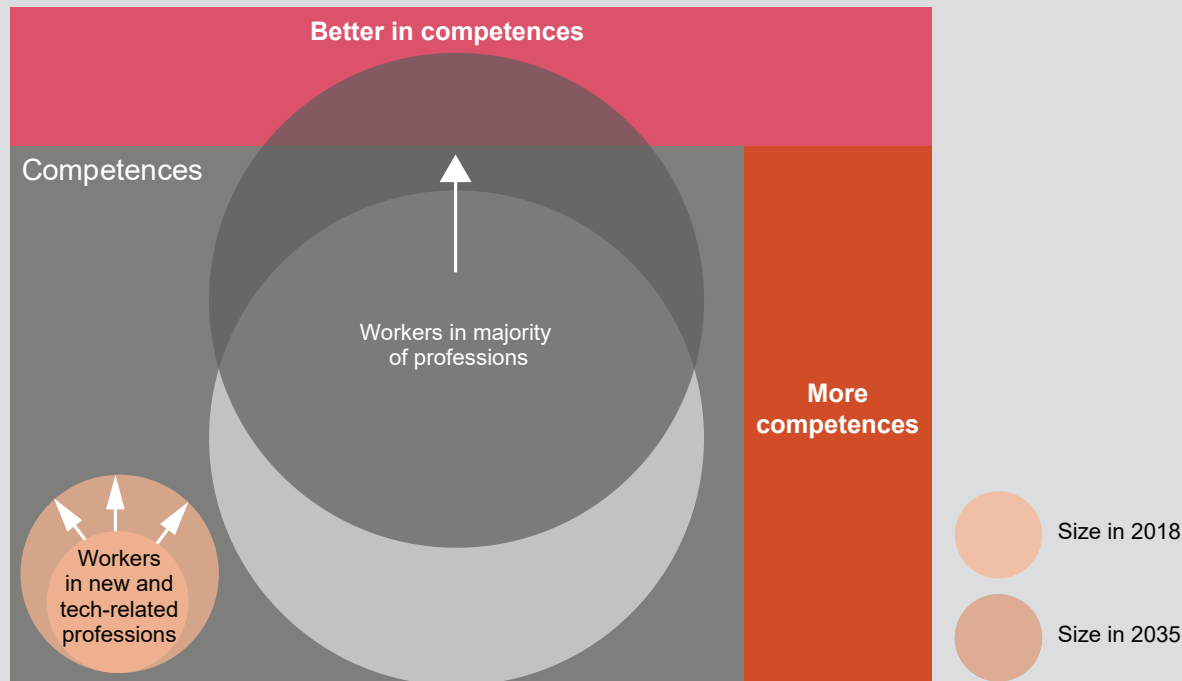
We need to accelerate the tectonic shifts that are happening. The focus should be on teaching people how to improve their current competences, especially social, creative, and learning skills, which are relevant to almost all jobs. These competences

add value to the tasks that smart automation and digitalisation struggle to do and ensure greater resilience and success in the face of a changing working environment. All Dutch workers should be at least proficient, and preferably highly skilled, in these competences. Businesses, workers and society should all focus on accomplishing this, to accelerate the tectonic shifts in our competences.

### 4.4 What does this mean for your business?

Many CEOs have been reporting for quite some time that they are having difficulties finding new employees with specific competences. PwC's 2019 CEO Survey showed an interesting trend: 46% of CEOs mentioned the upskilling of their employees as their main priority.<sup>35</sup> Unfortunately, many other CEOs are overlooking the fact that their current workers already have a lot of the competences that their companies need in the future. Current workers already fit in the organisational culture and know many of the procedures, processes and clients. It is usually easier – and cheaper – to upgrade an employee's knowledge or skills than to hire someone from the outside. Research suggests that outside hires take three years longer to perform as well as internal candidates in the same job.<sup>36</sup> Outsiders also require higher salaries.

Figure 9. Challenges for the majority of workers and for tech, IT and creative workers



Source: PwC

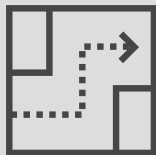
35 PwC (2019). CEO Survey

36 The Economist (5 May 2019). Why companies are so bad at hiring.

Upskilling employees regularly is more efficient than laying off or reskilling employees. Businesses and workers alike need to take accountability for their knowledge, skills and abilities remaining future-proof. Keeping the knowledge and skills of staff up to date really pays dividends. There are five steps that can help bridge a potential skills gap and make a workforce future-proof. Companies should:

1. **Optimise** the available data and data-analysis capabilities in their HR department; and make sure their HR systems capture the data you need about workers' characteristics, experience, knowledge, skills and abilities. The right data and technically skilled HR employees enable better decisions.
2. **Analyse** their data and provide insights into their current workforce, workforce development and workforce dynamics, such as recruitment, promotion and employee turnover; and assess the current characteristics, knowledge, skills and abilities of their employees. These insights should form the basis of their views and ideas about how they want their future workforce to look.
3. **Since** there is not just one scenario, formulate multiple future scenarios, taking into account their strategy and ambitions, but also the key developments in their industries; then create models for those future scenarios and use historical trends to demonstrate how the workforce will develop without interventions, and demonstrate what needs to be done to reach a preferable future state.
4. **Match** their current workers with their future workforce and find the best possible match; and formulate HR interventions to bridge the skills gaps. These could include things like upskilling, internal mobility, recruitment, retention and promotion.
5. **Seek** collaboration in their ecosystem with governments, other companies, educational and training organisations. The Skills Bridging Programme in Luxembourg is an excellent example of how working together makes it possible to match supply and demand more easily.

Figure 10. Five steps to make your workforce futureproof



Step 1:  
Optimise HR  
data and HR  
function



Step 2 :  
**Analyse** current work-  
force composition,  
including **employees'**  
**competences**



Step 2:  
**Define future**  
**workforce**



Step 4:  
**Match** current and  
future workforce  
and **design inter-**  
**ventions** to fill the  
gaps



Step 5:  
**Collaborate**  
**within your**  
**ecosystem**

Source: PwC





# Appendices



# Appendix 1: Our approach

## O\*NET

To assess the competences of Dutch workers, we used the knowledge, skills and abilities classified per occupation in O\*NET. The O\*NET database, provided by the United States Department of Labor, provides a list of occupations and their detailed job requirement profiles. These job requirements include 120 types of knowledge, skills and abilities, and the O\*NET data keeps track of their relative importance for a given occupation, expressed on a scale of 1 to 5. Most of the occupational information, including knowledge, is collected from job incumbents. Occupational analysts provide the importance and level information regarding the abilities and skills associated with these occupations.<sup>37</sup>

O\*NET provides a more extensive quantification of the required knowledge, skills and abilities in a specific job, compared to for example PIAAC of the Dutch Skills Survey (NSS).

## Mapping Dutch and US occupations

To determine the competences of Dutch workers, we first matched a Dutch occupation as defined by Statistics Netherlands (CBS) to a US occupation defined in O\*NET. As we found no direct link between the two, we applied a translation scheme that allowed us to match a Dutch occupation (with a BRC code) as defined by Statistics Netherlands (CBS) to a US occupation (with a SOC code). For this purpose, we used a mapping scheme (a 'crosswalk') created by our team of specialists. We applied this crosswalk using ISCO 08 codes.

And we performed a mapping through the following steps:

1. Obtain data on the number of Dutch workers in a set of occupations in 2011 and 2018 (116 different jobs) from CBS<sup>38</sup>
2. Obtain O\*Net SOC codes<sup>39</sup>
3. Obtain CBS BRC codes<sup>40</sup>
4. Obtain crosswalk from O\*NET to ISCO 08<sup>41</sup>
5. Obtain crosswalk from BRC to ISCO 08
6. Use crosswalk to create mapping from O\*NET to BRC codes<sup>42</sup>

We were able to map the jobs on both a two-digit (high-level) and a four-digit level (detailed level).

## Assessing past and current competences

We obtained the knowledge, skills and abilities and their ratings (from 1 to 5) from 2011 and 2018. We applied the knowledge, skills and abilities (121 competences in total) and their ratings for each US occupation in each year to the matching Dutch occupation. Using the equivalence between the O\*NET SOC codes and CBS BRC codes, all competence ratings could be mapped from an O\*NET job code to a CBS BRC code.

We then applied a weighing to our analysis, to take into account the number of workers in each occupation. For each 1,000 jobs we added a separate entry to our database indicating the job and its competence ratings. This resulted in a dataset of 8,587 entries, each of which represented a job with its related competence ratings.

## Assessing future competences

Next, we compared the actual Dutch occupation distribution to the same distribution corrected for Frey and Osborne automation probabilities.<sup>43</sup> Frey and Osborne estimated the automation probability in 2035 for each SOC code occupation. We replicated this analysis for Dutch occupations and used these Dutch automation probabilities to recalculate the future number of Dutch workers in all occupations. For each job, the total number of entries is equal to the following rounded amount:

**# rows = total amount of jobs \* F&O automation probability**

This resulted in a database of 5,060 entries, each of which represents a job with the related competence ratings.

We used automation probabilities obtained from PwC UK for a similar analysis. PwC UK created a biennial set of automation probabilities ranging from 2015 to 2035. These UK probabilities were set up in the same way as the Frey and Osborne probabilities, with the addition of PIAAC data and additional competences in their analysis, on a two-digit level. The PwC UK automation probabilities resulted in a dataset of 5,583 entries.

## Four scenarios

The datasets contain a certain number of entries per competence, which were used to create a dataset weighted by job numbers (2011 and 2018) and job numbers and automation probabilities (2035 based on F&O and PwC UK). To enable a comparison of the competence ratings across the scenarios, we took the 90th percentile of all ratings per competence. We chose this percentile because we consider that higher ratings reflect more important ratings per job. This took into account the highest part of the distribution of the competence ratings, while also making the output of the various scenarios comparable.

37 For more detailed information, see: [https://www.onetcenter.org/dl\\_files/AOSkills\\_ProcUpdate.pdf](https://www.onetcenter.org/dl_files/AOSkills_ProcUpdate.pdf)

38 <https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82808NED/table?ts=1563449499261>

39 <https://www.onetcodeconnector.org/oca/step1>

40 <https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/onderwijs-en-beroepen/beropenclassificatie--isco-en-sbc-->

41 <http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/>

42 <https://www.cbs.nl/-/media/imported/onze%20diensten/methoden/classificaties/documents/2015/09/schakelschema%20isco2008-brc2014.xls?la=nl-nl>

43 Frey, C. and Osborne, M. (2013). The future of Employment: How Susceptible Are Jobs to Computerisation?

Comparing these scenarios resulted in a ranking of competences that are likely to thrive in the future. As we were also interested in these analyses on a per-sector or a skill/ability/knowledge basis, we created overviews and comparisons of these analyses as well.

We decided to use the future scenario based on the replication of the Frey and Osborne study in our report, as this reflects the composition of the labour market in a more detailed way.

### Validating scenarios based on USG People data

To validate our scenarios, we used data from USG People to determine which O\*NET competences were mentioned most often in job vacancies and on a per-year/sector basis. This enabled us to test the evolution of the competences over time and per sector.

We received a database of 650,000 Dutch vacancy postings from 2010 to and including 2017. This dataset contained vacancy data, including job titles, sector titles, job requirements and job texts.

We applied two analyses to this dataset:

1. We ran a text-mining exercise where we looked for the O\*NET competences in the USG vacancy data.
2. We created a frequency table and a word cloud analysis on the text in the job requirements (deep learning).

With regards to the text mining of the O\*NET competences in the vacancy data, we took a fairly straightforward approach consisting of the following steps:

1. We prepared all vacancy data, resulting in a dataset of 649,549 entries and 18 columns.
2. We prepared all competence data. As the vacancy dataset is in Dutch, all O\*NET competences were translated into Dutch.
3. We performed text mining by looking for the competence words in the vacancy job requirements data using the R Agrep function and a 0.3 max distance (acceptable fuzziness). Each time a keyword was found, a 1 was added to an output matrix. If the keyword was not found, a 0 was added to the same matrix.

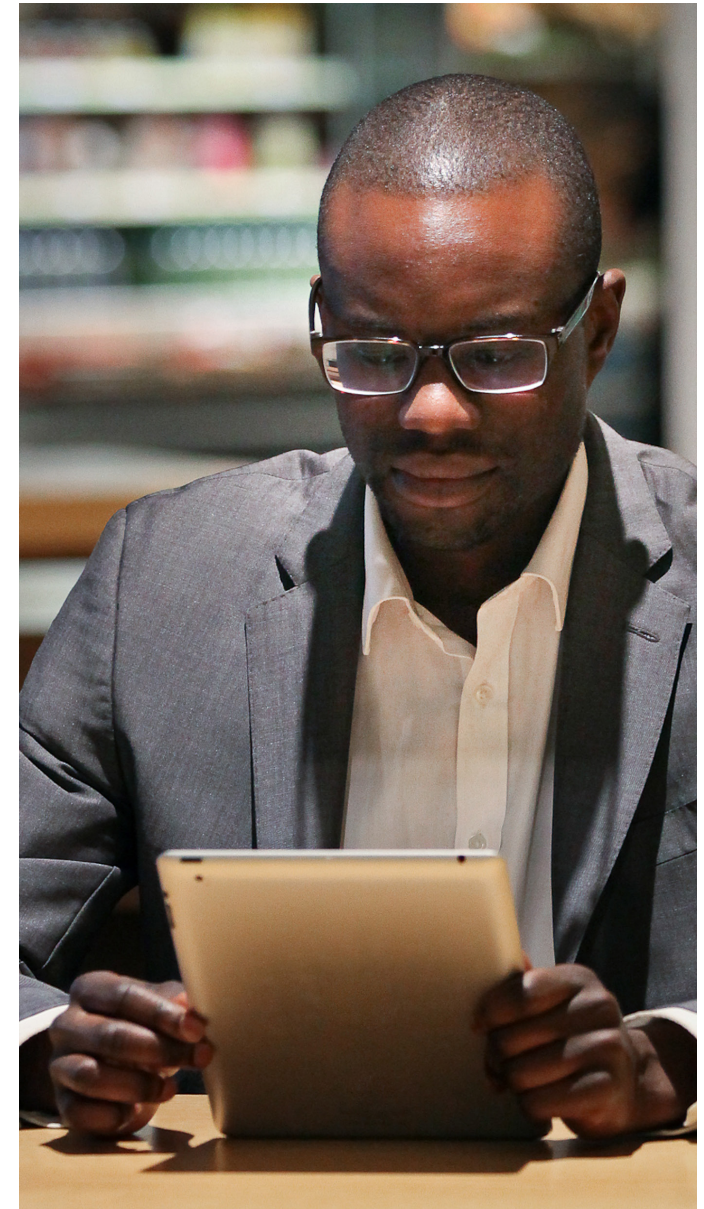
4. If we considered that a certain competence did not yield enough hits, we determined different words to describe the competence and re-ran the code.

To analyse our output, we created frequency tables of each competence where we counted the number of ones per competence. The output was then divided over the following characteristics:

- Sector
- Year
- Competence.

Based on the sector and the year, a frequency table was created and in turn used to compute the final word cloud. A total of 268 word clouds were created, covering a maximum of eight years per subsector.

NB: It's important to note that the word clouds may be biased as some sectors/years have very low amounts of vacancy data in them. This may have created a strong bias in certain outputs.



## Appendix 2. Competence ranking

	Name	Competence	Competence type	2011	2018	2035
1	Customer and Personal Service	Knowledge	Business and Management	4.31	4.22	4.20
2	Dutch Language	Knowledge	Arts and Humanities	4.09	4.21	4.29
3	Oral Expression	Ability	Verbal Abilities	4.25	4.13	4.19
4	Oral Comprehension	Ability	Verbal Abilities	4.23	4.12	4.12
5	Written Comprehension	Ability	Verbal Abilities	4.04	4.04	4.04
6	Speaking	Skill	Content	4.05	4.02	4.03
7	Reading Comprehension	Skill	Content	3.95	4.00	4.00
8	Active Listening	Skill	Content	4.03	4.00	3.99
9	Critical Thinking	Skill	Process	3.93	3.97	3.96
10	Problem Sensitivity	Ability	Idea Generation and Reasoning Abilities	4.00	3.96	3.95
11	Speech Clarity	Ability	Auditory and Speech Abilities	4.00	3.94	3.98
12	Deductive Reasoning	Skill	Idea Generation and Reasoning Abilities	3.88	3.93	3.96
13	Inductive Reasoning	Ability	Idea Generation and Reasoning Abilities	3.88	3.92	3.90
14	Written Expression	Ability	Verbal Abilities	3.88	3.86	3.88
15	Speech Recognition	Ability	Auditory and Speech Abilities	3.88	3.85	3.84
16	Monitoring	Skill	Process	3.75	3.78	3.82
17	Social Perceptiveness	Skill	Social Skills	3.75	3.78	3.86
18	Near Vision	Ability	Visual Abilities	3.69	3.77	3.75
19	Judgment and Decision Making	Skill	Systems Skills	3.67	3.75	3.75
20	Writing	Skill	Content	3.69	3.75	3.75
21	Coordination	Skill	Social Skills	3.69	3.69	3.71
22	Complex Problem Solving	Skill	Complex Problem Solving	3.67	3.69	3.69
23	Service Orientation	Skill	Social Skills	3.63	3.68	3.68
24	Information Ordering	Ability	Idea Generation and Reasoning Abilities	3.61	3.67	3.67

	Name	Competence	Competence type	2011	2018	2035
25	Administration and Management	Knowledge	Business and Management	3.75	3.60	3.64
26	Mathematics 1	Skill	Content	3.55	3.59	3.59
27	Mathematics	Knowledge	Mathematics and Science	3.55	3.59	3.59
28	Active Learning	Skill	Process	3.52	3.59	3.59
29	Education and Training	Knowledge	Education and Training	3.39	3.54	3.67
30	Persuasion	Skill	Social Skills	3.50	3.53	3.60
31	Time Management	Skill	Resource Management Skills	3.62	3.50	3.50
32	Fluency of Ideas	Ability	Idea Generation and Reasoning Abilities	3.37	3.47	3.48
33	Computers and Electronics	Knowledge	Engineering and Technology	3.51	3.47	3.47
34	Originality	Ability	Idea Generation and Reasoning Abilities	3.37	3.40	3.42
35	Sales and Marketing	Knowledge	Business and Management	3.48	3.40	3.70
36	Category Flexibility	Ability	Idea Generation and Reasoning Abilities	3.38	3.36	3.36
37	Negotiation	Skill	Social Skills	3.35	3.35	3.35
38	Clerical	Knowledge	Business and Management	3.25	3.35	3.26
39	Instructing	Skill	Social Skills	3.29	3.34	3.38
40	Systems Analysis	Skill	Systems Skills	3.36	3.33	3.33
41	Manual Dexterity	Ability	Fine Manipulative Abilities	3.36	3.33	3.33
42	Arm Hand Steadiness	Ability	Fine Manipulative Abilities	3.40	3.33	3.32
43	Systems Evaluation	Skill	Systems Skills	3.26	3.28	3.27
44	Multilimb Coordination	Ability	Control Movement Abilities	3.39	3.27	3.18
45	Law and Government	Knowledge	Law and Public Safety	3.17	3.25	3.21
46	Psychology	Knowledge	Mathematics and Science	3.43	3.25	3.52
47	Selective Attention	Ability	Attentiveness	3.25	3.23	3.18
48	Learning Strategies	Skill	Process	3.23	3.23	3.31

	Name	Competence	Competence type	2011	2018	2035
49	Public Safety and Security	Knowledge	Law and Public Safety	3.26	3.22	3.22
50	Control Precision	Ability	Control Movement Abilities	3.30	3.20	3.18
51	Transportation	Knowledge	Transportation	2.83	3.20	2.81
52	Mechanical	Knowledge	Engineering and Technology	3.27	3.19	3.22
53	Production and Processing	Knowledge	Manufacturing and Production	3.08	3.19	3.19
54	Far Vision	Ability	Visual Abilities	3.08	3.19	3.13
55	Finger Dexterity	Ability	Fine Manipulative Abilities	3.23	3.13	3.13
56	Mathematical Reasoning	Ability	Quantitative Abilities	3.13	3.13	3.13
57	Visualization	Ability	Spatial Abilities	3.23	3.13	3.13
58	Flexibility of Closure	Ability	Perceptual Abilities	3.19	3.13	3.13
59	Economics and Accounting	Knowledge	Business and Management	2.99	3.13	3.06
60	Management of Personnel Resources	Skill	Resource Management Skills	3.38	3.09	3.09
61	Number Facility	Ability	Quantitative Abilities	3.10	3.08	3.08
62	Operation Monitoring	Skill	Technical Skills	3.20	3.07	3.02
63	Trunk Strength	Ability	Physical Strength Abilities	3.08	3.05	3.05
64	Engineering and Technology	Knowledge	Engineering and Technology	3.17	3.04	3.04
65	Personnel and Human Resources	Knowledge	Business and Management	3.20	3.01	3.01
66	Perceptual Speed	Ability	Perceptual Abilities	3.07	3.00	2.99
67	Design	Knowledge	Engineering and Technology	2.97	2.99	2.99
68	Static Strength	Ability	Physical Strength Abilities	3.05	2.96	2.96
69	Quality Control Analysis	Skill	Technical Skills	2.94	2.94	2.85
70	Operation and Control	Skill	Technical Skills	3.03	2.93	2.86
71	Extent Flexibility	Ability	Flexibility, Balance, and Coordination	2.90	2.93	2.99
72	Time Sharing	Ability	Attentiveness	2.94	2.88	2.88

	Name	Competence	Competence type	2011	2018	2035
73	Visual Color Discrimination	Ability	Visual Abilities	2.90	2.88	2.88
74	Reaction Time	Ability	Reaction Time and Speed Abilities	2.94	2.84	2.75
75	Depth Perception	Ability	Visual Abilities	2.95	2.81	2.81
76	Auditory Attention	Ability	Auditory and Speech Abilities	2.85	2.79	2.73
77	Memorization	Ability	Perceptual Abilities	2.81	2.79	2.79
78	Communications and Media	Knowledge	Communications	2.65	2.77	2.77
79	Speed of Closure	Ability	Perceptual Abilities	2.77	2.75	2.76
80	Operations Analysis	Skill	Technical Skills	3.03	2.73	2.73
81	Hearing Sensitivity	Ability	Auditory and Speech Abilities	2.80	2.71	2.63
82	Rate Control	Ability	Control Movement Abilities	2.68	2.70	2.62
83	Sociology and Anthropology	Knowledge	Mathematics and Science	2.54	2.64	2.82
84	Therapy and Counseling	Knowledge	Health Services	2.72	2.64	2.65
85	Stamina	Ability	Endurance	2.75	2.63	2.71
86	Science	Skill	Content	2.74	2.58	2.76
87	Troubleshooting	Skill	Technical Skills	2.62	2.56	2.54
88	Building and Construction	Knowledge	Engineering and Technology	2.57	2.55	2.46
89	Gross Body Coordination	Ability	Flexibility, Balance, and Coordination	2.67	2.55	2.55
90	Chemistry	Knowledge	Mathematics and Science	2.56	2.54	2.54
91	Management of Financial Resources	Skill	Resource Management Skills	2.50	2.53	2.53
92	Telecommunications	Knowledge	Communications	2.40	2.52	2.50
93	Response Orientation	Ability	Control Movement Abilities	2.55	2.50	2.50
94	Management of Material Resources	Skill	Resource Management Skills	2.67	2.50	2.50
95	Dynamic Strength	Ability	Physical Strength Abilities	2.48	2.47	2.53
96	Geography	Knowledge	Mathematics and Science	2.31	2.43	2.43

	Name	Competence	Competence type	2011	2018	2035
97	Medicine and Dentistry	Knowledge	Health Services	2.50	2.42	2.82
98	Equipment Maintenance	Skill	Technical Skills	2.56	2.40	2.33
99	Repairing	Skill	Technical Skills	2.48	2.39	2.37
100	Physics	Knowledge	Mathematics and Science	2.32	2.32	2.32
101	Biology	Knowledge	Mathematics and Science	2.20	2.32	2.34
102	Equipment Selection	Skill	Technical Skills	2.32	2.32	2.29
103	Gross Body Equilibrium	Ability	Flexibility, Balance, and Coordination	2.31	2.24	2.21
104	Spatial Orientation	Ability	Spatial Abilities	2.30	2.23	2.23
105	Speed of Limb Movement	Ability	Reaction Time and Speed Abilities	2.38	2.17	2.17
106	Philosophy and Theology	Knowledge	Arts and Humanities	2.08	2.16	2.27
107	Wrist Finger Speed	Ability	Reaction Time and Speed Abilities	2.20	2.16	2.13
108	Food Production	Knowledge	Manufacturing and Production	1.93	2.08	1.89
109	Glare Sensitivity	Ability	Visual Abilities	2.25	2.07	2.06
110	Foreign Language	Knowledge	Arts and Humanities	1.88	2.00	2.02
111	Technology Design	Skill	Technical Skills	1.86	2.00	2.00
112	Peripheral Vision	Ability	Visual Abilities	2.06	2.00	1.97
113	Programming	Skill	Technical Skills	1.88	1.96	1.90
114	Sound Localization	Ability	Auditory and Speech Abilities	2.03	1.90	1.90
115	Night Vision	Ability	Visual Abilities	2.00	1.88	1.88
116	Fine Arts	Knowledge	Arts and Humanities	1.74	1.79	1.81
117	History and Archeology	Knowledge	Arts and Humanities	1.77	1.71	1.89
118	Explosive Strength	Ability	Physical Strength Abilities	1.40	1.67	1.67
119	Installation	Skill	Technical Skills	1.55	1.44	1.42
120	Dynamic Flexibility	Ability	Flexibility, Balance, and Coordination	1.23	1.38	1.42



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