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An analysis of the demand for skills in the labour market in 2035

Working Paper 3

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The Skills Imperative 2035

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List of Abbreviations

ANZSCO	Australian and New Zealand Standard Classification of Occupations
ASC	Australian Skills Classification
BLS	US Bureau of Labor Statistics
CASCOT	Computer Assisted Structured Coding of Text
CE	Cambridge Econometrics
DfE	Department for Education
EES	Essential Employment Skills
ESCO	European Skills, Competences, Qualifications and Occupations
ESS	Employer Skills Surveys
IAG	Information, Advice and Guidance
IER	Institute for Employment Research
ISCO	International Standard Classification of Occupations
LMI	Labour Market Information
NFER	National Foundation for Educational Research
OaSIS	Occupational and Skills Information System, Canada
ONS	Office for National Statistics
O*NET	Occupational Information Network
PIAAC	OECD Programme for the International Assessment of Adult Competencies
SOC	Standard Occupational Classification
SPB	Skills and Productivity Board
UFS	Unit for Future Skills, UK Department for Education

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The responsibility for the views expressed and for any remaining errors lies with the authors.

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Nuffield Foundation

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The Skills Imperative 2035: Essential Skills for tomorrow's workforce

Overview of The Skills Imperative 2035 programme

The global economy is changing rapidly. New technologies, coupled with major demographic and environmental change, will continue to disrupt national economies and their labour markets in the coming decades. These changes will have a significant impact on the jobs available and the skills needed to do them.

The impact of these drivers of change on the economy and labour market is expected to be one of the pre-eminent strategic challenges that the UK and wider global economy will face in the next 10 to 15 years and beyond. But the nature of the change in demand for jobs and skills in the future UK labour market is not currently well understood. We lack a detailed understanding both of future 'skills demand' – the skills which will be required in the labour market in the future – and of future 'skills supply' – the skills that can be expected to be available. Consequently, we do not have a clear picture of the skills gaps that are likely to exist in the future. *The Skills Imperative 2035* programme aims to address this knowledge gap.

If left unaddressed, mismatches between skills supply and demand could have severe consequences for: individuals, who may lack the requisite skills to access satisfying and economically sustaining work; employers, who may struggle to find workers with the skills they need; society as a whole, which may experience widening inequalities as well as continuing poor productivity and weak economic growth. *The Skills Imperative 2035* aims to help identify policy and practice responses that might mitigate – or even prevent – the potential adverse impacts of skills mismatches.

In the first stage of this research programme, our literature review identified the megatrends (e.g., automation) and events (e.g., Brexit) which are anticipated to impact on the jobs available in the economy and the skills needed to do them. This highlighted the importance of skills such as creativity, critical thinking, teamwork, problem solving and resilience, which, along with specialist skills, are expected to be critical for future employment.

In the second stage, the Warwick Institute for Employment Research (IER) and Cambridge Econometrics (CE) produced projections for the size and composition of the labour market in 2035. Whilst some sectors (e.g., Business and other services and Non-market services, which includes Health and Education) are projected to see increases in their share of UK employment, other sectors (e.g., Manufacturing) are expected to experience significant job destruction.

Up to two million jobs could be replaced by technology, with some sectors such as accommodation and transport experiencing significant job losses. Substantial changes are also expected in the *occupational structure* of employment, with some occupations (e.g., care workers and programmers) expected to grow, whilst other occupations (e.g., receptionists and warehouse operatives) likely to decline. Most new jobs will be in Professional and Associate Professional occupational groups, whereas Administrative and Secretarial and Skilled Trades will decline.

In this stage of the research programme, we produce projections of the skills that will be needed in these future jobs. We then combine the IER/CE estimates of the jobs that will be available together with the projections of the skills that will be used in those jobs to generate estimates of 'skills demand' in 2035. In particular, we identify which skills are likely to be used most intensively in employment in 2035. We call these 'Essential Employment Skills'.

In the next stage of the programme, we will build a profile of the 'skills supply' currently available in the workforce, focusing on these Essential Employment Skills that are identified as most vital for the future workforce. Finally, we will investigate how the education system can support the development of the Essential Employment Skills needed in future.

1 An analysis of the demand for skills in the labour market in 2035

1.1 Executive Summary

In this stage of *The Skills Imperative 2035* research programme, we assess ***What skills will be needed most in the labour market of the future?*** Our approach to addressing this question is to combine detailed forecasts of employment in the jobs of the future together with projections of the skills that will be used in those jobs. This enables us to produce estimates of future skills demands.

For employment, we use new labour market projections produced for *The Skills Imperative 2035* programme by the Warwick Institute for Employment Research (IER) and Cambridge Econometrics (CE). These projections provide our estimates of the numbers employed in the jobs of the future. We use the most detailed occupational employment classification that is available.

For skills, there is no systematic and comprehensive assessment of the different skills that are used in employment in the UK. We therefore first match information from the US Occupational Information Network (O*NET) – the primary source of occupational information in the US – to the occupations the UK Standard Occupational Classification 2020 (UK SOC2020). In total, we have 161 different skill descriptors from O*NET to characterise each of the 412 occupations in UK SOC2020. By combining these occupational skills profiles with information on the occupational composition of employment, we are able to identify the skills that are used most intensively in employment today.

As the skills required in jobs will not remain the same in the future, we then project how skills are likely to change within each occupation between 2020 and 2035, in part based on patterns of how skills have evolved in each occupation between 2010 and 2020. These skills projections are then combined with IER/CE's employment projections to produce estimates of skill requirements in 2035. These skills requirements are a result of both changes in skills utilisation *within* occupations (i.e. changes in skill requirements within jobs) and changes in skills utilisation *between* occupations (i.e., changes due to the changing occupational distribution of employment).

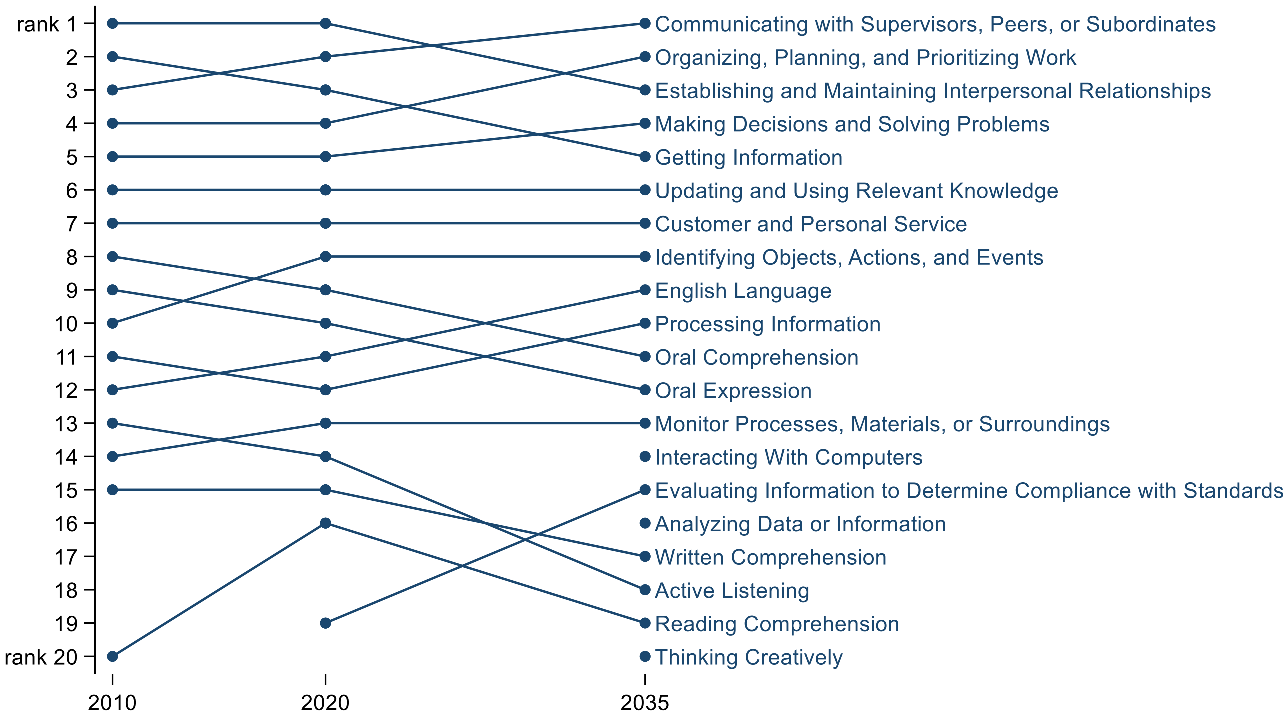
We can therefore identify the skills that are likely to be used most intensively in employment in 2035 – the 'Essential Employment Skills'.

1.2 Key research findings

While there are changes in the relative importance of skills between 2020 and 2035, the skills that are most utilised today are set to remain fundamental for future employment.

The occupational skills profiles clearly identify a set of skills that are used most intensively in employment today. These include communication, collaboration, decision making, problem solving, and information acquisition, processing and analysis. Projecting forward to 2035, there are some changes in the relative importance of different skills, reflecting both shifts in the utilisation of skills within occupations and changes in the occupational distribution of employment. Nevertheless, the top 10 skills used most intensively in the labour market in 2035 will broadly be the same as today. This is illustrated in Figure I below.

Figure I: Top 20 skills ranking 2010-2020-2035



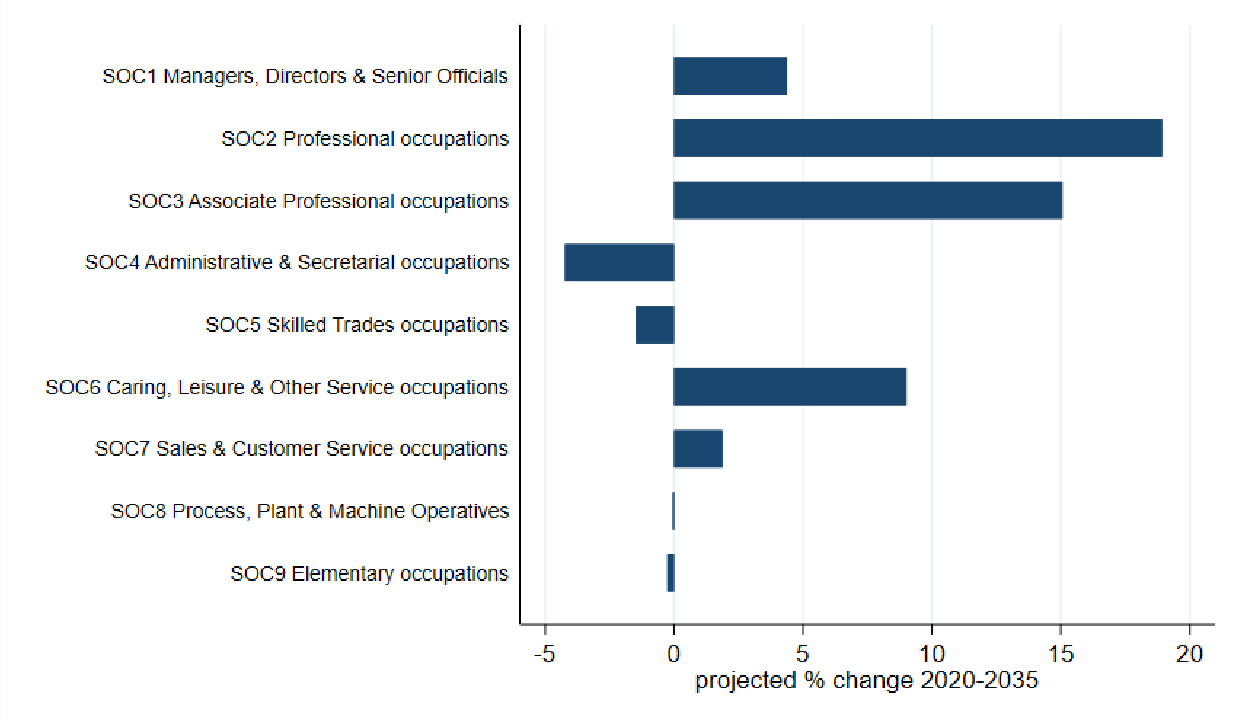
This finding is not unexpected given the generic and transferable nature of the top 10 skills – they are used intensively across *all* employment. It is important to note that these top skills are ranked highest amongst an extremely wide range of 161 different skill measures that include cognitive, non-cognitive and physical skills, as well as broad and specific subject knowledge, and individual abilities. This finding therefore demonstrates the continuing fundamental importance of transferable skills in employment.

As well as the baseline employment projections for 2035, we also consider two alternative scenarios for future employment which assume: (a) a more rapid adoption of new technologies and increased emphasis on 'green' initiatives; and (b) a greater focus, and investment, in the provision of social services – particularly in health, care and education. We also consider different methods of projecting future skill use within occupations. Under all of these variants, the set of top 10 skills identified is almost unchanged.

In 2035, the labour market will include more people in Professional and Associate Professional occupations, and people in these occupations require higher levels of the top 10 and other skills to perform their jobs.

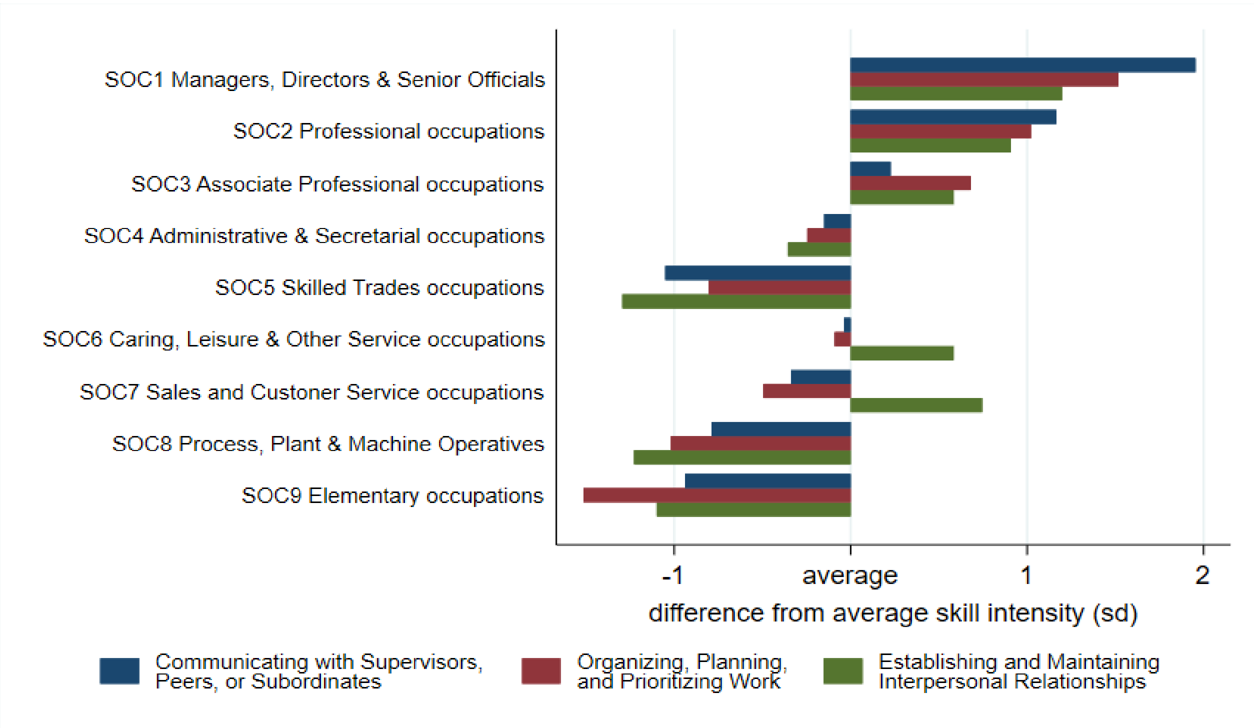
As shown in Figure II, most of the net growth in jobs created between 2020 and 2035 will be in Professional and Associate Professional occupations, which are towards the top of the occupational hierarchy.

Figure II: Projected changes in employment 2020-2035 by SOC2020 Major Group



In general, skill requirements increase as we move up the occupational hierarchy, from Elementary occupations at one extreme to Managers, Directors & Senior Officials at the other. For example, for the top three skills in 2035, Figure III presents the difference (measured in standard deviations (sd)) from the average occupational skill intensity for each SOC2020 Major Group.

Figure III: Differences from the average skill utilisation for the top 3 skills in 2035 by SOC2020 Major Group



Our analysis shows that demand for the top 10 skills is expected to increase between 2020 and 2035 – despite the fact they are already highly utilised in 2020 – and that new jobs will primarily be created in occupations that most require these skills.

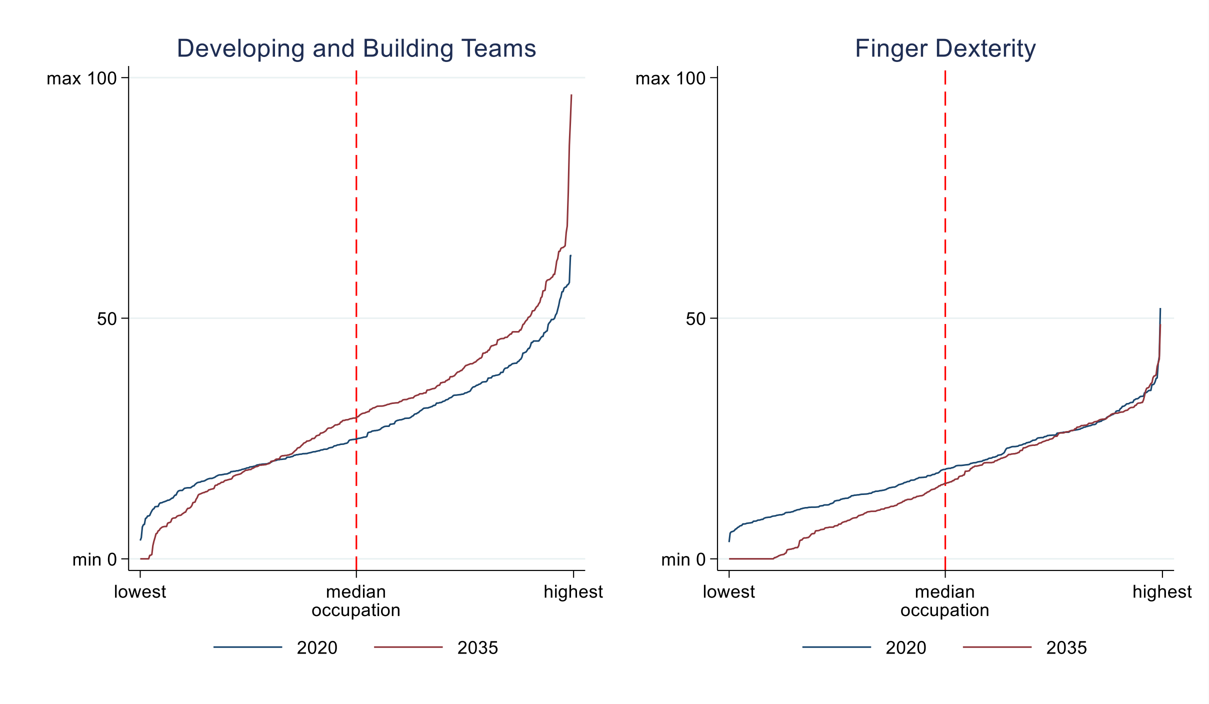
These findings highlight the need for a greater focus on the development of these skills in our education and training systems. To meet the skills demands of the future, we will need to increase the availability of these skills across the workforce, help and support more workers to acquire the skills to 'move up' the occupational hierarchy, and ensure young people have higher average levels of these skills than previous generations when they first enter the workforce.

Demand for many of the other skills which are outside of the top 10 most utilised skills in 2035 are also projected to grow, but physical and sensory skills which historically have been widely utilised, are set to decline.

The demand for skills outside of the top 10 most utilised skills is also increasing, on average. Of the other 151 skills considered, demand is projected to increase for 106 (70%) of these skills over the period 2020 to 2035. These include skills such as 'Developing and Building Teams', 'Providing Consultation and Advice to Others', and 'Developing Objectives and Strategies'. In contrast, demand is projected to decrease for 45 (30%) of these skills over this period. Of particular note are physical and sensory skills, which have, historically, primarily been utilised in the primary and secondary sectors (i.e. agriculture, extractive industries, manufacturing and construction). Demand for these types of skills has been in decline over the last few decades as the economy has increasingly become dominated by services. This trend is set to continue.

To illustrate, Figure IV below presents the occupational skills profiles for two skills: 'Developing and Building Teams', and 'Finger Dexterity'.

Figure IV: Occupational skills profiles for 2020 and 2035 for Developing and Building Teams, and Finger Dexterity



For both skills, occupations are ranked from lowest to highest on our skill utilisation score, which is scaled to range from a minimum of zero to a maximum of 100. For Developing and Building Teams, most occupations above the lowest quartile of utilisation are projected to require an increase in this skill between 2020 and 2035. In contrast, for Finger Dexterity, all of the occupations below the median usage are projected to see a decrease in the utilisation of that skill by 2035, even though it is already at a relatively low level of utilisation.

Changes in the composition of the labour market will also drive increases in the demand for certain specialist skills.

In general, demand for more *specialist* skills also increases as we move up the occupational hierarchy. Due to changes in the composition of the labour market, there will be increased skills demand for a wide range of specialist skills in 2035.

However, while demand for some specialist skills may increase markedly, they still do not appear highly in the rank order of the most important skills across the labour market in 2035. This is a consequence of the specialised nature of these skills – they tend to be important for particular jobs in specific sectors and industries – and our findings may be useful for planning purposes in those sectors. Nevertheless, these specialist skills are used intensively in relatively few jobs, and so their average utilisation across all employment is relatively low. This distinguishes them from skills in the top 10 of the ranking, where utilisation is high across all employment.

Six Essential Employment Skills emerge, which are projected to be in greatest demand in the labour market of 2035.

Using our projections of the top skills that will be used in employment in 2035, together with the findings of the earlier literature review for *The Skills Imperative 2035*, we identify six **Essential Employment Skills** – the most important skills for employment in 2035. These are:

- Collaboration
- Communication
- Creative thinking
- Information literacy
- Organising, planning and prioritising
- Problem solving and decision making

This set of six Essential Employment Skills also maps well to the skills shortages indicated by respondents in previous small-scale surveys of workers and employers which have all identified skills mismatches, with too many people without the right skills to meet employer need and enable productive sectors to grow. These are the Essential Employment Skills that we will investigate further in the subsequent stages of *The Skills Imperative 2035* programme.

1.3 Summary

While there is some churn in the relative ranking of different skills between 2020 and 2035, the skills most utilised in today's labour market will become even more important and ubiquitous in future employment.

Within these top-ranked skills, we have identified a group of **Essential Employment Skills** which are used most intensely in employment. Existing research suggests there are already mismatches in the overall supply and demand for many of these skills. Projected changes in the size and composition of the labour market are likely to exacerbate these shortages, particularly because the levels of ‘skill demand’ (i.e., the requirements of jobs) increases as we go up the occupational hierarchy, and job creation between 2020 and 2035 will be primarily towards the top of this hierarchy. It is therefore imperative that we build a better understanding of the availability of Essential Employment Skills in the labour market, and further our knowledge on how these skills develop, and the role that the education and training systems play in developing them. This is the focus of the next stage of *The Skills Imperative 2035* research programme.

2 Introduction

- *The Skills Imperative 2035* programme is focussed on the future skill needs of a changing economy. This report identifies the skills that will be most utilised in the labour market in 2035.
- This section outlines the approach used in the report. We combine new occupational employment projections produced by Warwick Institute for Employment Research (IER) and Cambridge Econometrics (CE) with information on skills derived from the US Occupational Information Network (O*NET).
- Together, these data enable us to produce projections for the skills that are anticipated to be most utilised in employment in the future – the 'Essential Employment Skills'.

2.1 Background and context to the research programme

The Skills Imperative 2035 programme aims to ensure that the workforce is equipped for the skill needs of a changing economy. However, we currently lack a detailed understanding of future 'skills demand' – the skills which will be required in the labour market in the future – and of future 'skills supply' – the skills that can be expected to be available. We also know relatively little on how skills demand and supply are likely to be distributed, and what skills gaps are likely to exist. *The Skills Imperative 2035* will help address these important questions.

The consequences of having skills mismatches and failing to implement effective long-term education and training strategies focussed on skills could be detrimental on many levels. Individuals without the appropriate skills may find themselves unable to access satisfying and economically sustaining work. Employers may struggle to find workers with the skills needed to adapt to the 'mega-challenges' associated with new technologies, continued demographic change and the transition to net zero. For society, an unequal distribution of skills may further exacerbate income inequalities and lead to social disaffection and disengagement. Having the right skills mix is also important for strategies focussed on addressing stagnating productivity growth and the more recent declines in living standards.

This report focusses on *The Skills Imperative 2035* programme's first substantive research question: ***What skills will be needed in the labour market in the future?*** It builds on the projections of the size and composition of the labour market which were published earlier in the research programme.

2.2 Overview of approach

The Skills Imperative 2035 programme has already provided projections for the composition of employment in 2035: how many jobs there will be, and how they will be distributed by occupation, industry and region. This report adds to these estimates of the number of jobs in the future by generating projections of the skill requirements for each job. By combining these two sets of projections – the number of jobs and the skill requirements for each job – we produce a uniquely detailed, data-driven assessment of the skills that will be required in the labour market in the future.

The new labour market projections produced for *The Skills Imperative 2035* programme by the Institute for Employment Research (IER) and Cambridge Econometrics (CE) are described in detail in Wilson *et al*., (2022a, 2022b, 2022c). These projections employ the same methodology used to produce IER/CE's longstanding series of employment projections for the UK Government, commonly referred to as *Working Futures* (Wilson *et al*., 2020a, 2020b). However, the new projections for *The Skills Imperative 2035* programme are the first to employ the new UK Standard Occupational Classification 2020 (UK SOC2020). The IER/CE occupational employment projections provide our estimates of the numbers employed in the jobs of the future. We use the most disaggregated occupational classification that is available, which is for 412 unit group (or 4-digit) occupations.

For skills, unfortunately there is no systematic and comprehensive assessment of the different skills that are used in employment in the UK. Currently, skills information in the UK mostly relies on piecemeal information, gathered from irregular, often small-scale surveys of workers (e.g. the Skills and Employment Surveys (SES), Felstead *et al.*, 2019), or from bespoke surveys of employers (e.g. Employer Skills Surveys, Winterbotham *et al*., 2020a, 2020b; Employer Pulse Survey, Winterbotham *et al*., 2022) which are necessarily partial. Such surveys are also often too limited in scale and scope to permit any detailed spatial disaggregation, which is necessary for assessing local skill needs to inform the levelling-up agenda (DLUHC, 2022).

The literature review undertaken for *The Skills Imperative 2035* programme (Taylor *et al.*, 2022) reveals that, at best, the extant literature suggests which skills are likely to be important and/or increasing in importance, but not by how much or in which particular occupations (beyond broad generalities). The literature also says almost nothing about which skills will be unimportant and/or decreasing in importance.

We therefore first produce 'occupational skills profiles' – an assessment of the level and importance of the various skills that are used in different clusters of jobs – by extending and updating the mapping between the US Occupational Information Network (O*NET) and the UK SOC2010 as first developed by Dickerson and Wilson (2012). O*NET is the primary source of occupational information in the US and comprises occupation-specific descriptors of skills and other dimensions for around 1,000 separate occupations, closely linked to the US SOC. This information is updated on a continuous rolling cycle using information from professional job analysts, occupational experts, and surveys administered to incumbent workers (see **Appendix A** for more details on O*NET). We first update the existing mapping between the O*NET2010 and UK SOC2010 classifications to the latest O*NET classification (O*NET2019) and the new UK SOC2020 classification to produce occupational skills profiles for our 412 4-digit UK SOC2020 occupations. In total, we have 161 indicators of the different skills used within each occupation. We then compile the historic data on the level and importance of each of these 161 skills in each of our 412 UK SOC2020 occupations over the period 2010 to 2020. The patterns of change in skills over the 2010-2020 period are then used to generate projections for each skill in each occupation in 2035. We experiment with different forms for the projections in order to ascertain whether our findings are sensitive to the particular assumptions we make regarding the future trends in skills.

Finally, we combine the employment and skills projections to produce an assessment of the changing patterns of skills utilisation in employment in 2035. These projections allow for changing skills utilisation within occupations over the next decade or so, as well as the changing occupational composition of employment. We are also able to compare and contrast these with the skills that are used most intensively in employment today. We then use these projections for occupational employment and skills for 2035 to identify the ‘essential skills’ that will be used most intensively in the labour market in 2035.

Our main findings are that our data-driven approach clearly identifies a set of skills that are being used more intensively in employment. These are typically generic and transferable skills such as communication, collaboration, planning, problem solving and decision making that are used in many jobs, rather than being more specific skills that are used intensively in relatively few jobs. Over the historic period covered by our analysis, 2010-2020, the relative importance of these different skills changes, reflecting changes in both the occupational distribution of employment and changes in the utilisation of skills within occupations. However, the 10 or so most important skills used in jobs are a fairly stable set over time.

Using the IER/CE projections for occupational employment, and our projections for skill use within those occupations, we generate predictions of the skills that will be used most intensively in employment in 2035. There is some further re-ranking of the top skills in employment, with increasing importance for communication for example. But the main finding is that the top 20 of our 161 skills remain a relatively stable set over the period 2020-2035. Notable, however, is the increasing importance of information evaluation and processing: Interacting With Computers and Analysing Data or Information are projected to both enter the top 20 skills for the first time by 2035. Our purely data-driven approach also confirms many of the conclusions reached in the existing literature on the future of skills, as reviewed by Taylor *et al*., (2022) for *The Skills Imperative 2035* programme.

Our analysis throughout is for England only, rather than for the whole of the UK. There are two main reasons for this focus on England. First, and most importantly, subsequent stages of *The Skills Imperative 2035* programme focus on building a profile of the *supply* of the skills that are projected to be most utilised in employment in 2035, and on identifying skill mismatches and exploring the role that education plays in skills development. This involves surveying adults in England about their skills, and linking their responses to other data help on the same individuals, including in administrative datasets that cover England only, and the responses that individuals provided as part of the second cycle (2022-23) of the OECD Survey of Adult Skills (PIAAC) (OECD, 2016) which, within the UK, is administered in England only. Thus, in order to identify the relevant skills to be included in our Skills Survey, we have restricted our analysis of the skills most in demand in 2035 to England only.

Second, since skills provision and funding are devolved responsibilities, then any policy and practice recommendations that follow from *The Skills Imperative 2035* programmes, and consideration of how they might be implemented, need to be nation-specific. However, we anticipate that the analysis presented in this report, and its conclusions, will have strong resonance for all of the nations of the UK, and intend to explore the extent to which this is the case later in the project.

2.3 Outline of this report

The remainder of this report is structured as follows:

- Section 2 describes the methodology that we use to derive our occupational skills profiles and the projections of skills used in employment in 2035.
- In Section 3, we describe the main findings of our analysis. We describe how the ‘skills landscape’ is changing over time and produce rankings for the skills that we consider will be used most intensively in employment in 2035. We also examine the robustness and sensitivity of our main findings to the different assumptions that we

use, including investigating the implications of the *Alternative scenarios* for employment that IER/CE have produced for the employment situation in 2035.

- In Section 4, we use our skill utilisation rankings together with the conclusions of the literature review conducted in the first stage of *The Skills Imperative 2035* programme (Taylor *et al.*, 2022). to identify a set of six ‘Essential Employment Skills’ which we anticipate will be in most demand in the labour market in 2035.
- Finally, Section 5 presents some concluding remarks and outlines the next stages of *The Skills Imperative 2035* programme.

3 Assessing skills demand: methodology

- We produce a systematic mapping between the 412 unit group (4-digit) occupations in the latest UK Standard Occupational Classification (SOC2020) and the 1,016 occupations in the current US O*NET system (O*NET2019).
- We map the information from 161 elements from the Abilities, Knowledge, Skills and Work Activities domains of O*NET to our UK SOC occupations to produce 412 'occupational skills profiles'.
- We have measures of both the importance and the level with which these 161 skills are used in each occupation, although these two measures are highly correlated. We therefore also combine the importance and level metrics to produce a third measure – the 'prevalence' of skill use, which we utilise in our main analysis.
- Using historic information from O*NET for the period 2010 to 2020, we generate projections for the utilisation of each these 161 skills in each of our 412 occupations in 2035.
- Finally, we combine the IER/CE occupational employment forecasts with our occupational skills projections to produce estimates for the overall utilisation of each skill in 2035.

Our task in this phase of *The Skills Imperative 2035* programme is to assess the skills that will be in most demand in the labour market in 2035. Clearly this will be a function of: (i) the jobs that workers are doing in 2035; and (ii) the skills that are being utilised most intensively in those jobs.

An assessment of the jobs that workers will be doing in 2035 has been produced by IER/CE for *The Skills Imperative 2035* programme by updating and extending the *Working Futures* labour market projections (Wilson *et al.*, 2022a). First, there is a set of *Baseline projections* which encompass all our existing knowledge regarding future demographic change, as well as current trends in innovation, automation and environmental transition, and the longer-term impacts of Brexit and the Covid-19 pandemic. The *Baseline projections* also incorporate any changes to the policy landscape which have been made or announced (Wilson *et al.*, 2022b). But because the future is inherently uncertain, IER/CE have also produced a range of '*Alternative scenarios*' (Wilson *et al.*, 2022c). Two main *Alternative scenarios* are considered which build upon the *Baseline projections*: a '*Technological opportunities scenario*' which assumes a more rapid adoption of new technology and increased emphasis on 'green' initiatives, and a '*Human-centric scenario*' which assumes greater focus, and investment, in the provision of social services – particularly in health, care and education. We use the *Baseline projections* of employment for our main analysis of the skills in most demand in 2035 as presented in Section 3 of this report, but we also investigate the differences that these two alternative employment scenarios imply for skills demand in 2035 in **Appendix D**.

The evaluation of the skills being utilised in employment in 2035 is the main focus of this report. A serious limitation in our understanding of skills demand and supply (and therefore of the extent of skill shortages and skills gaps), is the absence of systematic, consistent and comparable information on skills for the UK. The lack of a UK-specific skills 'taxonomy' hinders the production of labour market information (LMI) on current and future skills demand. It also limits the assessment of the supply of skills – measured as the current stock of skills in the working age population and also as the flow of skills into and out of the labour force. (We are aware that the Unit for Future Skills (UFS) within the Department of Education (DfE) is currently conducting a scoping study for the development of a UK skills taxonomy, and so hopefully this absence of a skills taxonomy will be resolved in the near future).

The absence of a comprehensive skills taxonomy has wider implications beyond those seeking to understand the role of skills and skilled labour in the current and future labour market. The provision of good quality LMI on skills is also crucial for the various government departments and agencies tasked with shaping the education and training ecosystem, as well as for those providing advice to young people, and to adults, about the changing labour market and its opportunities (e.g. Information, Advice and Guidance (IAG) practitioners, Work Coaches etc). A better understanding of the impact of the 'mega-trends' – such as the transition to net zero, AI and digitisation, and demographic change – for the labour market of the future would also be facilitated by having a structured skills framework (i.e. a taxonomy) within which these anticipated changes could be considered.

In contrast to the situation in the UK, there are several skills taxonomies in use around the world. A short and partial review was recently commissioned by the DfE's Skills and Productivity Board (Popov *et al*., 2022). The best known are the US Occupational Information Network (O*NET) and the EU's European Skills, Competences, Qualifications and Occupations (ESCO) system:

- O*NET is the primary source of occupational information in the US. It is over 20 years old. Occupation-specific descriptors for around 1,000 occupations, closely linked to the US SOC, are updated on a continuous rolling cycle using information from professional job analysts, occupational experts and surveys administered to incumbent workers. For each occupation, a wide range of almost 250 indicators of skills, knowledge, abilities, work activities and work styles are captured, together with measures of experience and training, and education requirements. This information is also linked to statistics from the Bureau of Labor Statistics (BLS) on earnings, employment, and the future employment outlook for each occupation.
- ESCO is a more recent development (version 1.1 was released in January 2022). ESCO is the EU multi-lingual classification of skills, qualifications and occupations, providing descriptions of around 13,500 'skills' (many are occupation-specific) for 3,000 occupations. It therefore provides more granularity than O*NET (arguably at the cost of some duplication/overlap in some definitions). ESCO has three 'pillars': occupations, skills (encompassing skills, knowledge and competencies), and qualifications. Both occupations (which are mapped to the International Standard Classification of Occupations (ISCO-08)) and skills can be hierarchically grouped and thus aggregated to higher levels. Unfortunately, progress on developing the qualifications pillar linking qualification to skills and occupations has been limited to date – perhaps in part because of the scale of the task and the country-specific nature of qualifications. A crosswalk between the O*NET and ESCO systems has been developed very recently which will enable future interoperability between the two classification systems.

Other skill classification systems that are also of particular interest and relevance are the recent developments in Australia and Canada. The Australian Skills Commission (now 'Jobs and Skills Australia') released the first version of the Australian Skills Classification (ASC) in March 2021. The ASC has three categories of skills: 10 'core competencies' (generic or transversal skills); specialist tasks (specific skills); and technology tools. Data for the initial classification for around 1,000 occupations drawn from the ANZSCO (the Australian and New Zealand SOC) was heavily based on mapping O*NET to ANZSCO and adopting the skills calibration and values for the matched occupations. Subsequently, Jobs and Skills Australia is investing heavily in developing the ASC further to make it more 'Australia-specific', including establishing linkages to the Australian Qualification Framework. Similarly, Canada is developing a Skills and Competencies Taxonomy for around 900 occupations, using a combination of O*NET and a range of Canadian data sources. This will be used as the basis for a new Occupational and Skills Information System (OaSIS). While a full version of their taxonomy has yet to be released, the information available suggests a structure with a level of detail very similar to that provided by O*NET for the US. It is interesting to note that both the ASC and OaSIS frameworks utilise occupational mappings with O*NET to populate and calibrate, at least initially, these skills classification systems. The 'transportability' of O*NET skills metrics to other countries has been previously analysed by Taylor *et al*., (2008) amongst others.

Within the UK, the O*NET and ESCO skills classifications have been explored by a number of researchers seeking to measure and evaluate skills and skilled work, and to provide useful information to individuals and advisers on career progression. A systematic O*NET to UK SOC mapping that matches O*NET2010 and UK SOC2010 classifications at the unit group or 4-digit occupation level was initially developed by Dickerson and Wilson (2012). This has been used to provide skills information in the DfE's LMI for All portal for example (Bimrose *et al*., 2013, 2015), as well as underpinning academic and policy-related research on skills (e.g. Dickerson and Morris, 2019; Cominetti *et al*., 2022; Costa and Yu, 2022; SPB, 2022).

For The Skills Imperative 2035 programme, given the extant mapping between O*NET and UK SOC, as well as the utilisation of O*NET in both the ASC and OaSIS classification systems, it was decided to exploit O*NET data to inform the assessment of skills in use in jobs in the UK labour market in 2035. A brief description of O*NET is provided in Appendix A.

Our analysis utilises the most recent available data from The Occupational Information Network (O*NET) - a comprehensive and detailed database of skills, competencies and occupational requirements in the US. This database is continually being updated. We also utilise data from the multi-sector dynamic macroeconomic model of the UK economy created by CE, and the resulting projections of occupational employment produced by Warwick IER. Updates and changes to the various datasets employed in the CE/IER analysis may affect the findings.

The remainder of this section of the report outlines the methodology that was used in order to exploit this data for *The Skills Imperative 2035* project. Subsection 2.1 describes the mapping process between O*NET and UK SOC that is used to generate occupational skills profiles for the UK, and outlines how projections for the skills in use in 2035 were subsequently generated. Subsection 2.2 explains how these skills projections were combined with the IER/CE employment projections to produce estimates of the skills that are expected to be most in demand in 2035.

3.1 Measuring skills

A brief description of the matching methodology used to construct our skills indices and the occupational skills profiles is provided in this subsection; further details are provided in **Appendix B**.

3.1.1 Mapping O*NET2019 to UK SOC2020

In order to be able to exploit the occupational skills information in O*NET, we first need to match similar O*NET and UK SOC occupations. We can then assign the skills measures from O*NET to the UK. Essentially, in undertaking this mapping exercise, we are assuming that the skills of, for example, a plumber in the UK are similar to the skills that a plumber uses in the US (and are more similar than the skills that a CEO, or a carer, or a mechanic would use).

The main downside of using the skills information in the US O*NET system to proxy the skills used in jobs in the UK is that some types of jobs in the US may use somewhat different skills to those jobs in the UK. Some testing of the validity of making such comparisons between the US and UK has been provided by Dickerson and Morris (2019) using the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) 'International Survey of Adult Skills' (OECD, 2016). PIAAC is an internationally comparable survey that assesses the proficiency of adults in numeracy, literacy and 'problem-solving in technology-rich environments'. PIAAC collects data on the same skills in different countries, using the same methodology and questions, and is coded to a common occupational classification (namely ISCO-08). This enables a *direct* comparison of occupational skills in the UK and the US, although this is only possible at the ISCO sub-major group (2-digit) level due to sample sizes. Dickerson and Morris (2019) find that the skills for US and UK occupations have very high correlations for both the levels and the rankings of numeracy, literacy and problem-solving skills. Taylor *et al*., (2008) provide some more direct comparisons of the applicability of O*NET descriptors between countries. They compare the means and rank orderings for a range of O*NET elements across a selection of occupations for US workers, with those obtained for representative samples of workers in the same occupations in New Zealand, Hong Kong and China. Taylor *et al*., (2008) find small absolute differences between the mean ratings for the elements in different countries, suggesting close similarity in job profile 'levels', with 88% of the mean absolute effect sizes ($|d|$) in the 0.2 to 0.5 range (small to medium size effects). In terms of the job profile 'shape' as captured by the rank orderings for the O*NET elements in different countries, Taylor *et al.,* (2008) report Spearman's (rank) correlation coefficients mostly in excess of 0.80 between the ranking of the elements in the US and the rankings in the other three countries, for each occupation. They therefore conclude that:

> *'… job demands for the same job performed across countries appear quite similar and that generic job information developed in one country, such as job information provided through O*NET, can be useful for understanding jobs performed in other countries.'* (Taylor *et al*., 2008, pp.106-7)

Thus, in the absence of a UK skills taxonomy, we conclude that matching the O*NET data to UK occupations is appropriate for the purposes of our analysis.

We begin with the original mapping between O*NET2010 and UK SOC2010 as illustrated on the left-hand side of the grid in Figure B1. This is a one-to-many mapping between the 369 unit groups (i.e. 4-digit occupations) of UK SOC2010 and the 1,110 occupations in O*NET2010 (which is aligned to the US SOC2010). Unit group/4-digit occupations is the most disaggregated (i.e. most detailed) classification of occupations that is available for the UK. The original mapping was a result of a process that used a Computer Assisted Structured Coding Tool (CASCOT), together with human input from an experienced CASCOT coder. CASCOT uses the detailed job title index files for O*NET and UK SOC in order to produce an initial range of possible O*NET matches for each UK SOC 4-digit occupation based on the similarities in the jobs indexes (there are approximately 50,000 US job titles and 30,000 UK job titles). The selection of the matching occupation codes then chosen is determined by the expert CASCOT coder. While this introduces an element of subjectivity, the expert coder removes ambiguities and obvious errors (Bimrose *et al.*, 2013, 2015; Dickerson and Wilson, 2012).

There are a number of possible strategies that we could use to update this mapping to the latest O*NET classification (O*NET2019, which is aligned to the US SOC2018) and the latest UK occupational classification (UK SOC2020). Most obviously, we could start from scratch, and undertake the mapping exercise all over again using the two new classifications as shown on the right-hand side of the grid in Figure B1. An alternative strategy is to use the existing mapping together with the published 'crosswalks' (or correspondences) between O*NET2010 and O*NET2019, and between UK SOC2010 and UK SOC2020, to produce the same outcome – a match between O*NET2019 and UK SOC2020. This 'reverse mapping' strategy is also illustrated in the grid in Figure B1. The crosswalk between O*NET2010 and O*NET2019 is published on the O*NET webpages. There is a fairly close correspondence between US SOC2010 and US SOC2018 that provide the underlying bases for the two O*NET classifications, and hence most of the O*NET occupation categories are unchanged between O*NET2010 and O*NET2019. The UK SOC2010 to UK SOC2020 crosswalk is provided by the ONS 'relationship tables' which were updated in July 2021 and are based on 'dual-coding' (i.e. using both SOC2010 and SOC2020) two different individual-level data sets. There is a choice here either to include all of the UK SOC2010 occupations that match to each UK SOC2020 unit group (a many-to-one 'complete' mapping), or to include only the largest/most significant in terms of employment (a 'restricted' mapping) and make the SOC2020 to SOC2010 mapping one-to-one. Further details on the different mapping processes are provided in **Appendix B**.

We undertook all three of these alternative methods for updating the O*NET-UK SOC mapping and compared the differences that resulted. IER provided an expert CASCOT coder to implement the 'new mapping' from scratch using the new O*NET and UK SOC classifications, while the strategy of using the two crosswalks to update the existing mapping was undertaken completely independently. The resulting mappings were then compared. The differences between the 'new mapping' and the 'complete' and 'restricted' reverse mapping produced using the crosswalks were very minor in general – see **Appendix B** for details. For our main analysis as presented in Section 3, we therefore use the 'complete mapping', while we investigate any sensitivity of our findings to the choice of mapping in **Appendix D.3**.

The mapping process yields a many-to-one mapping between the O*NET2019 occupations and the 412 unit group occupations in UK SOC2020. This enables us to read across the different skills that are utilised in each occupation in order to generate 'occupational skills profiles' for UK occupations. Where the mapping is many-to-one between O*NET and UK SOC, we simply average the O*NET occupational skills in the absence of any further information on the US-UK relative occupational employment structures.

3.1.2 Defining skills

We regard skills as competences acquired over time to perform specific activities. This definition of skills also includes the application of knowledge to help complete particular work tasks and activities. However, traits and personal characteristics that might affect how somebody approaches and performs in their job, such as resilience, persistence, adaptability, conscientiousness etc., are not considered as skills in our analysis. We use all of the separate ‘elements’ from the Abilities, Knowledge, Skills, and Work Activities domains from O*NET version 26.2 (February 2022) as listed in Table 1 to populate the occupational skills profiles for each of the 412 UK SOC2020 occupations. As can be seen, these 161 elements from O*NET encompass an extremely wide range of cognitive and non-cognitive skills, physical skills, and abilities, as well as many areas of subject-specific knowledge. In aggregate, they clearly allow for a very broad conceptualisation of ‘skills’. However, rather than restricting our analysis by imposing any narrower definition of ‘skill’ and thereby limiting the O*NET elements that we consider, we allow the data to determine which of these 161 elements are regarded as being utilised most in employment.

For each of these elements, O*NET provides both a Skill Importance measure and a Skill Level measure. The two measures are designed to reflect different dimensions of any particular skill utilisation. (In fact, despite this intention, the skills importance and skills levels measures tend to be highly correlated as has been noted by Handel, 2016, amongst others). We consider these two dimensions of skills separately, but also construct a composite measure as the *product* of skills importance and skills level which is intended to capture a measure of each skill’s ‘pervasiveness’ or ’primacy’ within each occupation. We label this composite of skills importance and levels as Skill Prevalence in our analysis.

Table 1: Description of the 161 O*NET 'skills' elements

Domain: Abilities	Domain: Knowledge	Domain: Skills	Domain: Work Activities
Arm-Hand Steadiness	Administration and Management	Active Learning	Analyzing Data or Information
Auditory Attention	Biology	Active Listening	Assisting and Caring for Others
Category Flexibility	Building and Construction	Complex Problem Solving	Coaching and Developing Others
Control Precision	Chemistry	Coordination	Communicating with Persons Outside Organization
Deductive Reasoning	Clerical	Critical Thinking	Communicating with Supervisors, Peers, or Subordinates
Depth Perception	Communications and Media	Equipment Maintenance	Controlling Machines and Processes
Dynamic Flexibility	Computers and Electronics	Equipment Selection	Coordinating the Work and Activities of Others
Dynamic Strength	Customer and Personal Service	Installation	Developing Objectives and Strategies
Explosive Strength	Design	Instructing	Developing and Building Teams
Extent Flexibility	Economics and Accounting	Judgment and Decision Making	Documenting/Recording Information
Far Vision	Education and Training	Learning Strategies	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
Finger Dexterity	Engineering and Technology	Management of Financial Resources	Establishing and Maintaining Interpersonal Relationships
Flexibility of Closure	English Language	Management of Material Resources	Estimating the Quantifiable Characteristics of Products, Events, or Information
Fluency of Ideas	Fine Arts	Management of Personnel Resources	Evaluating Information to Determine Compliance with Standards
Glare Sensitivity	Food Production	Mathematics (Skill)	Getting Information
Gross Body Coordination	Foreign Language	Monitoring	Guiding, Directing, and Motivating Subordinates

Domain: Abilities	Domain: Knowledge	Domain: Skills	Domain: Work Activities
Gross Body Equilibrium	Geography	Negotiation	Handling and Moving Objects
Hearing Sensitivity	History and Archeology	Operation Monitoring	Identifying Objects, Actions, and Events
Inductive Reasoning	Law and Government	Operation and Control	Inspecting Equipment, Structures, or Material
Information Ordering	Mathematics	Operations Analysis	Interacting With Computers
Manual Dexterity	Mechanical	Persuasion	Interpreting the Meaning of Information for Others
Mathematical Reasoning	Medicine and Dentistry	Programming	Judging the Qualities of Things, Services, or People
Memorization	Personnel and Human Resources	Quality Control Analysis	Making Decisions and Solving Problems
Multilimb Coordination	Philosophy and Theology	Reading Comprehension	Monitor Processes, Materials, or Surroundings
Near Vision	Physics	Repairing	Monitoring and Controlling Resources
Night Vision	Production and Processing	Science	Operating Vehicles, Mechanized Devices, or Equipment
Number Facility	Psychology	Service Orientation	Organizing, Planning, and Prioritizing Work
Oral Comprehension	Public Safety and Security	Social Perceptiveness	Performing Administrative Activities
Oral Expression	Sales and Marketing	Speaking	Performing General Physical Activities
Originality	Sociology and Anthropology	Systems Analysis	Performing for or Working Directly with the Public
Perceptual Speed	Telecommunications	Systems Evaluation	Processing Information
Peripheral Vision	Therapy and Counseling	Technology Design	Provide Consultation and Advice to Others
Problem Sensitivity	Transportation	Time Management	Repairing and Maintaining Electronic Equipment
Rate Control		Troubleshooting	Repairing and Maintaining Mechanical Equipment

Domain: Abilities	Domain: Knowledge	Domain: Skills	Domain: Work Activities
Reaction Time		Writing	Resolving Conflicts and Negotiating with Others
Response Orientation			Scheduling Work and Activities
Selective Attention			Selling or Influencing Others
Sound Localization			Staffing Organizational Units
Spatial Orientation			Thinking Creatively
Speech Clarity			Training and Teaching Others
Speech Recognition			Updating and Using Relevant Knowledge
Speed of Closure			
Speed of Limb Movement			
Stamina			
Static Strength			
Time Sharing			
Trunk Strength			
Visual Color Discrimination			
Visualization			
Wrist-Finger Speed			
Written Comprehension			
Written Expression			

Source: O*NET Center https://www.onetcenter.org/content.html

Note: The definitions for each of these elements can be found in the O*NET Content Reference Manual

The respondents are asked to rate a skill's importance for the performance in their job on a 5-point Likert scale ranging from *Not Important* ('1') to *Extremely Important* ('5'). If they respond *Somewhat Important* ('2') or above, they are then asked what level of the skill is required to perform the job on a 7-point scale, from '1' (*low*) to '7' (*high*), and they are provided with skill-specific scale anchors to aid comparability. However, if the respondent rates the skill as *Not Important* ('1') in the importance question, then they are not asked the subsequent skill level question and, in common with other users of the O*NET data, we assign a skill level of '0' in such cases (see **Appendix A** for further details).

Given the range of its two constituent components, our measure for skills prevalence ranges from a minimum of 0 (when skill importance = 1 and hence skill level = 0 by construction) to a maximum of 35 (when skill importance = 5 and skill level = 7).

It is important to note that both skill importance and skill level are each recorded in O*NET on an ordinal rather than a cardinal scale. Both are being linearised in assigning numeric scores to the responses. Clearly, given the commonality of the skill importance Likert scale for all 161 skill elements, skills can be legitimately compared across occupations by their ranked importance. For skill levels, while the scale anchor descriptors are necessarily specific to each skill, they have been calibrated to be comparable as far as possible. We therefore treat them as such in our analysis, and rank them accordingly. However, we cannot legitimately use the responses to compute how much more important a skill is over time, nor how much more important one skill is than another. Nor is it possible to interpret the magnitude of any difference in the level of skill between one occupation and another, only that one has a higher or lower skill level. Our analysis is therefore confined to the ordinal ranking of skills and occupations. (Other researchers who have utilised the O*NET data for measuring skills have also typically employed an ordinal approach – see for example, Cortes *et al.*, 2021).

The use of rankings is a compromise. We are still *comparing* skills but we cannot ascribe any interpretation to the numeric values of, or to the change in the values of the skills metrics (importance, level or prevalence) over time, only to their *relative* ranking. However, given our primary objective is to identify the most important skills in future employment, we only need to rank them, and hence this is not a limitation for our analysis.

3.1.3 Occupational skills profiles

The resulting occupational skills profiles enable us to identify the relative importance, level and prevalence of the 161 skills in use in each of the UK SOC2020 4-digit occupations in 2022. To illustrate the occupational skills profiles that the mapping generates, Figure 1 to Figure 8 present the skills profiles for eight exemplar skills:

- Establishing and Maintaining Interpersonal Relationships
- Interacting with Computers
- Making Decisions and Solving Problems
- Mathematics
- Programming
- Science
- Service Orientation
- Social Perceptiveness

(we underline the names of O*NET elements throughout this report).

Figure 1: Skill Profile: Establishing and Maintaining Interpersonal Relationships

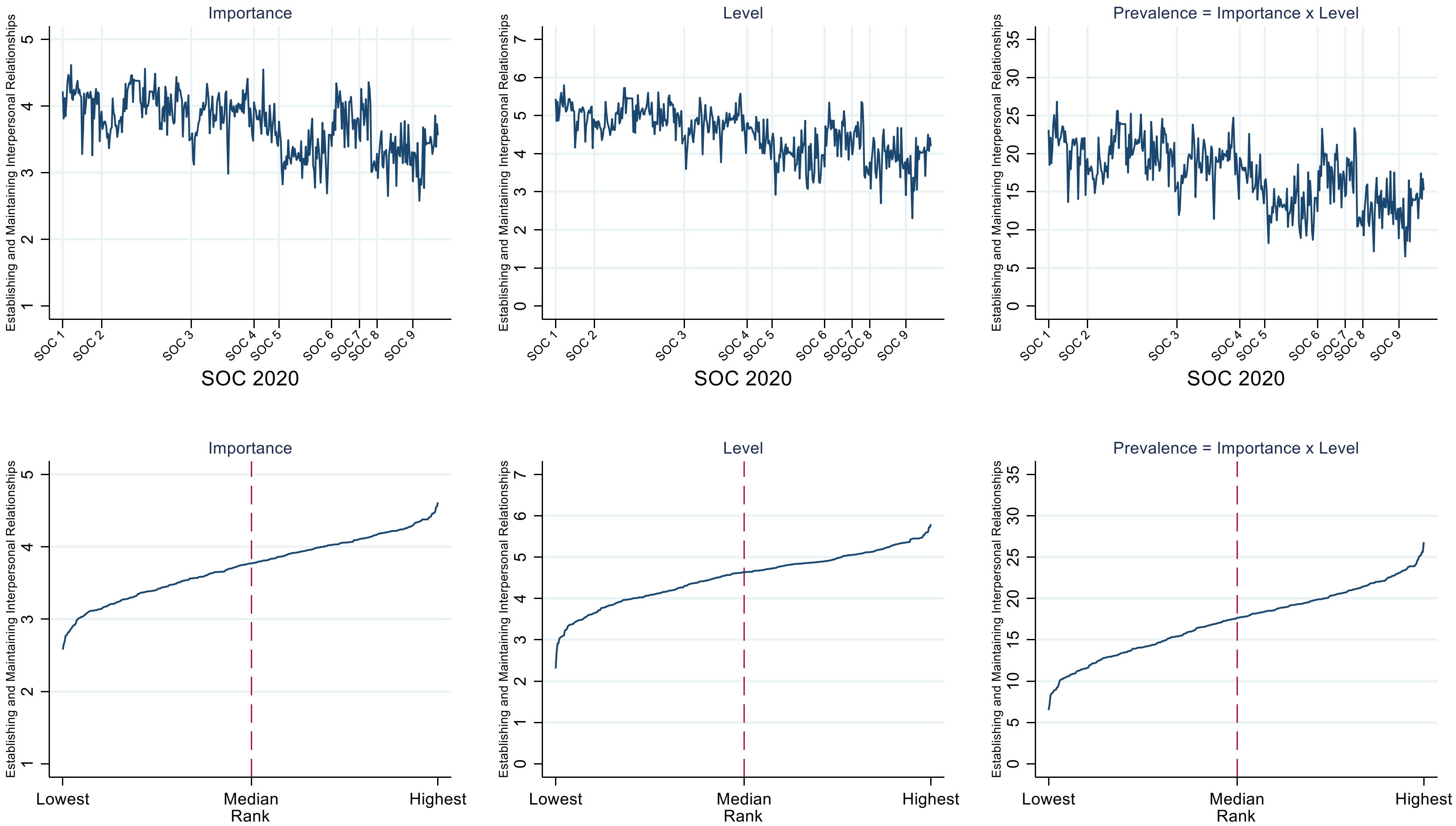


Figure 2: Skill Profile: Interacting with Computers

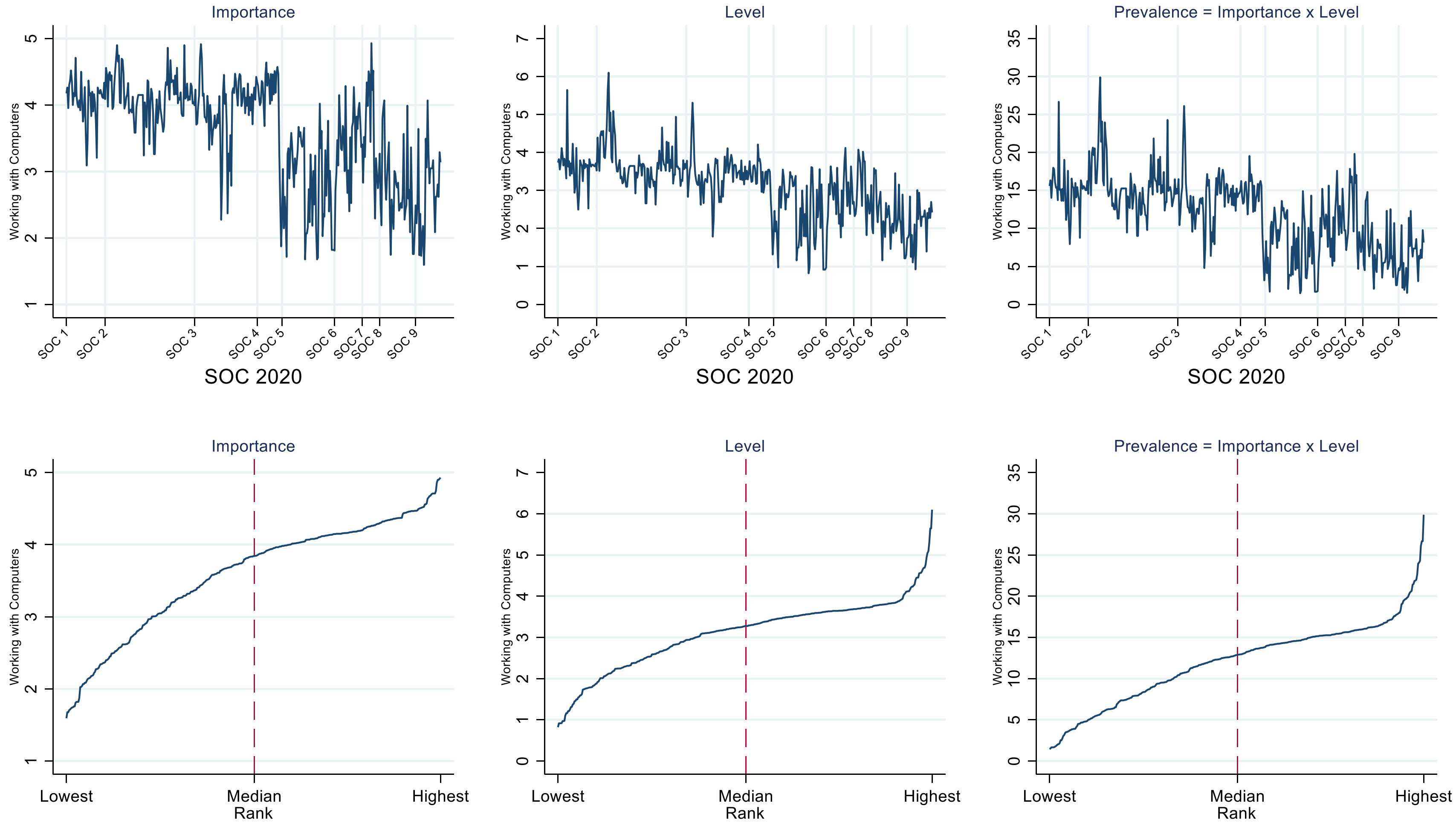


Figure 3: Skill Profile: Making Decisions and Solving Problems

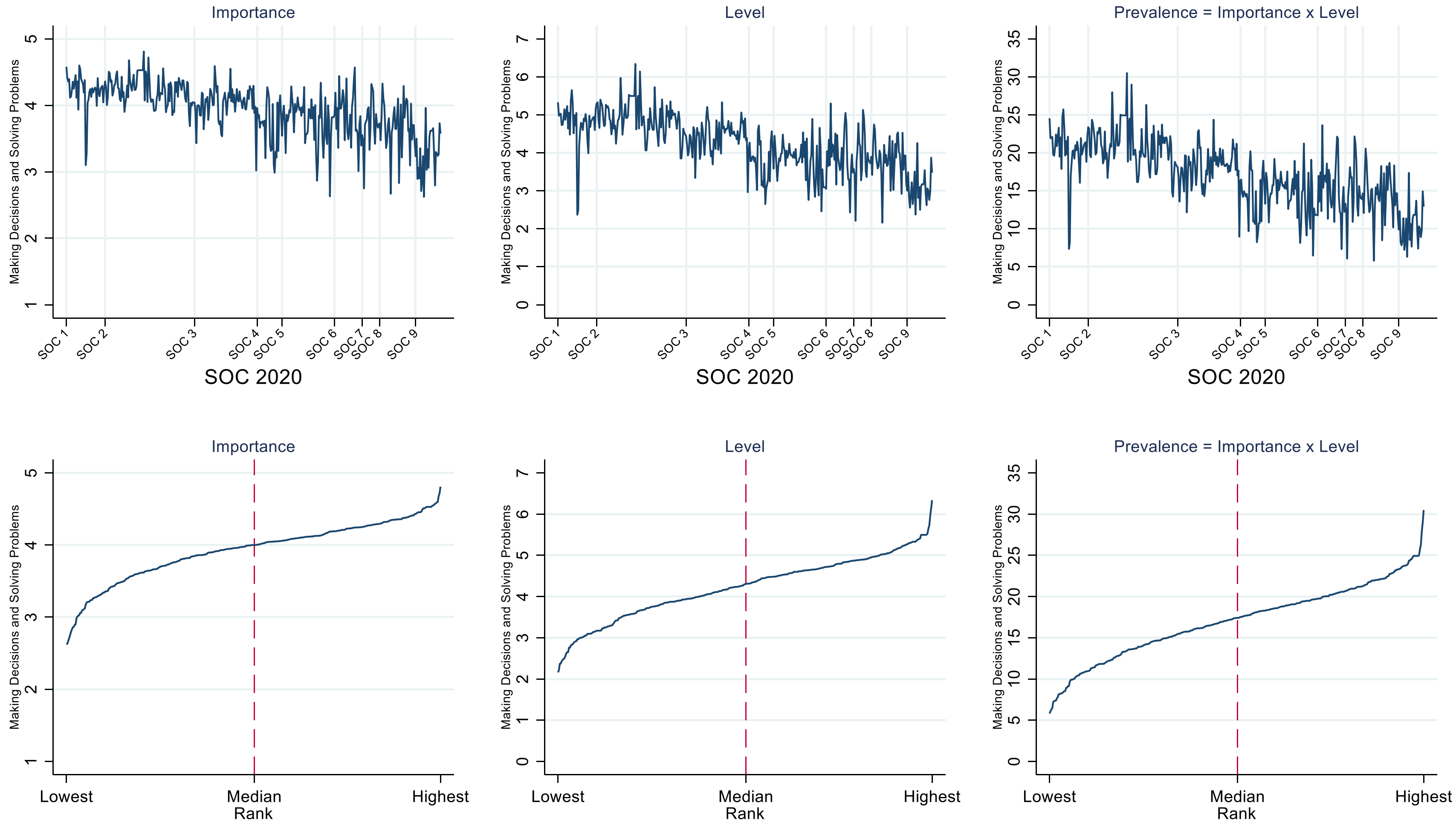


Figure 4: Skill Profile: Mathematics

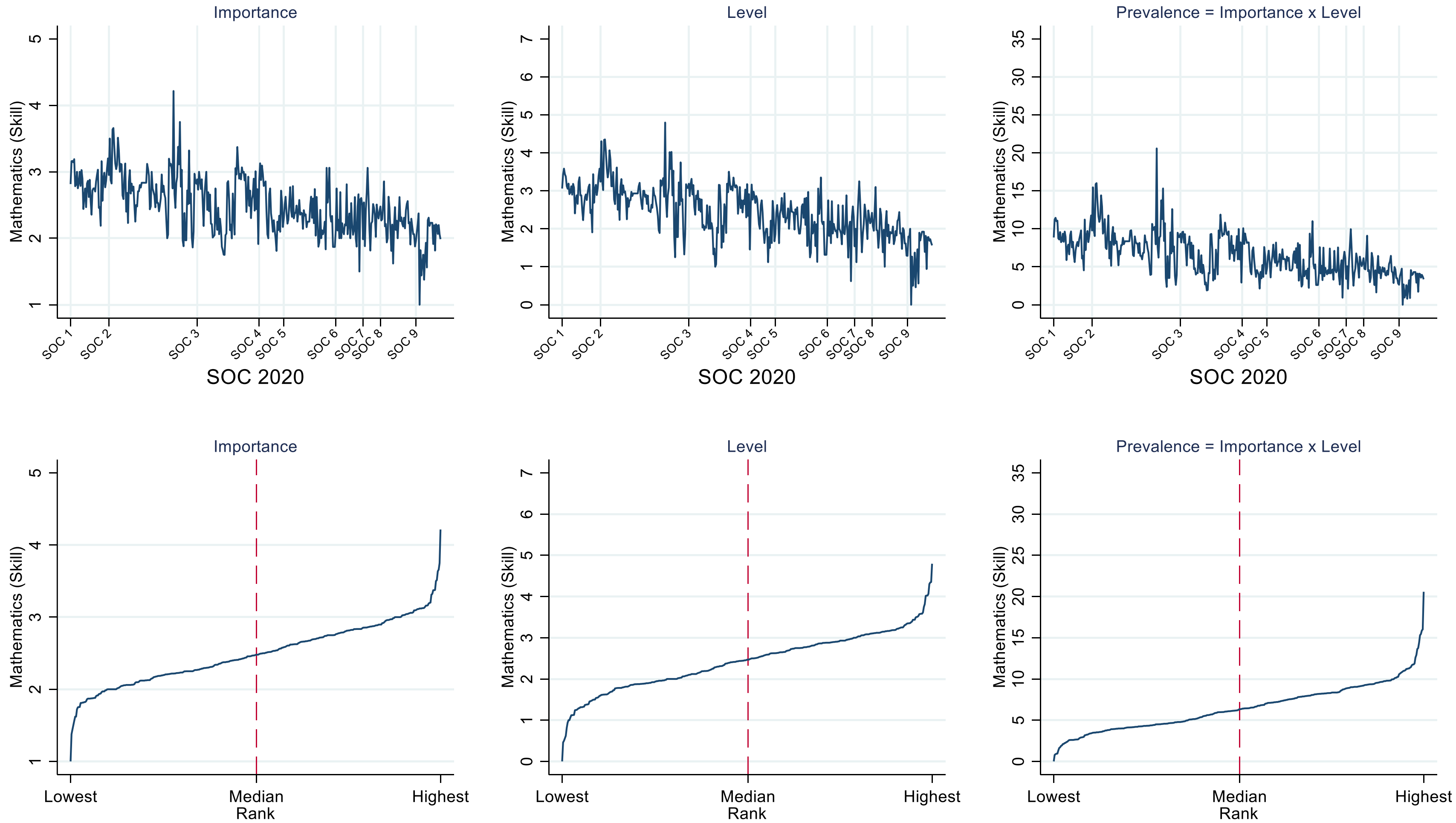


Figure 5: Skill Profile: Programming

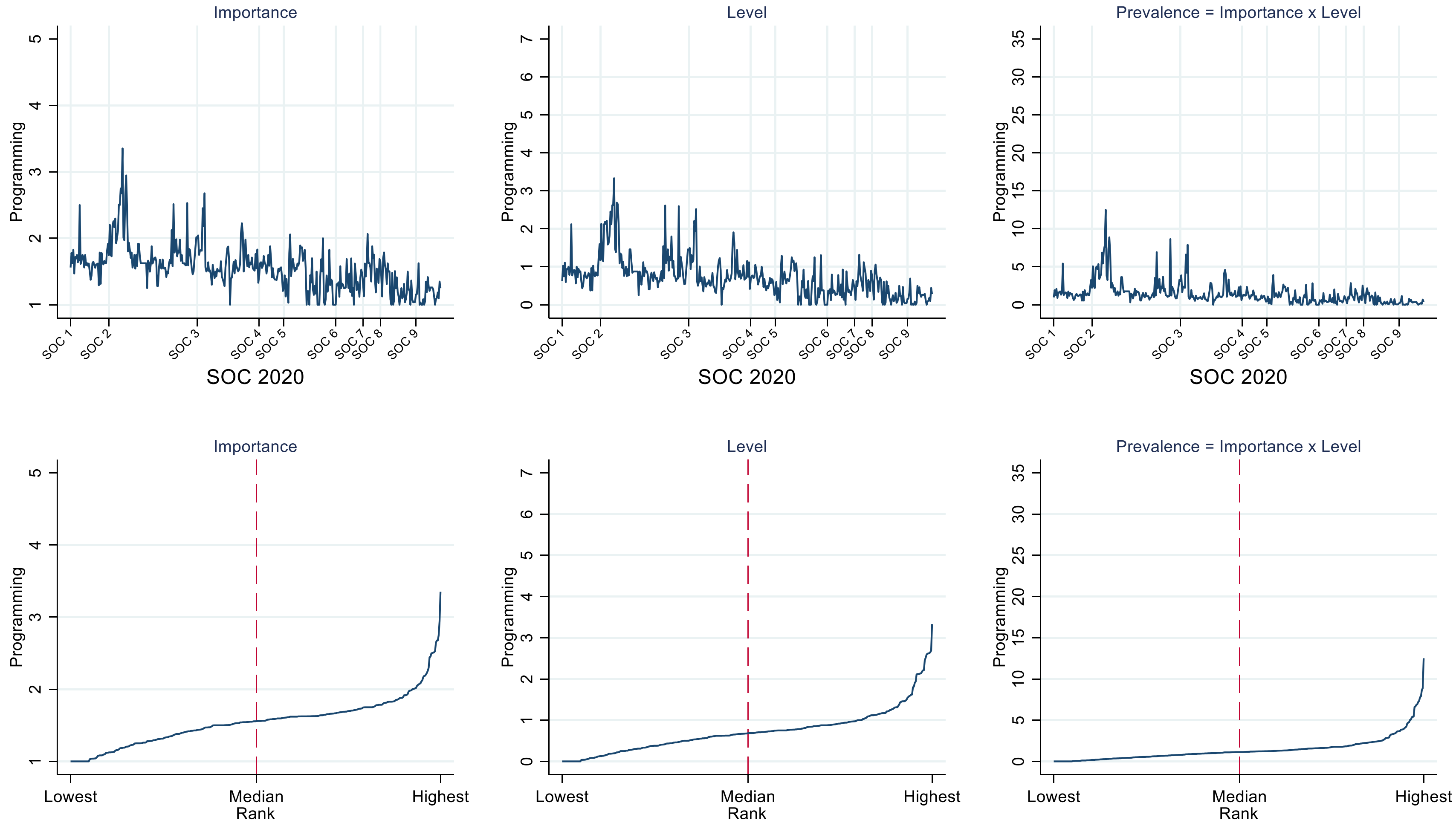


Figure 6: Skill Profile: Science

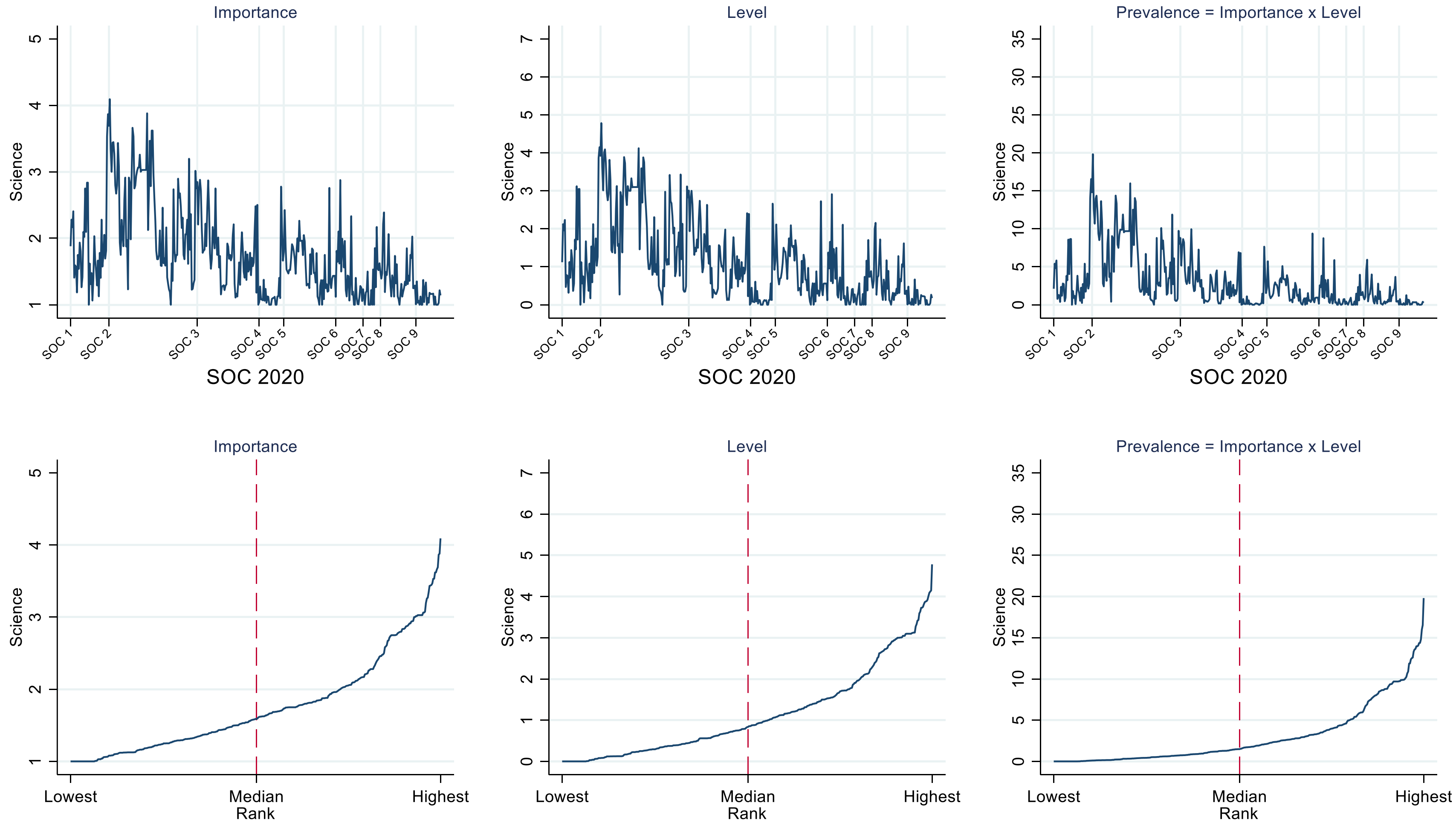


Figure 7: Skill Profile: Service Orientation

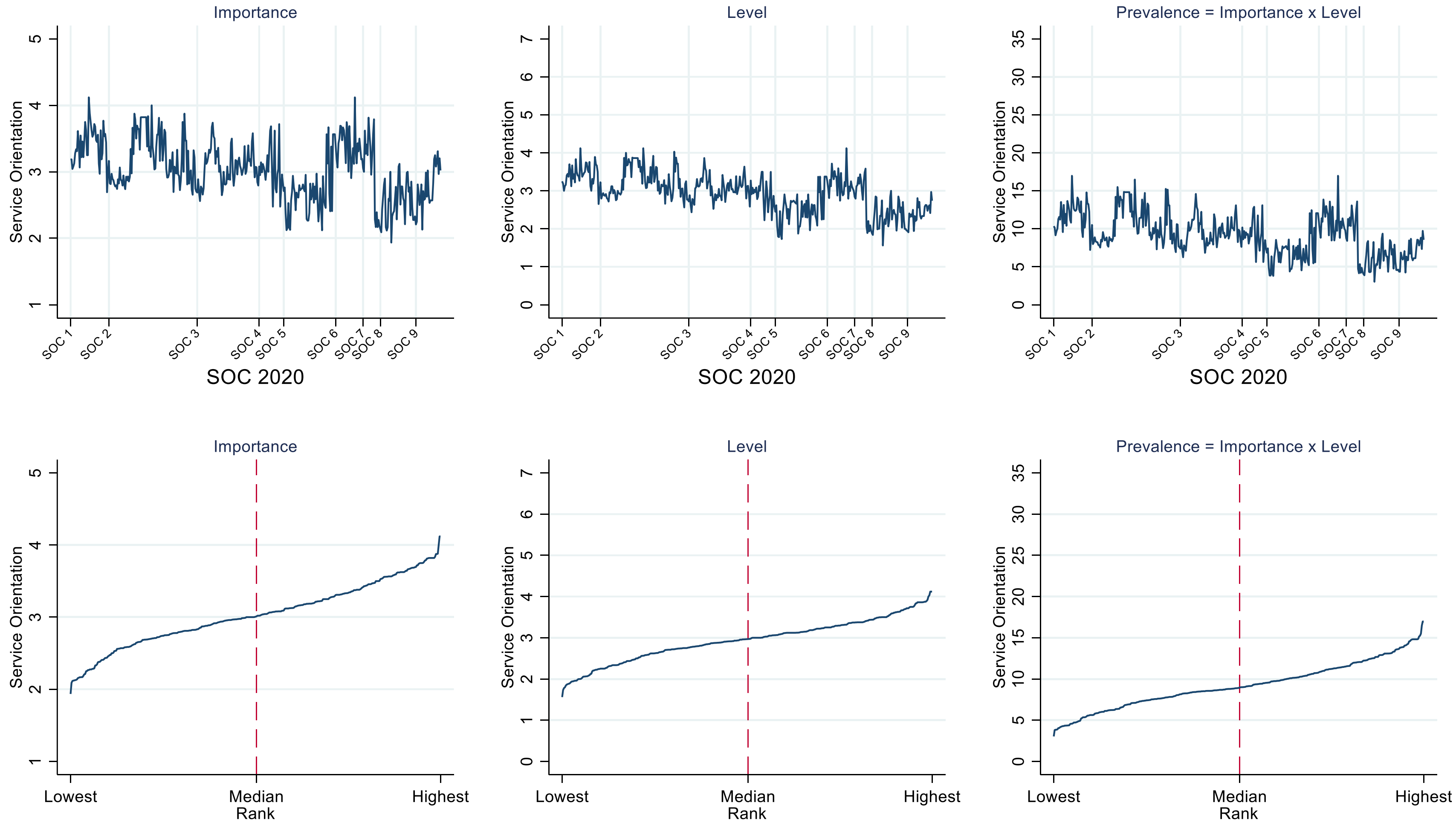
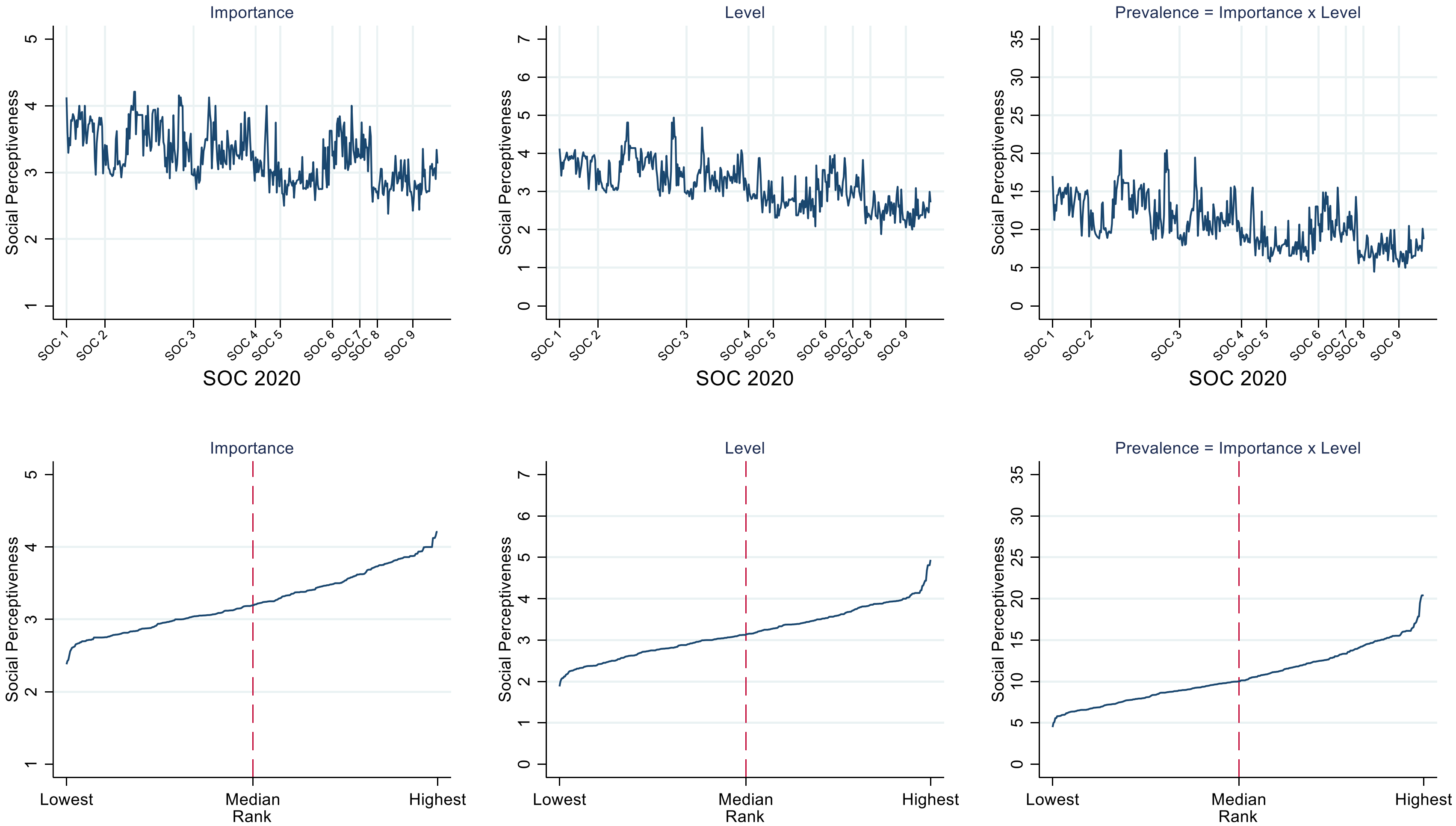


Figure 8: Skill Profile: Social Perceptiveness



There are six graphs shown for each skill. The top row in each Figure presents the indices of skill importance, skill level and skill prevalence (= skill importance × skill level) respectively, ordered by the 412 UK SOC2020 4-digit occupation codes, from 1111: Chief Executives and Senior Officials through to 9269: Other Elementary Services Occupations n.e.c. (not elsewhere classified). The boundaries between UK SOC2020 major groups (1-digit) are labelled on the horizontal axis (see Table 2 for definitions). In general, both skill level and skill importance (and thus skill prevalence) decline on average as we move down the occupational hierarchy from SOC1 to SOC9. The bottom row in each figure presents the corresponding ranked skill measure running from lowest to highest value, with the median value also being highlighted.

Table 2: UK SOC2020 major groups

SOC	SOC2020 Major groups
SOC 1	Managers, directors and senior officials
SOC 2	Professional occupations
SOC 3	Associate professional occupations
SOC 4	Administrative and secretarial occupations
SOC 5	Skilled trades occupations
SOC 6	Caring, leisure and other service occupations
SOC 7	Sales and customer service occupations
SOC 8	Process, plant and machine operatives
SOC 9	Elementary occupations

Source: SOC2020 Volume 1: structure and descriptions of unit groups
https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume1structureanddescriptionsofunitgroups

These profiles are helpful in describing the distribution of skills across occupations. For example, for Establishing and Maintaining Interpersonal Relationships (Figure 1), there is a very steady (i.e. linear) increase in both skill importance and skill level (and hence also correspondingly for skill prevalence = importance × level) across almost the whole of the ranked occupation distribution. Skill importance ranges from a minimum of 3 ('Important') to a maximum of around 4.5 (midway between 'Very Important' and 'Extremely Important'). Skill level ranges from just above 2 to almost 6 (recall this is on a scale from a minimum of 1 to a maximum of 7). This distribution for Establishing and Maintaining Interpersonal Relationships can be contrasted with Mathematics for example (Figure 4), which has a more 'S-shaped' distribution, with a greater number of occupations in both tails, and hence a higher overall variance in the skill across occupations. Mathematics also has a distribution with a lower average importance and level than Establishing and Maintaining Interpersonal Relationships (the median Mathematics occupation has a skill importance of 2.5 and skill level of 2.5 as compared to 3.75 and 4.5 for Establishing and Maintaining Interpersonal Relationships). This distributional profile is again distinctive from e.g. Programming (Figure 5) which has a 'hockey stick' profile (an ice-hockey stick, on its side). For most occupations, Programming skills are not at all important and are required at a very low level if at all (the median skill level is less than 1), but there is a set of occupations for which Programming skills are much more important (and are required at a much higher level), as reflected in the sharp up-tick towards the top of the rank-ordered distribution. The top row of Figure 5 reveals that these occupations are mainly in SOC2: Professional occupations and SOC3: Associate professional occupations major groups, just as we would anticipate. A somewhat similar profile is evident for Science as shown in Figure 6, although the increase over the ranked distribution is much less 'kinked' than for Programming, with the increase in skill importance and skill level more steady above the median occupation.

Some skills display a much greater variance than others across the occupational distribution. For example, Interacting with Computers (Figure 2) displays a sharply increasing ranked profile for the importance of this skill, with occupations spread across almost the whole range of possible scores. The range is similarly wide for the level of this skill, although there is a very clear kink in the top decile or so for the ranked occupations. The skill prevalence score reflects both patterns. There are also marked differences in Interacting with Computers across SOC major groups as shown in the top row of Figure 2, with skill importance for SOC1 to SOC4 major groups being at a rather higher level than for SOC5 to SOC9.

Interacting with Computers is also a skill that displays wide variance even within SOC major groups, in contrast to Service Orientation (Figure 7) or Social Perceptiveness (Figure 8) for example. Although these two skills have rather flat profiles across the occupational distribution for both skill importance and skill level (and hence skill prevalence), it is clear from the top row in each figure that for SOC6: Caring, leisure and other service occupations and SOC7: Sales and customer service occupations major groups, the importance of this skill is rather higher than for other, especially immediately adjacent, major groups.

3.2 Projecting skills in 2035

We now turn to consider the extent to which skills might change within occupations over the time horizon under consideration by *The Skills Imperative 2035* programme. There are two main approaches that could be employed in order to assess any future skill changes over time: (i) a simulation-based approach informed by the existing literature (as reviewed, for example, for the first phase of *The Skills Imperative 2035* programme, Taylor *et al.*, 2022); and (ii) a projections-based approach based on recent (historic) changes in skill use within occupations.

While a simulation approach would give complete control over the path of future skills development (e.g. which skills are increasing or decreasing, in which occupations, and by how much), there are lots of parameters to assign values to – we have 161 different skills across each of 412 occupations, for two skill metrics (skill importance and skill level). Moreover, these values would be largely arbitrary given the paucity of skills information for the UK as noted in the introduction. Thus, our preference is to use a projections-based approach using the historic patterns of changes in skills. (This is also consistent with the approach used for the projections of future employment produced by IER/CE, although the employment projections are generated by a sophisticated underlying macro-econometric model, see Wilson *et al.*, 2022a, 2022b).

Of course, the future is inherently unknown and uncertain, and using historic patterns of changes in skills may not capture the impact of unanticipated shocks and technological innovations that can impact on skill utilisation. One such example could be the recent developments in AI (Open AI's recent launch of its AI-powered ChatGPT on 30 November

2022 was after the main analysis for this study was undertaken). It remains to be seen if this new technology will produce a fundamental paradigm shift in skills demand and thus in employment as some have suggested. Others are more circumspect, and suggest that there may be yet another repeat of the so-called ‘Solow paradox’. (This is the concept, first attributed to Robert Solow in 1987, that “you can see the computer age everywhere but in the productivity statistics” in reference to the large scale investment in information technology in the US in the 1970s and 1980s which failed to produce commensurate increases in productivity. The more recent adoption of digital technologies has also not led to accelerated productivity growth as might have been expected).

Our historic data on skills is compiled from O*NET data over the period 2010 to 2020. This period enables us to utilise data consistently recorded using the O*NET2010 classification, which we then map onto UK SOC2020 using the stages of the mapping from O*NET2010 to UK SOC2020. This only requires the old mapping together with the SOC2010 to SOC2020 correspondence tables (see Figure B1). More specifically, we use skills data for three time points:

1. 2010, taken from O*NET version 16.0, which was the first major update to use the O*NET2010 classification;
2. 2015, from O*NET version 21.0; and
3. 2020, from O*NET version 25.0, which was the last O*NET version before the new O*NET2019 classification was introduced.

These three data points – 2010, 2015 and 2020 – provide information on the recent patterns of change in skills which we use to inform our projections for 2035. (Recall that the O*NET data is updated on a rolling cycle, with approximately 10% of occupations updated each year. Hence there is little value in using all of the intermediate time points since many O*NET occupations’ skills are unlikely to have been reassessed).

A full description of the methodology used to generate the 2035 skills projections is presented in **Appendix C**. For each skill (161 elements) and for each occupation (412 4-digit occupations), and separately for the three skills metrics (skill importance, skill level and skill prevalence), we first compute the linear projection of the change in skill over the period from 2010 to 2020 (using a linear least squares regression function), and then project this forward to 2035. While this forecast method is easy to implement, it comes with the assumption that the rate of change over time is constant. In other words, if the utilisation of a particular skill is increasing rapidly over the period 2010 to 2020, the linear functional form will continue to project a strong increase into the future, at the risk of hitting the upper bounds of our skills measures (i.e. 5 for skill importance, 7 for skill level and 35 for skill prevalence). Even without this bounds issue, it might not be realistic to assume that skills utilisation keeps evolving at the same rate over time. For this reason, we also investigate three alternative functional forms for our projections.

First, we consider an Inverse Hyperbolic Sine (IHS) functional form which presumes that any increase or decrease in skill occurs at a diminishing rate over time. This function has the same shape as $\log(t)$ but can accommodate the initial point at $t = 0$ where $\log(t)$ is not defined. Our other two functional forms for the projections take into account the constraints that the lower and upper bounds for each of the skills metrics impose by adopting a logistic functional form which explicitly incorporates these bounds into the specification. Further details are provided in **Appendix C**. For most skills, the skill metrics are not close to the lower or upper bounds for most occupations over the observation period of 2010-2020, and the projections do not approach either of the extremes by 2035. As a consequence, these latter two methods typically produce projections which are very close to the linear projections.

To illustrate the historic **and** projected future patterns in the skills distributions, Figure 9 to Figure 16 present the ranked occupational skills profiles for our eight exemplar skills. The O*NET data for 2010, 2015 and 2020 (using the O*NET2010 classification mapped to UK SOC2020) is shown together with the skill projections for 2035 resulting from the linear projections. In each figure, we present the three metrics for skill importance, skill level and skill prevalence. As can be seen, for most skills, there are only relatively small differences in the shape and position of the ranked occupational profiles of skills for 2010, 2015 and 2020. Moreover, and importantly, these do not conceal significant re-ranking within the profiles – the average (Spearman) rank correlation coefficient across the 412 occupations for these eight skills between 2010 and 2020 is above 0.92 for all three of our skills metrics.

In general, there is more movement in the 'tails' of the occupational profiles than in the middle of the distributions. For our linear projections for 2035, these differences are accentuated. Establishing and Maintaining Interpersonal Relationships (Figure 9) is projected to be more important (and to be used at a higher level) in 2035 in those occupations in which it is already relatively important, and less important (and used at a lower level) in those occupations where it is already comparatively unimportant. In contrast, Interacting with Computers (Figure 10), which has been growing in importance over the historic period 2010-2015-2020, is projected to further increase in importance across the whole of the occupational distribution by 2035. The level with which this skill is employed is growing rather faster above the median occupation than below the median occupation as can be seen in the second panel of Figure 10. Making Decisions and Solving Problems (Figure 11) is expected to increase in importance and level by 2035 mainly in occupations which already use this skill more than average. For both Mathematics (Figure 12) and Programming (Figure 13), we anticipate increasing importance of these skills for occupations in the top half of the occupational distribution, although there is comparatively little expected increase in the level with which these skills will be used in 2035. For Science (Figure 14), both skill importance and skill level have been declining over the last decade for the average occupation, and are projected to continue to do so in the period to 2035. However, at the very top of the occupational distribution for Science skills, both importance and level have been relatively constant. Finally, some skills show very little movement over the historic period, and hence the skills profiles for 2035 are quite similar to the observed values for 2010, 2015 and 2020. Amongst our eight exemplar skills, Service Orientation (Figure 15) and Social Perceptiveness (Figure 16) are representative of these skills.

For our main findings presented in Section 3 below, we use these linear projections for the 161 skills. However, we investigate the sensitivity of our main findings to the functional form chosen for the skills projections for 2035 in **Appendix D** of this report.

Figure 9: Historic and future skill projections – Establishing and Maintaining Interpersonal Relationships

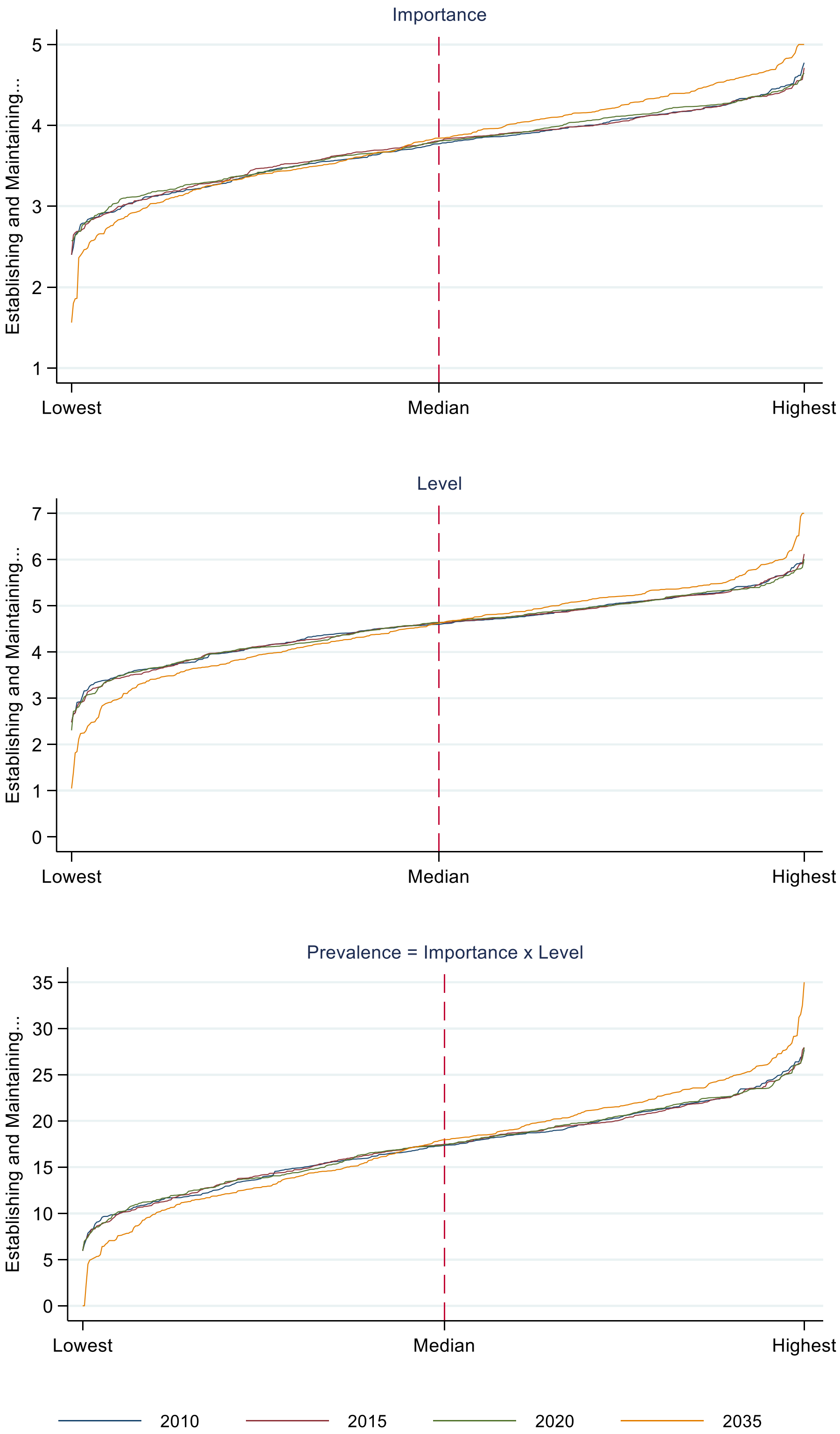


Figure 10: Historic and future skill projections – Interacting with Computers

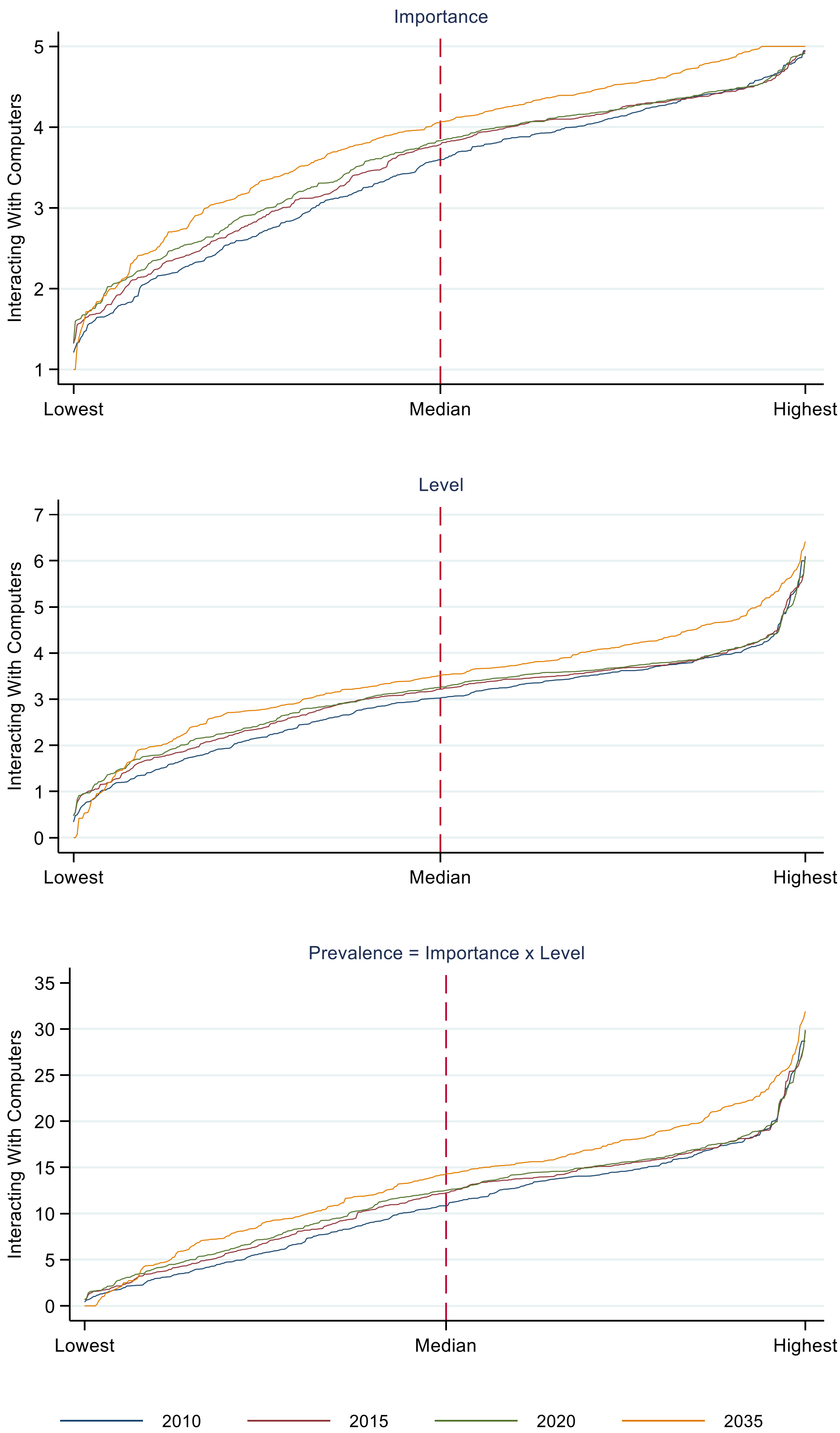


Figure 11: Historic and future skill projections – Making Decisions and Solving Problems

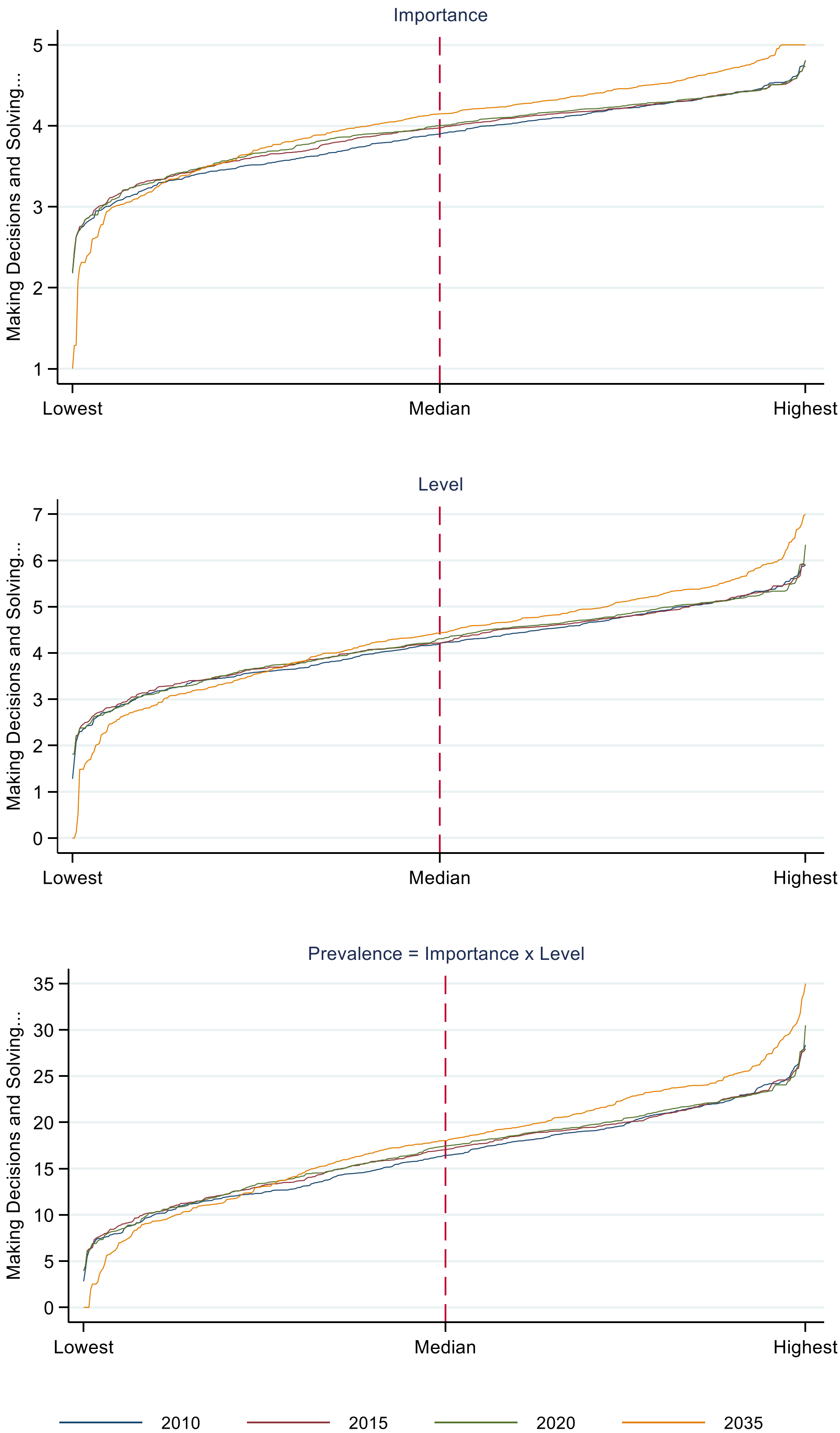


Figure 12: Historic and future skill projections – Mathematics

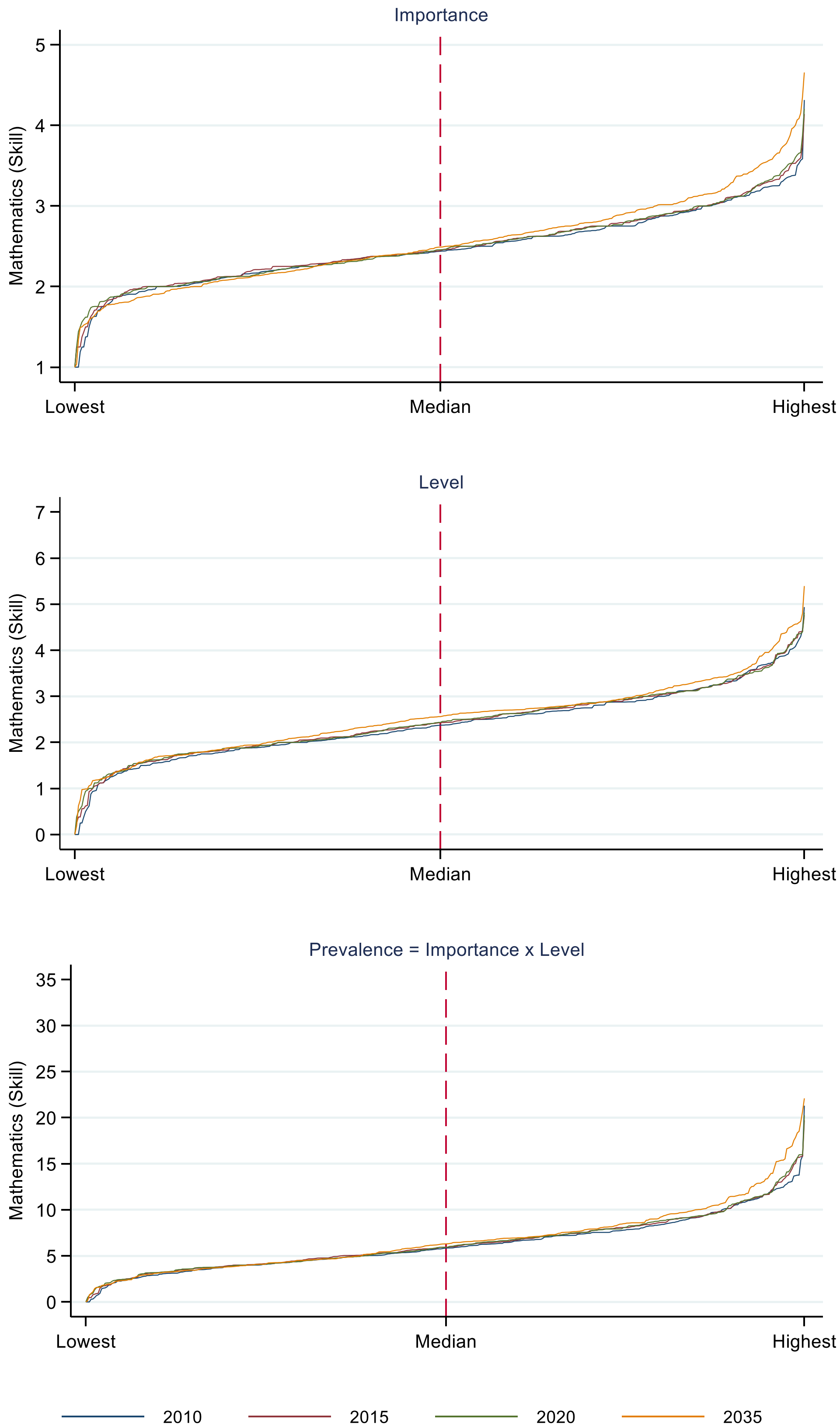


Figure 13: Historic and future skill projections – Programming

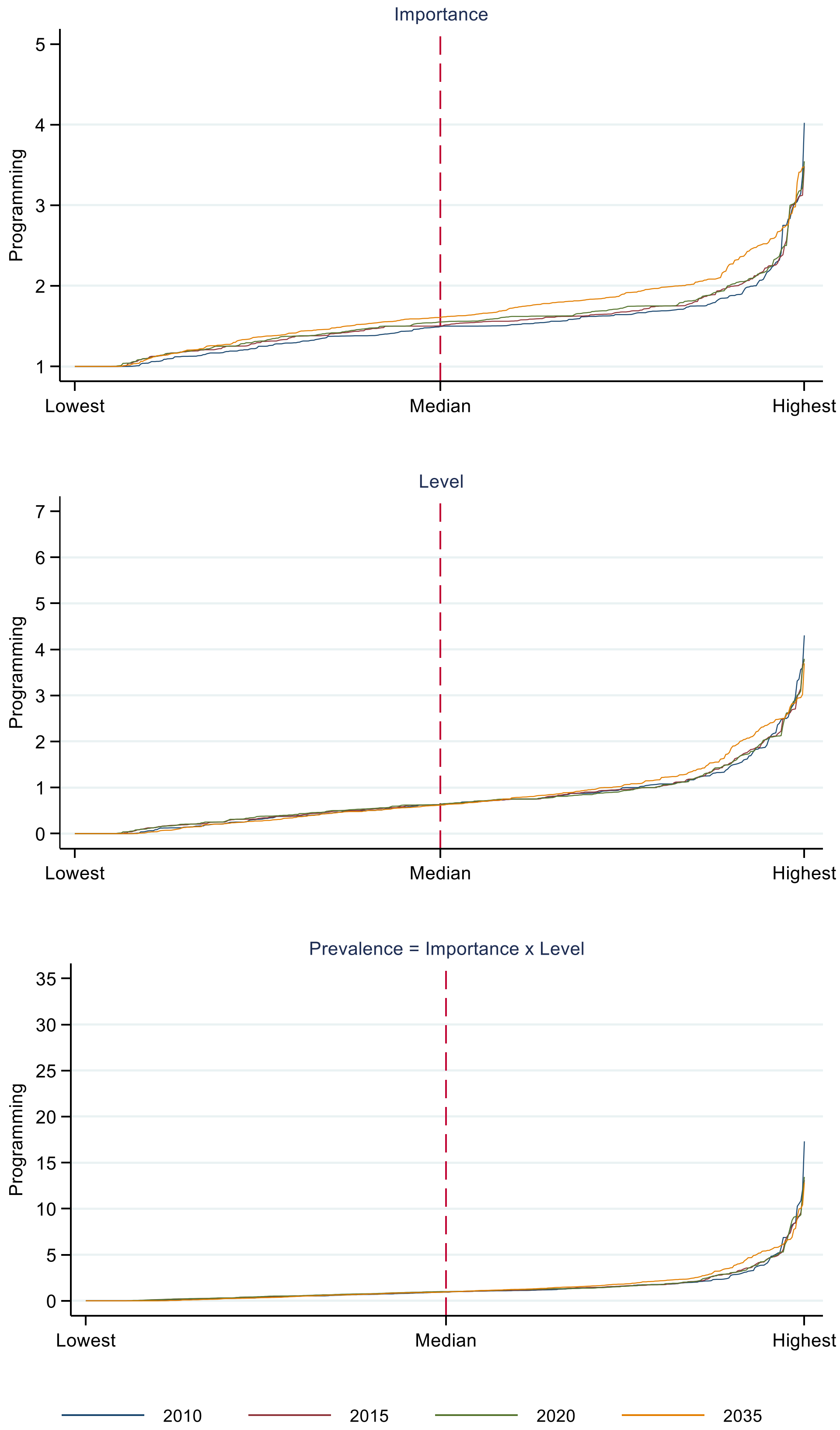


Figure 14: Historic and future skill projections – Science

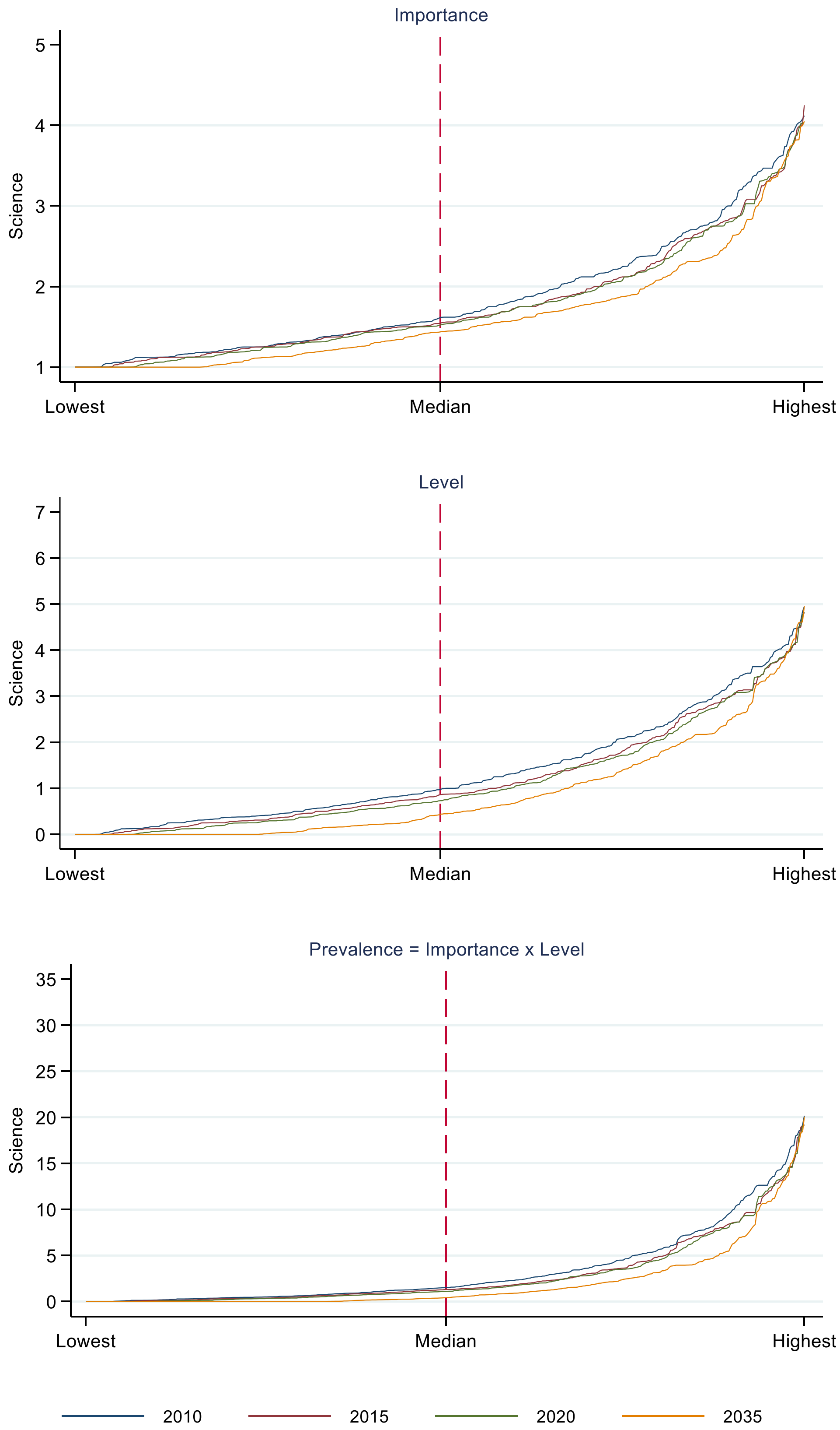


Figure 15: Historic and future skill projections – Service Orientation

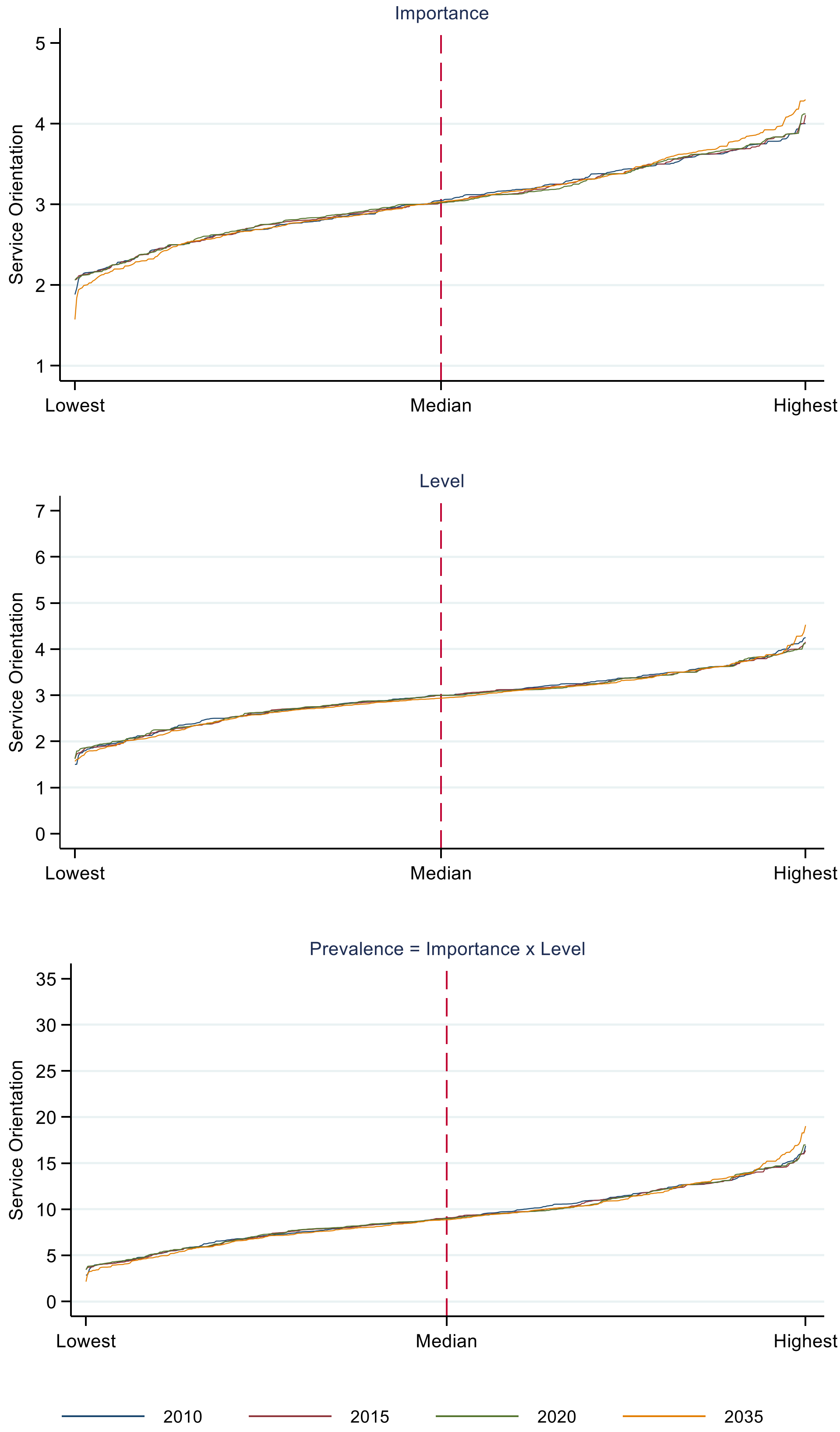
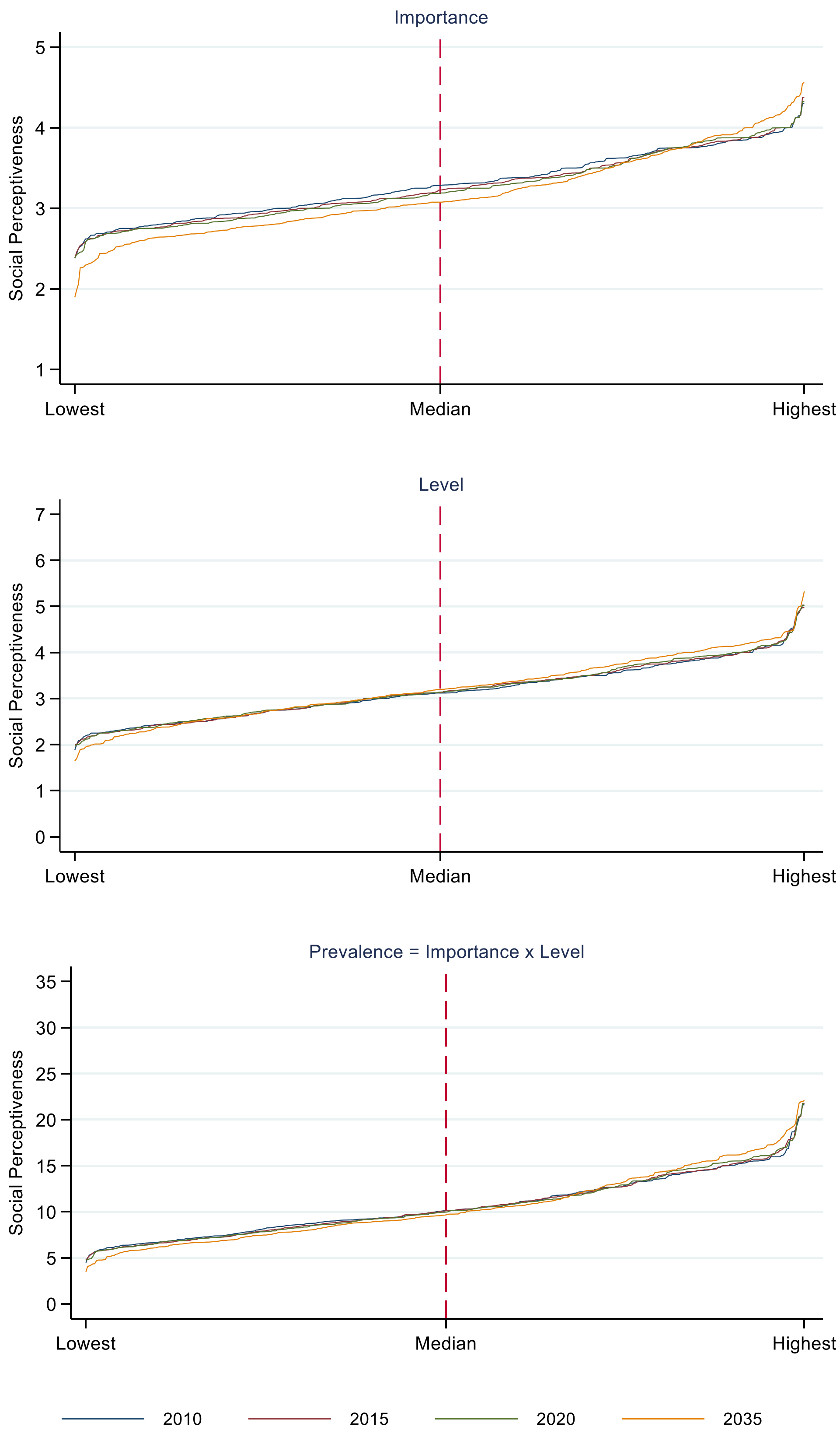


Figure 16: Historic and future skill projections – Social Perceptiveness



3.3 Estimating skills demand: Combining projections of skills and IER/CE projections of employment

In order to estimate the relative utilisation or demand for skills, we combine our estimates of the intensity of skill use within occupations together with the number in employment in each occupation. We aggregate by taking the employment-weighted average of our skills measures, separately for each of the skill metrics – skill importance, skill level and skill prevalence. The employment weights are equal to the occupational share of employment as projected in the IER/CE forecasts of occupational employment (recall that our analysis is for England only). Our measure of a skill's demand therefore takes into account both the utilisation of the skill in each job and the number of jobs in which that skill is being used. Scaling by total employment facilitates the comparison of changes in skill utilisation over time, since the score is then simply the average skill intensity per job. Given that aggregate employment in England is projected to only increase fairly modestly over the forecast period 2020-2035 – by around 2.2 million new jobs, or 7.4 percent (Wilson *et al.*, 2022a, 2022b) – then using employment shares rather than levels is not restrictive when interpreting the results we obtain.

In order to assess the most important skills in 2035, we compute the rankings of skills demand across the 161 skills, and the absolute and percentage changes in skills demand between 2010, 2020 and 2035. We present our main findings in Section 3 using the *Baseline projections* for employment that IER/CE have produced, but also investigate the sensitivity of our conclusions to the two main *Alternative scenarios* for employment – the *Technological opportunities scenario* and the *Human-centric scenario* – in **Appendix D.1** of this report

4 The skills landscape in 2035

- Total employment in England is projected to grow by around 2.2 million jobs (around 7.4%) between 2020 and 2035.
- All of this growth is anticipated to be in higher skilled occupations; total employment in lower skilled employment is projected to be numerically unchanged (and thus to represent a declining share of total employment).
- Combining occupational employment with occupational skill utilisation enables us to compute the overall skill demand for the 161 skills under consideration.
- The five most significant skills in use in 2035 are anticipated to be: Communicating with Supervisors, Peers, or Subordinates, Organizing, Planning, and Prioritizing Work, Establishing and Maintaining Interpersonal Relationships, Making Decisions and Solving Problems and Getting Information.
- While there is some re-ranking, these are also the top five skills in use in employment in both 2010 and 2020. The most important skills utilised in employment are generic and transferable, and are used widely across all employment.
- There is greater re-ranking of the top skills outside this top 5, with new skills such as Interacting with Computers and Thinking Creatively entering the top 20 for the first time in 2035. In contrast, Oral, Written and Reading Comprehension are projected to fall in the relative skill ranking between 2020 and 2035.
- While the utilisation of other skills increases between 2020 and 2035, none are used widely enough to be able to change the overall top 20 ranking.

In this section of the report, we document our main findings regarding the skills that will be most utilised for employment in 2035. We also compare how these are changing over time. As described in the previous section, there are a number of variants that we have developed based on alternative measures of occupational skills, and for their projections into the future, and of the different employment scenarios that IER/CE have developed. In this section, we present our main findings using: (i) the *Baseline projections* for employment for the period up to 2035; (ii) the skill prevalence metric (= skill importance × skill level) obtained using (iii) the complete mapping between O*NET and UK SOC2020; and (iv) the linear skills projections. The sensitivity of our main findings to the possible variants of (i) to (iv) are described in **Appendix D.1** to **Appendix D.4** respectively.

4.1 The changing structure of employment 2020-2035

We first summarise the changes in employment in 2035 as provided by the IER/CE projections for *The Skills Imperative 2035* programme (Wilson *et al.*, 2022a, 2022b). These projections employ the UK SOC2020 classification of occupations as noted above. UK SOC2020 classifies jobs by broad skill level and skill specialisation. The SOC Skill levels are approximated by 'the length of time necessary for a person to become fully competent in the performance of the tasks associated with a job' by gaining formal qualifications or through work-based training (ONS, 2020). Four broad skill levels are distinguished in UK SOC2020, from Skill level 1 (low skill) to Skill level 4 (high skill) – see **Appendix E**. Skill specialisation is then used to distinguish groups of occupations within each of the four broad skills levels according to the field of knowledge required – see Table 3 for details:

Table 3: Skill levels and the sub-major group structure of UK SOC2020

Skill level	UK SOC2020 sub-major groups
Level 4 (highest)	11 Corporate managers and directors 21 Science, research, engineering and technology professionals 22 Health professionals 23 Teaching and other educational professionals 24 Business, media and public service professionals
Level 3	12 Other managers and proprietors 31 Science, engineering and technology associate professionals 32 Health and social care associate professionals 33 Protective service occupations 34 Culture, media and sports occupations 35 Business and public service associate professionals 51 Skilled agricultural and related trades 52 Skilled metal, electrical and electronic trades 53 Skilled construction and building trades 54 Textiles, printing and other skilled trades
Level 2	41 Administrative occupations 42 Secretarial and related occupations 61 Caring personal service occupations 62 Leisure, travel and related personal service occupations 63 Community and civil enforcement occupations 71 Sales occupations 72 Customer service occupations 81 Process, plant and machine operatives 82 Transport and mobile machine drivers and operatives
Level 1 (lowest)	91 Elementary trades and related occupations 92 Elementary administration and service occupations

Source: SOC2020 Volume 1: structure and descriptions of unit groups
https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume1structureanddescriptionsofunitgroups

The distribution of employment in England in 2020 and projected for 2035, by UK SOC2020 broad Skill level, is depicted in Figure 17 below. As can be clearly seen, all of the projected increase in aggregate employment between 2020 and 2035 (c. 2.2 million new jobs, or 7.4% of the 2020 employment level) is driven by an increase in the number of jobs at Skill level 3 and Skill level 4, the highest two skill levels. Employment at the lower two skill levels – Skill level 1 and Skill level 2 – is projected to be almost unchanged between 2020 and 2035. In 2035, over 10.5 million of the 32.1 million jobs are expected to be at Skill level 4 , and jobs at Skill level 4 are expected to comprise the largest share (33%) of total employment for the first time.

This broad upskilling of aggregate employment as reflected in the SOC skill levels is a continuation of a trend that is evident over the last few decades. Note, however, that the IER/CE employment projections are based on an underlying macroeconomic model which does not impose trends in occupational employment shares as an underlying assumption. While it uses historic data that exhibits an upward trend in the skills composition of employment, future patterns are dependent on the projected developments in the macroeconomy, which then have implications for the future patterns of occupational employment.

Figure 17: Employment 2020 and 2035 by UK SOC2020 Skill levels

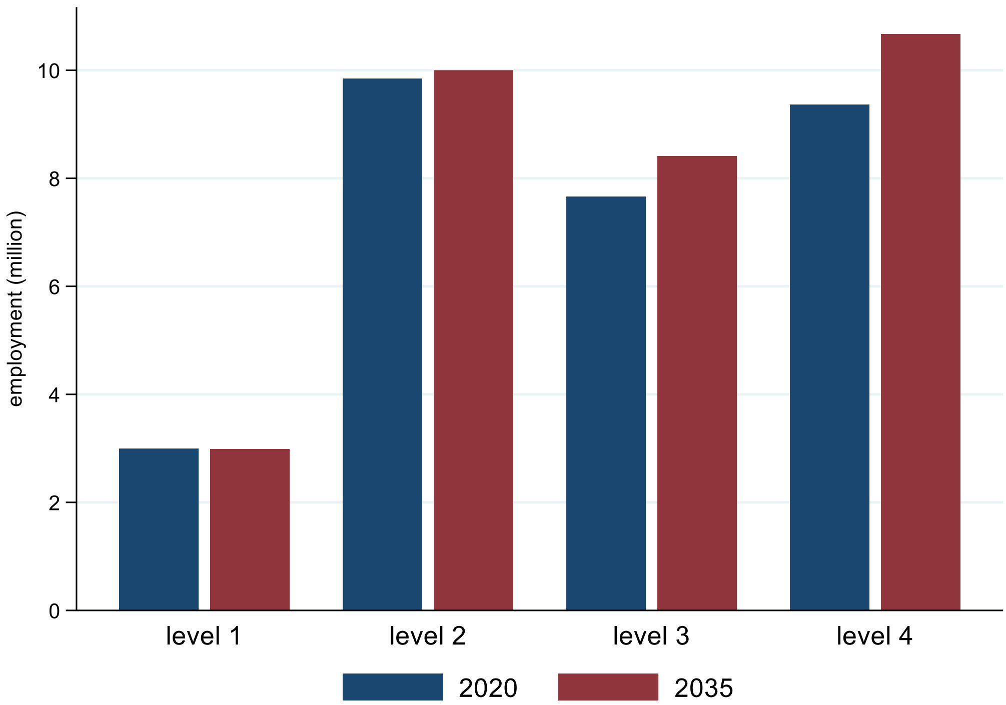
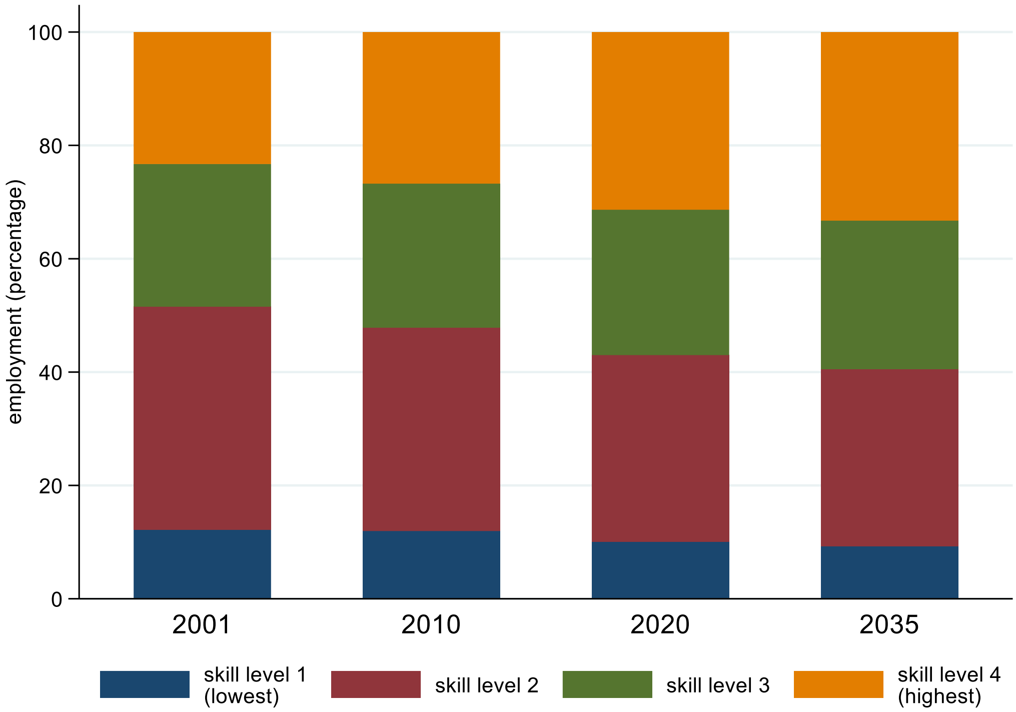


Figure 18: Employment shares 2001-2010-2020-2035 by SOC2020 Skill levels



To illustrate, Figure 18 presents the shares of employment by SOC broad skill level for 2001-2010-2020 and the projected shares for 2035. The share of employment in the top two skill categories has increased monotonically over this period. In 2001, employment at Skill level 3 and Skill level 4 comprised approximately 50% of all jobs; by 2035, it is projected it will encompass 60% of all jobs, an increase of one fifth.

In summary, the broad patterns of change in the occupational distribution of employment indicate a continuation of the increasing average skill utilisation in employment, with the growth in jobs all at the upper end of the skills distribution. We now turn to our investigation of the nature of the skills that are projected to be most important in employment in 2035 – that is, the Essential Employment Skills that are the focus of *The Skill Imperative 2035* programme.

4.2 Skill utilisation 2010-2020-2035

By combining our estimates of the intensity of skill use within occupations together with the number in employment in each occupation, we can compute our measure of overall skills demand for each of the 161 skills under consideration. Our assessment of the 'Top 20' skills that will be most utilised in employment in 2035 is presented in the final column of Table 4. The top 20 skills for 2010 and 2020 are also provided for comparison. These are the top 20 from the list of all 161 skill elements as listed in Table 1. The third column of Table 4 reveals that the five most significant skills in use in employment in 2035 are anticipated to be: Communicating with Supervisors, Peers, or Subordinates, Organizing, Planning, and Prioritizing Work, Establishing and Maintaining Interpersonal Relationships, Making Decisions and Solving Problems and Getting Information. While there is some re-ranking, these are also the top five skills in use in employment in both 2010 and 2020 as shown in the first and second columns of Table 4.

The ranking and re-ranking of the top 20 skills over time is perhaps best illustrated in the ‘bump-chart’ presented in Figure 19. This graphically shows the re-ranking amongst the top five skills with Establishing and Maintaining Interpersonal Relationships being ranked first in both 2010 and 2020, but projected to fall to rank 3 by 2035. In contrast, Communicating with Supervisors, Peers, or Subordinates moves from rank 3 in 2010, to rank 2 in 2020 and finally is projected to move to rank 1 in 2035. The figure also shows clearly which skills enter the top 20 ranking in 2020 (e.g. Evaluating Information to Determine Compliance with Standards) and 2035 (e.g. Thinking Creatively) – for these ‘new entries’, Figure 19 shows no corresponding rank in 2010 and/or 2020.

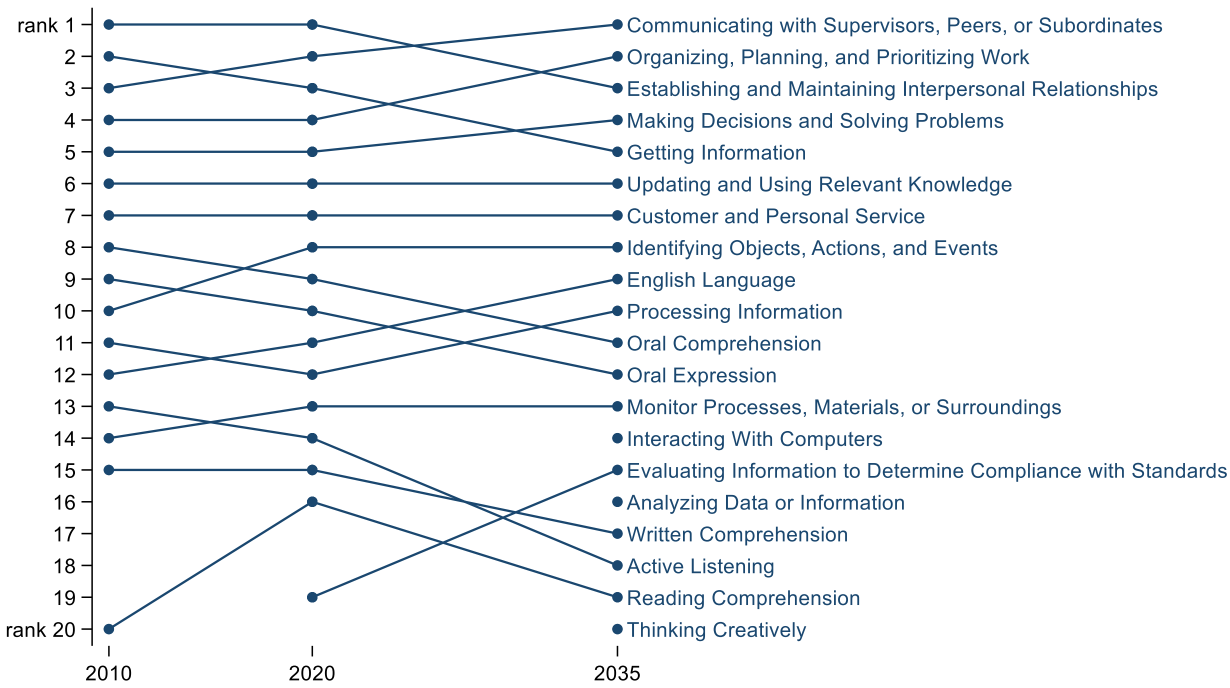
Amongst the other 15 skills ranked in the top 20 skills in 2035, there is rather greater volatility than in the top five skills. New skills that are projected to enter the top 20 in 2035 for the first time include Interacting with Computers, which was at rank 35 in 2010 and rank 24 in 2020, and is forecast to be the 14th most significant skill in 2035. Likewise, Analyzing Data or Information rises from rank 33 in 2010, to rank 27 in 2020 and is projected to be rank 16 in 2035. These new skills appearing in the top 20 are consistent with the expected increasing significance of Processing Information which enters the top 10 skills for the first time in 2035.

Table 4: Top 20 skills ranking 2010-2020-2035 – Skills Prevalence measure, linear skills projections

Rank	2010	2020	2035
1	Establishing and Maintaining Interpersonal Relationships	Establishing and Maintaining Interpersonal Relationships	Communicating with Supervisors, Peers, or Subordinates
2	Getting Information	Communicating with Supervisors, Peers, or Subordinates	Organizing, Planning, and Prioritizing Work
3	Communicating with Supervisors, Peers, or Subordinates	Getting Information	Establishing and Maintaining Interpersonal Relationships
4	Organizing, Planning, and Prioritizing Work	Organizing, Planning, and Prioritizing Work	Making Decisions and Solving Problems
5	Making Decisions and Solving Problems	Making Decisions and Solving Problems	Getting Information
6	Updating and Using Relevant Knowledge	Updating and Using Relevant Knowledge	Updating and Using Relevant Knowledge
7	Customer and Personal Service	Customer and Personal Service	Customer and Personal Service
8	Oral Comprehension	Identifying Objects, Actions, and Events	Identifying Objects, Actions, and Events
9	Oral Expression	Oral Comprehension	English Language
10	Identifying Objects, Actions, and Events	Oral Expression	Processing Information
11	Processing Information	English Language	Oral Comprehension
12	English Language	Processing Information	Oral Expression
13	Active Listening	Monitor Processes, Materials, or Surroundings	Monitor Processes, Materials, or Surroundings
14	Monitor Processes, Materials, or Surroundings	Active Listening	Interacting With Computers
15	Written Comprehension	Written Comprehension	Evaluating Information to Determine Compliance with Standards
16	Communicating with Persons Outside Organization	Reading Comprehension	Analyzing Data or Information

17	Speaking	Speaking	Written Comprehension
18	Problem Sensitivity	Communicating with Persons Outside Organization	Active Listening
19	Near Vision	Evaluating Information to Determine Compliance with Standards	Reading Comprehension
20	Reading Comprehension	Problem Sensitivity	Thinking Creatively

Figure 19: Top 20 skills ranking – Skills Prevalence measure, linear skills projections

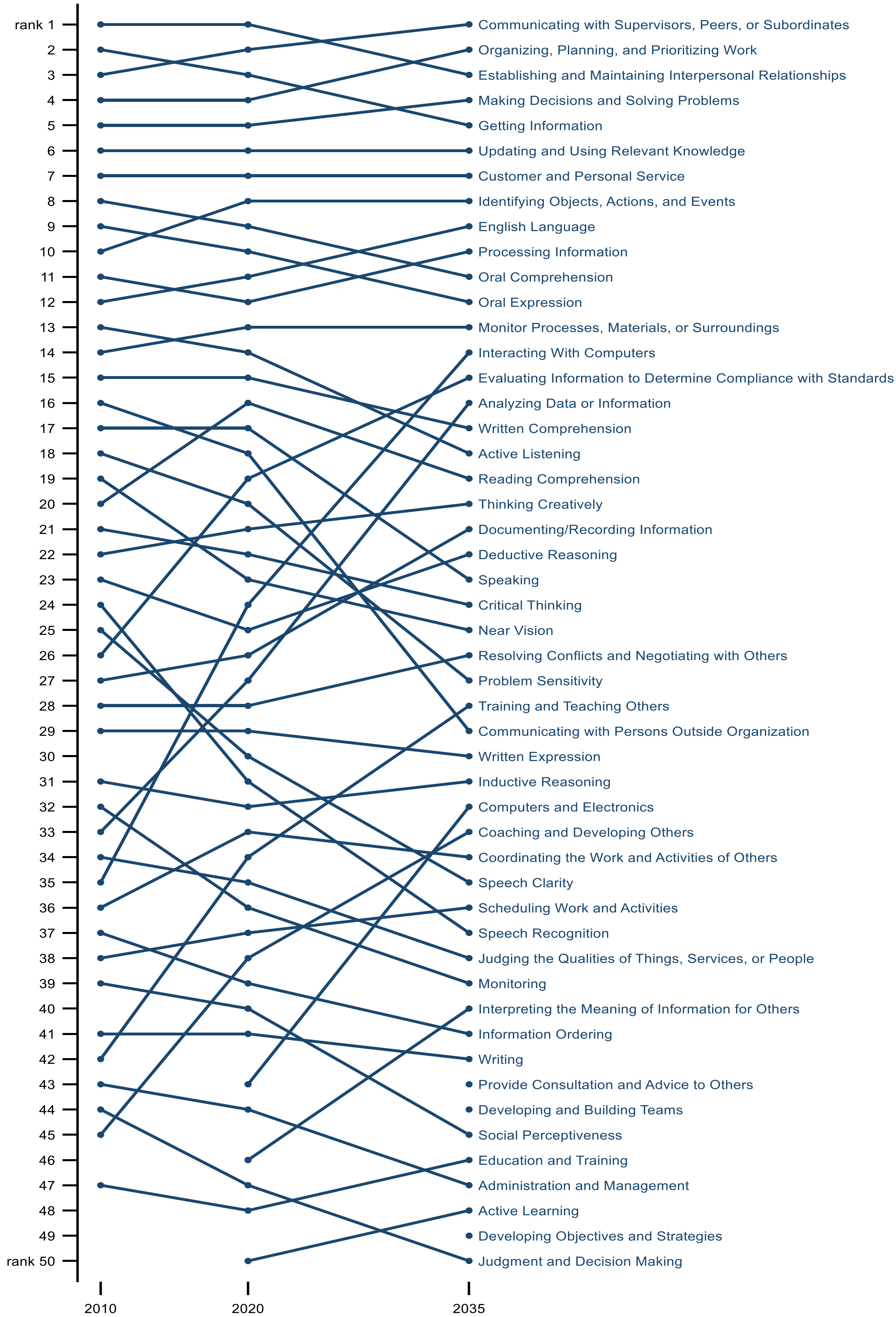


In contrast, Oral Comprehension, Oral Expression, Written Comprehension and Active Listening are all seen to be falling in the top 20 ranking over time (although are still ranked within the top 20 in 2035). The declining relative importance of these communication-related skills is in contrast with Communicating with Supervisors, Peers, or Subordinates which is ranked first in 2035, and also the increasing relative rank for English Language which rises from rank 12 in 2010 to rank 9 in 2035. This may reflect the changing nature of workplace communication – Communicating with Supervisors, Peers, or Subordinates is defined in O*NET as 'Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person' i.e. is specifically associated with the provision of *information,* rather than simply being associated with listening, speaking or writing.

Other skills that have declined in the ranking and have dropped out of the top 20 by 2035 can be seen in the first two columns of Table 4 (we leave these unlabelled and unconnected in Figure 19 to simplify the figure). These include Communicating with Persons Outside Organization which drops from rank 16 in 2010, to rank 18 in 2020 and is rank 29 in 2035. Likewise Speaking, which is ranked 17 in 2010 and in 2020, is projected to fall to rank 23 in 2035, and Problem Sensitivity (defined in O*NET as 'The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem.') drops from rank 18 in 2010 to rank 20 in 2020 and is projected to decline to rank 27 by 2035. Despite these falls in the overall ranking, it is important to note that in 2035 these are all still projected to be in the top quintile of the 161 skills that we are considering.

Beyond the top 20 skills in 2035, there is evidence of somewhat more re-ranking of skills over time. Figure 20 illustrates the top 50 skills in 2035 and the changes in their rankings over 2010-2020-2035 using a bump-chart format.

Figure 20: Top 50 skills ranking – Skills Prevalence measure, linear skills projections



Once again, we leave skills that are projected not to be in the top 50 by 2035 unlabelled. In Figure 20, the movement up the rankings of Analysing Data or Information and Interacting With Computers are particularly noteworthy, rising from rank 33 and 35 in 2010 to rank 16 and 14, respectively, by 2035. Similarly, the large decline in the ranking of Speech Clarity and Speech Recognition, and also of Communicating with Persons Outside Organization are notable. This may perhaps reflect a move to digitally-based communication over the period.

It might perhaps be argued that a potential omission from our list of top skills are 'digital skills', especially given the widespread adoption of digital technologies in the world of work over the last two decades or so. However, as commonly used in the literature, 'digital skills' is an 'umbrella' term, rather than being a well-defined or specific skill. For example, one definition of digital skills is:

> *'… a range of abilities to use digital devices, communication applications, and networks to access and manage information. They enable people to create and share digital content, communicate and collaborate, and solve problems for effective and creative self-fulfillment in life, learning, work, and social activities at large'* (UNESCO, 2022).

Similarly, the UK Government's Essential Digital Skills (EDS) framework, which was launched in 2018, outlines five categories of digital skills needed for life and work. These are (DfE, 2019):

1. Communicating: The skills required to communicate, collaborate, and share information, for example, by using word processing software and sending email.
2. Handling information and content: The skills required to find, manage and store digital information and content securely, for example, the ability to use search engines.
3. Transacting: The skills required to register and apply for services, buy and sell goods and services, and administer and manage transactions online, for example, to book and pay for travel tickets.
4. Problem solving: The skills required to find solutions to problems using digital tools and online services, for example, using an online live chat facility to fix an issue, or using a tutorial video to learn how to do something.
5. Being safe and legal online: The skills required to stay safe, legal and confident online, for example controlling privacy settings on social media and recognising suspicious links in emails.

Clearly, many of the work-related components in both the UNESCO and the EDS categorisations of digital skills are encompassed within the set of top skills identified above. Both UNESCO and EDS definitions include communication, collaboration, accessing and managing information, and problem solving, for example, and these are all ranked in the top 10 skills. Thus we consider digital skills to be a higher-order construct that runs through many of the specific skills that are identified to be most prevalent in employment.

Finally, it is also interesting to note which skills our methodology suggests are the least significant in employment. The 'Bottom 20' skills is also a relatively stable subset of the 161 elements when considered over time. These bottom 20 elements are mainly from the Abilities domain (see Table 1), and include a number of physical characteristics related to strength and the senses (e.g. Spatial Orientation, Dynamic Flexibility, Night Vision), as well as a few very specialised areas of Knowledge (e.g. Fine Arts, History and Archeology). That these skills are, relatively, not widely used in employment is no surprise. However, their low ranking does serve to provide some further corroboration for the validity of the methodology that we have employed.

The overall demand for a skill depends on both the number of workers using that skill in their job and the intensity with which they utilise that skill. In order to gauge the relative importance of: (i) the changing occupational distribution of employment, and (ii) the changing skill prevalence within occupations, for the overall changes in skill demand, we can separate this total change into its two components. That is, the overall change in skill demand can be separated (or decomposed) into the 'between occupation' changes, and the 'within occupation' changes. For each skill, the change in skill utilisation over time, ΔS, can be written as:

$$\Delta S = \sum_{i=1}^{I} \Delta e_i \bar{S}_i + \sum_{i=1}^{I} \Delta S_i \bar{e}_i$$

where i indexes occupations, an overscore denotes an average over time, $e_i = \frac{E_i}{E}$ is the share of total employment E in occupation i, and S_i is the measure of skill in occupation i. The first term on the right-hand side of the equation is the 'between-occupation' change in skill use, while the second term is the 'within-occupation' change.

We compute the between- and within-occupational changes for each of the 161 skills under consideration, and compare the period 2010-2020 for which we have observations on skills from O*NET and historic employment estimates, with the period 2020-2035 over which we have utilised the IER/CE employment projections and our skills projections. Once again, for employment, we use the *Baseline projections*, while for skills we use the skill prevalence measure with the complete mapping and the linear projection method.

Table 5 summarises the results. (We use the median as our summary measure rather than the mean since there are some outliers, particularly associated with very small changes in overall skill demand which give rise to a small denominator when calculating the relative shares). Over the 2010-2020 period, the between-occupation changes in skill demand are, on average, slightly more important than the within occupation changes for the overall change in skill demand when considered across all 161 skills under consideration as shown in the top row of the table. However, there is variation when we examine the elements separately across the four O*NET domains (Abilities, Knowledge, Skills and Work Activities) from which these 161 elements are taken. As shown in the other rows in Table 5, for the O*NET domains of Abilities and Skills (i.e. the elements listed in column 1 and column 3 of Table 1), the between-occupation changes dominate. In contrast, for Knowledge and Work Activities (the elements listed in column 2 and column 4 of Table 1), the within-occupation changes dominate.

Table 5: Between-Within decomposition of total skill change – Skills Prevalence, linear projections

Skill elements:	Observation 2010-20 % between : % within	Forecast 2020-35 % between : % within	Whole period 2010-35 % between : % within
All 161 skill elements	58 : 42	10 : 90	32 : 68
Abilities (52)	65 : 35	16 : 84	42 : 58
Knowledge (33)	39 : 61	8 : 92	24 : 76
Skills (35)	77 : 23	25 : 75	54 : 46
Work Activities (41)	42 : 58	8 : 92	27 : 73

Note: The pairs of numbers in the table are the median between : within shares of the total change in skill demand over the period in the column heading. Hence for 2010-2020, calculated across all 161 skill elements, the average 'between' share was 58% and the average 'within' share was 42%. The interpretation is that, on average, 58% of the total change in skills demand was due to changes in skill utilisation *between* occupations, while 42% was due to changes *within* occupations.

For the forecast period 2020-2035, for which we use both employment and skills projections, the within-occupation changes are anticipated to dominate in the overall changes in skill demand, and also for all of the four subcategories of 'skills'. That is, the increase in the demand for skills is projected to be dominated by increased utilisation within all occupations rather than because of the changing composition of occupational employment. This is likely to be a reflection of the skill projections method – recall we are using the linear skills projections here which are the most 'naïve' projections as shown in **Appendix C** – and so we examine how sensitive this conclusion is to the projection method in detail in **Appendix D.4** below. In summary, for the logarithmic-based projections, the between-within decomposition of the total changes in skills over the period 2020-2035 are much closer to the patterns exhibited in the historic 2010-2020 period, with the between-occupation changes being more important than the within-occupation changes.

4.3 Domain-specific rankings

It is interesting to note that it is primarily elements from the O*NET Work Activities domain that are typically ranked most highly in the distribution of skills utilisation, rather than specific Knowledge, or Abilities, or particular Skills, that are dominant in the ranking. For example, of the top 20 skills in 2035 as presented in Table 4, 13 are categorised as Work Activities (including all of the top five), while three are classified as Abilities (Oral Comprehension, Oral Expression and Written Comprehension), two are Skills (Active Listening and Reading Comprehension) and two are from the Knowledge domain (Customer and Personal Service and English Language). This is perhaps not surprising given we are trying to identify the skills that are used across many jobs (i.e. those that are *essential* in employment) rather than skills that are used in particular jobs or are highly specialised. This preponderance of

Work Activities in the top 20 overall ranking is not simply because of the relative number of elements in the Work Activities domain – there are 52 Abilities, 33 Knowledge elements, 35 Skills and 41 Work Activities – see Table 1. And, for our purposes, this dominance of Work Activities in the top 20 skills in use in 2035 is not problematic – *The Skills Imperative 2035* programme is seeking to identify the 'essential' skills required in employment in 2035, and we think these Essential Employment Skills can be well-captured by the dominant Work Activities or 'tasks' that many/most people are doing in their jobs.

While acknowledging that the distinctions between the different domains of Abilities, Knowledge, Skills and Work Activities are not always clear-cut (see, for example, Handel, 2016), it is interesting to examine the top 20 elements in 2035 in each of the separate domains.

Figure 21 to Figure 24 presents these domain-specific bump-charts for Abilities, Knowledge, Skills and Work Activities respectively. As with the overall rankings presented in Figure 19, there is relative stability in the rankings in the top 10 or so elements in each domain, and a greater degree of re-ranking within the next 10 elements.

Figure 21: Top 20 rankings – Abilities (skill prevalence measure with linear projections)

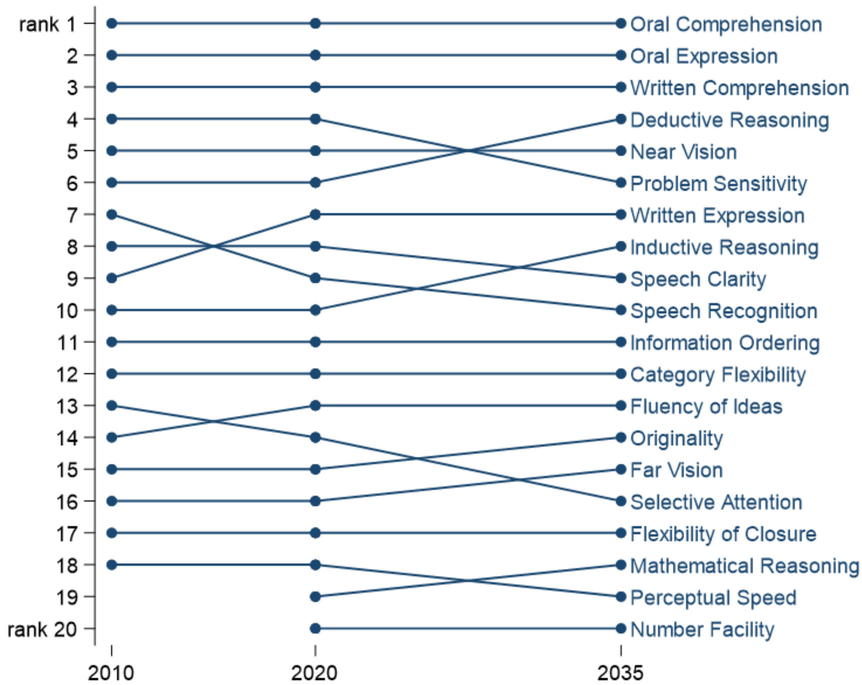


Figure 22: Top 20 rankings – Knowledge (skill prevalence measure with linear projections)

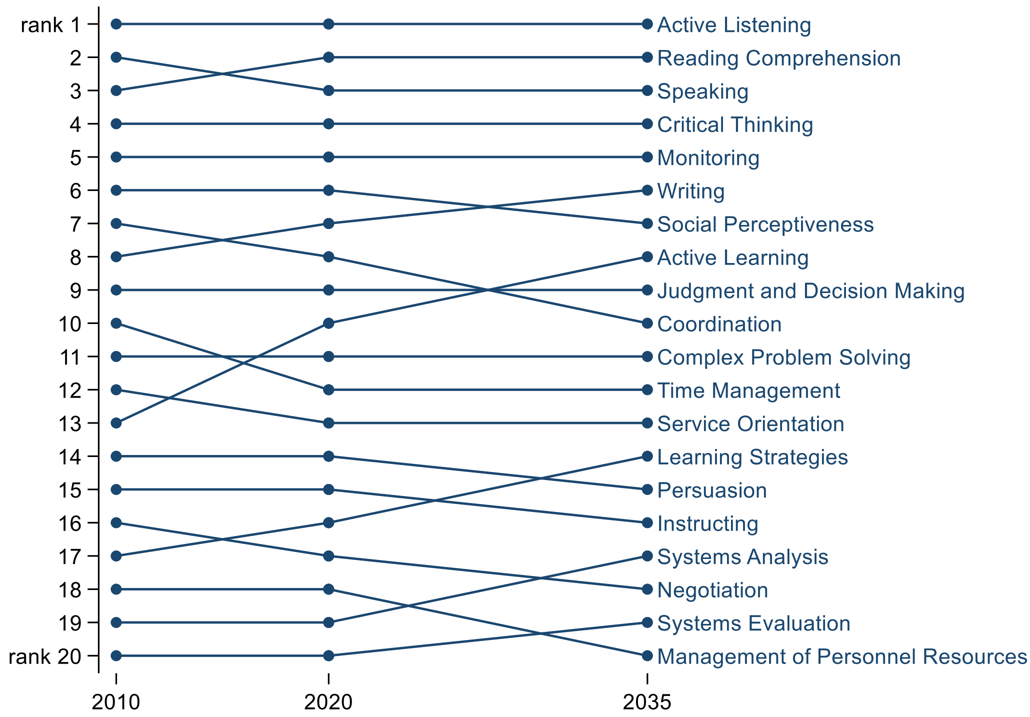


Figure 23: Top 20 rankings – Skills (skill prevalence measure with linear projections)

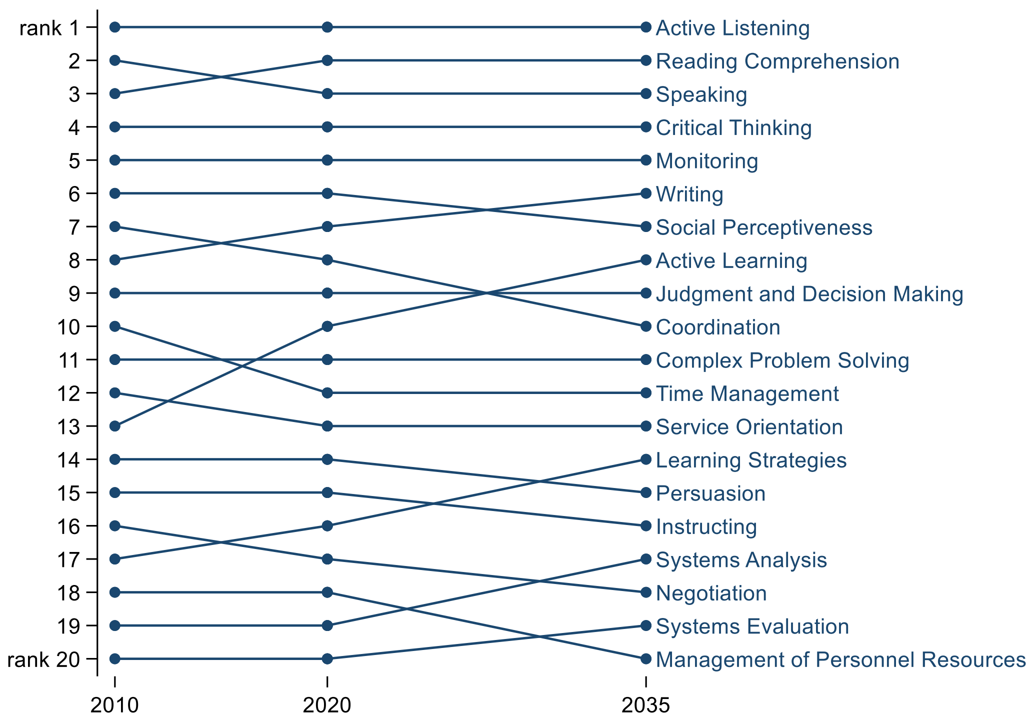
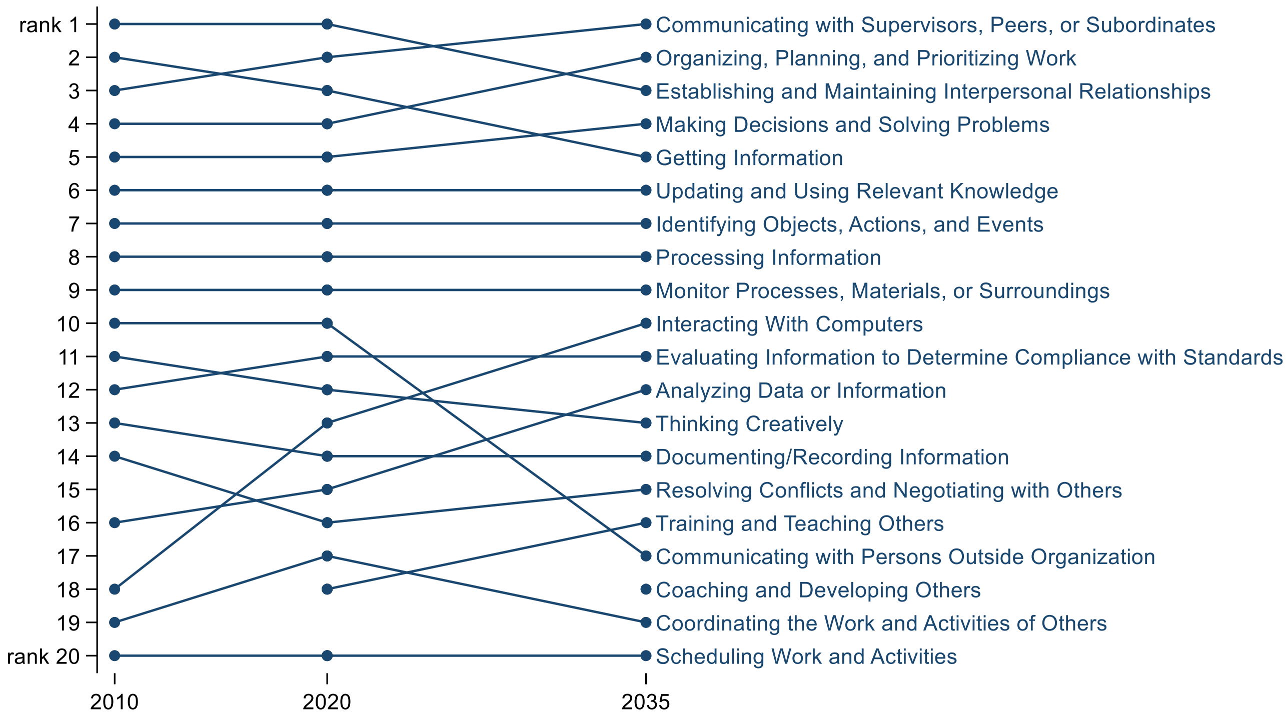


Figure 24: Top 20 rankings – Work Activities (skill prevalence measure with linear projections)



4.4 Skills growth and decline 2020-2035

Despite the caveat that the metrics we are using are ordinal rather than cardinal indices of skill utilisation as noted in Subsection 2.1 above, it is also of interest to consider which skills are projected to increase or decrease most in their utilisation over the period of interest.

Table 6 presents the 20 skills that are projected to have greatest absolute growth in their utilisation in the period 2020-2035, again using the *Baseline projections* for employment and the skill prevalence measure with linear projections for 2035. Four of the top five elements could be considered to be different dimensions within a broad composite that we could describe as digital skills (Interacting With Computers, Computers and Electronics, Analyzing Data or Information, and Evaluating Information to Determine Compliance with Standards). Ten of these top 20 skills overlap with the top 20 skills utilisation ranking for 2035 as presented in Table 4. These are Communicating with Supervisors, Peers, or Subordinates, which is rank 1 in the 2035 utilisation ranking (Table 4) and is rank 16 in the growth of utilisation ranking (Table 6) (1,16), Organizing, Planning, and Prioritizing Work (2, 8), Making Decisions and Solving Problems (4, 7), Updating and Using Relevant Knowledge (6,11), English Language (9, 3), Processing Information (10, 12), Monitor Processes, Materials, or Surroundings (13, 15), Interacting With Computers (14,1), Evaluating Information to Determine Compliance with Standards (15, 5), and Analyzing Data or Information (16, 4).

Other skills which are projected to grow significantly in absolute terms are more domain-specific knowledge skills concerned with technology and communication such as Computers and Electronics (which is projected to increase from rank 43 in 2020 to rank 32 in 2035 in the skills ranking), Communications and Media (from 93 to 85), and Engineering and Technology (from 105 to 97). Other skills projected to have strong growth are focussed on the transfer and development of others' skills including Training and Teaching Others (up from rank 34 in 2020 to rank 28 in 2035), Developing and Building Teams (from 54 to 44), Coaching and Developing Others (from 38 to 33), and Provide Consultation and Advice to Others (from 53 to 43). However, clearly none of these are ranked in the top 20 skills in terms of their utilisation across all jobs in 2035.

Table 6: Top 20 skills ranked by absolute increase in skill utilisation 2020-2035

Rank	Skill	score 2020	score 2035	Δ score
1	Interacting With Computers	12.5	14.2	1.7
2	Computers and Electronics	10.7	12.2	1.5
3	English Language	14.4	15.9	1.5
4	Analyzing Data or Information	12.4	13.8	1.4
5	Evaluating Information to Determine Compliance with Standards	12.8	14.2	1.4
6	Training and Teaching Others	11.4	12.7	1.3
7	Making Decisions and Solving Problems	16.8	18.1	1.3
8	Organizing, Planning, and Prioritizing Work	17.1	18.3	1.2
9	Provide Consultation and Advice to Others	10.0	11.1	1.1
10	Developing and Building Teams	9.9	11.1	1.1
11	Updating and Using Relevant Knowledge	16.5	17.6	1.1
12	Processing Information	14.3	15.3	1.0
13	Communications and Media	5.9	6.9	1.0
14	Interpreting the Meaning of Information for Others	10.6	11.5	1.0
15	Monitor Processes, Materials, or Surroundings	13.6	14.6	1.0
16	Communicating with Supervisors, Peers, or Subordinates	17.7	18.7	1.0
17	Coaching and Developing Others	11.2	12.1	1.0
18	Engineering and Technology	4.5	5.4	1.0
19	Developing Objectives and Strategies	9.8	10.8	1.0
20	Documenting/Recording Information	12.4	13.3	0.9

Note: The skill scores are scaled by total employment, and so can be interpreted as the average skill prevalence per job 2020 and 2035.

In contrast, Table 7 presents the 20 skills that are projected to have the greatest percentage or proportionate increase in their utilisation in the same period.

Table 7: Top 20 skills ranked by percentage increase in skill utilisation 2020-2035

Rank	Skill	score 2020	score 2035	% change
1	Explosive Strength	0.7	1.3	73
2	Dynamic Flexibility	0.1	0.2	48
3	Geography	3.2	4.0	26
4	Wrist-Finger Speed	1.8	2.2	25
5	Food Production	1.3	1.6	23
6	Engineering and Technology	4.5	5.4	22
7	Foreign Language	1.8	2.1	19
8	Communications and Media	5.9	6.9	17
9	Repairing and Maintaining Electronic Equipment	3.1	3.6	16
10	Dynamic Strength	2.1	2.5	15
11	History and Archaeology	1.4	1.6	14
12	Interacting With Computers	12.5	14.2	14
13	Computers and Electronics	10.7	12.2	14
14	Design	3.8	4.3	14
15	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	2.9	3.3	13
16	Installation	0.4	0.5	12
17	Fine Arts	1.0	1.1	12
18	Technology Design	1.6	1.8	12
19	Repairing and Maintaining Mechanical Equipment	3.4	3.8	12
20	Biology	2.3	2.6	12

Note: The skill scores are scaled by total employment, and so can be interpreted as the average skill prevalence per job 2020 and 2035.

Some of the physical and sensory skills are increasing from a very low utilisation base, and hence even their high projected percentage changes still render them largely un-utilised in employment, as can be seen from the skill prevalence scores presented in Table 7.

A similar argument can be made for the knowledge skills such as History and Archaeology and Fine Arts which, while ranked highly in terms of their projected percentage increase over the period 2020-2035, are amongst the least utilised skills in employment; as noted above – they are in the bottom 20 skills in 2035. There are two exceptions – Interacting with Computers and Computers and Electronics – which are not only ranked highly in terms of their projected percentage increase in utilisation over the period 2020-2035, but are also highly ranked in terms of their projected absolute change, as shown in Table 6. Indeed, Interacting with Computers is projected to increase sufficiently over the period 2020-2035 that it appears in the top 20 ranked skills in 2035, as shown in Table 4.

We can also examine the skills that are expected to decline most in significance over the period 2020-2035. The skills projected to have the largest absolute decrease and the biggest percentage decreases in their utilisation are presented in Table 8 and Table 9 respectively.

Table 8: Top 20 skills ranked by absolute decrease in skill utilisation 2020-2035

Rank	Skill	score 2020	score 2035	Δ score
1	Finger Dexterity	5.9	4.6	-1.4
2	Operations Analysis	3.7	2.5	-1.2
3	Science	2.3	1.6	-0.7
4	Hearing Sensitivity	4.0	3.4	-0.7
5	Psychology	6.9	6.3	-0.6
6	Selective Attention	8.6	8.0	-0.6
7	Operation Monitoring	4.7	4.1	-0.6
8	Depth Perception	3.1	2.6	-0.6
9	Performing for or Working Directly with the Public	10.8	10.3	-0.6
10	Speed of Limb Movement	1.2	0.7	-0.5
11	Communicating with Persons Outside Organization	12.8	12.3	-0.5
12	Management of Personnel Resources	7.6	7.1	-0.5
13	Control Precision	4.1	3.7	-0.4
14	Visual Color Discrimination	5.4	5.0	-0.3
15	Multilimb Coordination	3.7	3.4	-0.3
16	Arm-Hand Steadiness	4.8	4.5	-0.3
17	Negotiation	8.0	7.7	-0.3
18	Response Orientation	1.8	1.6	-0.3
19	Auditory Attention	4.8	4.5	-0.3
20	Time Management	10.0	9.8	-0.2

Note: The skill scores are scaled by total employment, and so can be interpreted as the average skill prevalence per job 2020 and 2035.

The majority of these elements are physical and sensory skills from the Abilities domain (see Table 1) – 11 (14) of the largest 20 absolute (percentage) declines in forecast skill utilisation over the period 2020-2035 are for such skills. Moreover, the elements projected to have the largest absolute and percentage decreases overlap to a large degree – Finger Dexterity, Hearing Sensitivity, Selective Attention, Depth Perception, Speed of Limb Movement, Control Precision, Visual Color Discrimination, Multilimb Coordination, Arm-Hand Steadiness, Response Orientation, and Auditory Attention are in both tables. Most of these skills are also projected to be in the bottom quintile of skills utilisation in 2035. This reflects the continuing decline in importance of physical/manual skills more generally in the workplace over at least the last five decades.

Table 9: Top 20 skills ranked by percentage decrease in skill utilisation 2020-2035

Rank	Skill	score 2020	score 2035	% change
1	Speed of Limb Movement	1.2	0.7	-43
2	Operations Analysis	3.7	2.5	-32
3	Science	2.3	1.6	-29
4	Finger Dexterity	5.9	4.6	-23
5	Depth Perception	3.1	2.6	-18
6	Hearing Sensitivity	4.0	3.4	-16
7	Response Orientation	1.8	1.6	-14
8	Glare Sensitivity	0.8	0.7	-14
9	Operation Monitoring	4.7	4.1	-12
10	Control Precision	4.1	3.7	-10
11	Gross Body Coordination	2.3	2.1	-9
12	Psychology	6.9	6.3	-9
13	Multilimb Coordination	3.7	3.4	-8
14	Night Vision	0.6	0.5	-7
15	Therapy and Counseling	3.4	3.2	-7
16	Selective Attention	8.6	8.0	-7
17	Visual Color Discrimination	5.4	5.0	-6
18	Management of Personnel Resources	7.6	7.1	-6
19	Arm-Hand Steadiness	4.8	4.5	-6
20	Auditory Attention	4.8	4.5	-5

Note: The skill scores are scaled by total employment, and so can be interpreted as the average skill prevalence per job 2020 and 2035.

Outside these top 20 movers, there are other skills that are also projected to be in rapid decline over the period 2020-2035. Focussing on only the skills with above median utilisation in 2020, other skills that are projected to move down by more than 5 rank places by 2035 are: Coordination (down 7 rank places, from rank 45 to rank 52 in the utilisation ranking); Speaking (down 6, from 17 to 23) and Speech Recognition (down 6, from 31 to 37); the percentage changes in their utilisation are small, however.

4.5 Robustness and sensitivity of the findings

Overall, the average skill utilisation of employment is projected to increase between 2020 and 2035. The mean prevalence score across all 161 skills is anticipated to increase from 7.35 to 7.59, with 116 skills expected to increase their average utilisation in employment (and 45 expected to decrease) over the period. The mean prevalence score for the top 20 skills in 2035 is projected to increase from an average of 14.9 in 2020 to an average of 15.5 in 2035, an increase of 5 percentage points. This is all consistent with the increase in the skill composition of employment summarised in Subsection 3.1 which showed that the share of employment at SOC Skill level 3 and Skill level 4 is projected to increase still further over the period 2020 to 2035. While there are some differences in which skills are ranked most highly in 2035 (Subsection 3.2) and the skills that are anticipated to be growing most strongly in utilisation over the 2020-2035 period (Subsection 3.3), there is substantial overlap in these two sets of skills. In summary, the skills that are used most intensively in employment in 2035 are set to increase their utilisation still further over the period 2020-2035.

Our focus in *The Skills Imperative 2035* programme is on the skills which will be in most demand in employment in 2035, since these are the skills that the education and training systems, and employment/employers, need to deliver. Clearly, these are most directly identified by the overall utilisation rankings reported in Subsection 3.2. We are also interested in how these skills are changing over time. Our results indicate that the most significant skills used in employment are relatively stable set given the forecast occupational changes in employment and our projections of changes in the prevalence of skill use within occupations over the period 2020-2035.

However, the skills that exhibit most growth are also of interest, since if we assume that new skills are easier to develop while individuals are still in full-time education or training, then these might be a greater priority for the education and training system. Nevertheless, as noted above, our analysis of the skills projected to have the largest absolute increases in their utilisation over the period 2020-2035 identifies many of the same skills that are in the top 20 skills. And, of course, some of these skills (being skills used in employment) may not be able to be developed or enhanced in the classroom – by their nature, they are employment skills.

In **Appendix D**, we investigate in detail how sensitive these findings are to the various decisions that we have made regarding the analysis that we have undertaken.

First, we examine the implications that the two *Alternative scenarios* for employment that IER/CE have developed might have for the skills that we anticipate will be most important in employment in 2035 (**Appendix D.1**). These two *Alternative scenarios* – a *Technological opportunities scenario* and a *Human-centric scenario* – both suggest rather greater employment in SOC2: Professional occupations and in SOC6: Caring, leisure and other service occupations in 2035 as compared to the *Baseline projections*. This is counter-balanced by significantly less employment in SOC5: Skilled trades occupations, SOC7: Sales and customer service occupations and SOC9: Elementary occupations. The net impact is an increase in employment at ONS Skill level 4 (the highest level) as compared to the *Baseline projections.* However, re-running our analysis using these *Alternative scenarios* for future employment does not impact on the top 20 skills ranking in 2035. While the demand for certain specific technical and scientific skills will be enhanced under the two *Alternative scenarios*, these skills are not used intensively across the whole of employment, and therefore they are typically ranked quite low in the distribution of all skills.

Second, we examine the projected rankings in skills in 2035 when we use skills importance and skills levels metrics separately, rather than the skills prevalence measure (skills importance × skills level) that we employ in our main analysis presented above. As shown in **Appendix D.2**, there is a considerable degree of overlap in the top 20 skill importance and top 20 skill level rankings in 2035, and hence it is not surprising that there is a high correlation of both these rankings with the skill prevalence top 20 ranking list for 2035 too. For example, Communicating with Supervisors, Peers, or Subordinates is rank 2 for skills importance and rank 4 for skills level in 2035, and hence it is unsurprising that it is rank 1 for skill prevalence. In part, this finding reflects the high correlation between skills importance and skills level as noted above. While there are some differences in skill importance and skill levels rankings (see **Appendix D.2** for details), our general conclusions on the skills that we anticipate will be utilised most in employment in 2035 are not conditional on having focussed on the skill prevalence metric.

Thirdly, we consider the implications for our occupational skills profiles of the choices we have made in compiling the mapping between O*NET and UK SOC2020. As explained in Subsection 2.1.1. and in **Appendix B**, we consider three main variants: the ‘complete mapping’ which uses all of the SOC2010 codes that match to each UK SOC2020 occupation (this is the version of the mapping that we have employed in our main analysis); the ‘restrictive mapping’ which only uses the largest (by employment) SOC2010 code to match to each SOC2020 occupation; and the ‘new mapping’ generated by the independent expert CASCOT coder from scratch. As shown in **Appendix D.3** the occupational skills profiles are very similar in all three cases, and thus the resulting rankings of skills utilisation in 2035 is not impacted by the choice of mapping used in our analysis.

Finally, in **Appendix D.4** we investigate the effect that the method we have used to generate our skills projections may have on our findings. As described in **Appendix C**, as well as the linear projections, we also investigate the impact of assuming a logarithmic trajectory for skills utilisation. This functional specification assumes that skills increase or decrease into the future (according to their historic trend), but do so at a diminishing rate. Such projections are therefore more ‘conservative’ than the ‘naïve’ linear projections. There is rather less re-ranking of the top 20 skills when using the logarithmic projections, and this more moderate basis for the future trajectories of skills is also reflected in the corresponding between-within decomposition of the total change in skill use over the forecast period. For the logarithmic projections, a greater proportion of the change in skill utilisation is attributed to the changing occupational distribution of employment (i.e. changes in skills demand due to changes between occupations), rather than to changes of skills within occupations. The magnitudes of the between-within decomposition shares using the logarithmic projections are also more similar to the observation period 2010-2020. However, it is important to emphasise that the ranking of the top 20 skills in 2035 is almost unchanged whichever of the two methods of skills projections – linear or logarithmic – is employed.

In summary, our assessment of which skills are likely to be the most important skills in use in employment in 2035 is not impacted by: either of the two *Alternative scenarios*; the choice of skills metrics examined; the particular O*NET to UK SOC2020 mapping selected; nor the method of projecting future skills use in each occupation. While the magnitudes of the changes may differ, and the precise ranking within the top 20 may change somewhat, it is still primarily the same skills that are ranked most highly in terms of their projected utilisation in 2035.

5 Essential Employment Skills

- In this section we use our top skills rankings and *The Skills Imperative 2025* literature review to inform the selection of a set of 'Essential Employment Skills' – the skills which are expected to be critical for future employment
- Our six Essential Employment Skills are:
    - Collaboration
    - Communication
    - Creative Thinking
    - Information literacy
    - Organizing, planning and prioritizing
    - Problem solving and decision making
- These skills are clearly generic and transferable – as anticipated, since they are, by definition, widely utilised in employment
- These are the skills that will be used in the next stage of *The Skills Imperative 2035* programme

1.

Having derived the ranking of skills that are anticipated to be most in demand in 2035 using our purely data-driven approach, we now turn to use this ranking to inform the selection of a set of 'Essential Employment Skills' (EES), which will be the focus of the next stage of *The Skills Imperative 2035* programme. By 'Essential Employment Skills', we mean those skills

> *'… which complement the new technologies and other changes taking place (and) which are also expected to be critical for future employment'*
> (Taylor *et al*., 2022, p.8).

5.1 Identifying the most essential employment skills needed in 2035

In this stage of *The Skills Imperative 2035* programme, we have identified the skills projected to be most in *demand* in 2035. While there are changes in the relative importance of skills between 2020 and 2035, we have found that the top 10 skills used most intensively in the labour market in 2035 will broadly be the same as today. However, the aim of this research programme is not just to estimate future skills demand; our intent is to identify and estimate skills *mismatches* and explore the implications of these mismatches for different groups in the economy. To do this, we need to estimate skills *supply* in the current labour market, project forward skills supply in 2035, and equate and compare future skills supply and skills demand. To this end, we have developed a skills survey to measure the current 'supply' of skills in the adult population. We will project future skills supply, taking into account anticipated demographic and employment changes between now and 2035.

Clearly, it would be challenging to develop reliable and valid scales covering the full mix of skills, knowledge, abilities, and work activities in the O*NET content model. Instead, our focus has been on developing an instrument for measuring the supply of the skills projected to be *most heavily utilised in the labour market in 2035.* More specifically, we have identified and defined six skills - labelled 'Essential Employment Skills' - which our skills survey will be based around. These are:

- Collaboration
- Communication
- Creative thinking
- Information literacy
- Organizing, planning and prioritizing
- Problem solving and decision making

5.1.1 Process for selecting our six 'Essential Employment Skills'

These six 'Essential Employment Skills' are identified from two sources; our 2035 skills projections, and the literature review conducted earlier in the Skills Imperative 2035 research programme:

A: 2035 skills projections

Our six 'Essential Employment Skills' primarily match-up with the highest-ranked O*NET elements for 2035 and are defined, in part, using the O*NET descriptors. As shown in Table 4 and Figure 19, the 10 skills rated highest based on their 2035 skills prevalence scores are:

1. Communicating with Supervisors, Peers, or Subordinates
2. Organizing, Planning, and Prioritizing Work
3. Establishing and Maintaining Interpersonal Relationships
4. Making Decisions and Solving Problems
5. Getting Information
6. Updating and Using Relevant Knowledge
7. Customer and Personal Service
8. Identifying Objects, Actions, and Events
9. English Language
10. Processing Information

We also consider the skills with the greatest projected *absolute* skill prevalence score increase between 2020 and 2035 (Table 6). This criterion captures the magnitude of the increase in the demand for each skill by 2035. Elements that rank highly according to this measure overlap considerably with the skills which are expected to have a high skill prevalence score in 2035. As shown in Subsection 3.3 above, when comparing Table 4 and Table 6, ten skills appear both in the list of the top 20 highest ranked skills and the 20 skills with the greatest projected absolute skill prevalence score increases. These are (in alphabetical order):

- Analyzing Data or Information
- Communicating with Supervisors, Peers, or Subordinates

- English Language
- Evaluating Information to Determine Compliance with Standards
- Interacting With Computers
- Making Decisions and Solving Problems
- Monitor Processes, Materials, or Surroundings
- Organizing, Planning, and Prioritizing Work
- Processing Information
- Updating and Using Relevant Knowledge

The lists of skills identified using both methods are robust to the analytical choices discussed in Section 3 (i.e., the choice of *Baseline projections* for employment, the complete mapping, and the linear skills projections for the skill prevalence measure), and the alternative variants described in **Appendix D**.

An alternative approach might have been to prioritise the skills projected to experience the greatest increase in demand in proportionate or percentage terms between 2020 and 2035. However, this would have focused the next stage of our research on the skills with expanding demand, not the skills that will be most in-demand across the labour market in 2035. Indeed, as shown in Table 7 the largest proportionate increases are projected in skills that are utilised by a relatively small proportion of the labour market, whereas, by contrast, our six 'Essential Employment Skills' are work activities that are common across a very large number of occupations and are performed in almost all job families and industries. To illustrate this point, the five skills that are anticipated to have the greater percentage increase in their utilisation between 2020 and 2035 are: Explosive Strength; Dynamic Flexibility; Geography; Wrist-Finger Speed; and Food Production, which are ranked 151, 161, 111, 138 and 147 respectively in terms of their utilisation ranking in 2035 – all comfortably in the bottom third of the ranked skills distribution. To illustrate the difference between using absolute or percentage increases, the skill prevalence utilisation score for Thinking Creatively is projected to increase from 12.7 to 13.3 between 2020 and 2035, whereas the score for Programming is projected to rise from 1.52 to 1.61. Thinking Creatively has a much larger absolute score change than Programming (+0.58 vs. +0.09) but a smaller increase in percentage terms (+4.6% vs. +5.9%).

B: Literature review

We triangulated the skills projected to be in greatest demand with those identified in our earlier literature review as likely to be most important (Taylor *et al*., 2022). Based on a comprehensive and systematic literature search and review, Taylor *et al*., (2022, p.29) rank the following ten 'essential employment skills' as being the most important for future employment:

1. Problem solving/decision making
2. Critical thinking/analysis and evaluation
3. Communication
4. Collaboration/cooperation/teamwork
5. Creativity/innovation/originality
6. Leadership/management
7. Self-motivation/learning orientation

8. Flexibility/adaptability
9. Resilience/optimism/persistence
10. Empathy/social perceptiveness

Skill 1, Skill 3 and Skill 4 in the above list clearly mirror O*NET elements ranked in the top 10 most utilised skills in 2035. We conceptualise 'critical thinking' (discussed below) as a meta-skill that encompasses several of the top-10 ranked O*NET elements relating to how people deal with information, all of which are highly correlated. 'Creativity/ innovation/ originality' did not appear in the list of the top-10 ranked O*NET elements but is included in our final selection of 'Essential Employment Skills' because the literature review identifies it as the fifth most important skill by number of mentions. Skills 6 to 10 above do not feature in the O*NET elements considered, potentially reflecting the fact that leadership/ management is, arguably, a higher-order construct, and 'skills' like self-motivation, flexibility, resilience, and optimism are variously conceptualised as 'skills' by some, but as character traits/ virtues (i.e., distinct from skills) in other frameworks.

5.2 Defining and describing our six 'Essential Employment Skills'

Initial definitions of our six Essential Employment Skills were drafted from the O*NET descriptors and the skills definitions in our literature review. To add depth to our definitions, we additionally incorporated other relevant descriptions from skills frameworks such as the Skills Builder Universal Framework, UNICEF's Life Skills and Citizenship Education (LSCE) framework and the Australian Core Skills Framework (ACSF). This enabled us to break each skill down into its constituent attributes, which we then grouped into 'sub-domains' for each skill. Our skills survey will include items that ensure sufficient coverage across these sub-domains. We define and describe our six Essential Employment Skills as follows:

1. **Collaboration** – This relates to the O*NET element Establishing and Maintaining Interpersonal Relationships, defined as 'Developing constructive and cooperative working relationships with others, and maintaining them over time'. This is projected to be the third most utilised skill in 2035 and was also ranked fourth in our literature review (based on frequency of mentions). Collaboration involves working and interacting effectively with others towards a common purpose or goal(s). It encompasses the following sub-domains: (i) forming and maintaining constructive / collaborative relationships with others; and (ii) interacting effectively in collaborative situations.
2. **Communication –** This relates to the O*NET element Communicating with Supervisors, Peers, or Subordinates, which is defined as 'Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person'. This is projected to be the most in-demand skill in 2035. It also featured prominently in our literature review. Communication involves speaking, listening, writing, and presenting effectively to share meaning and build a common understanding with others. It encompasses: (i) recognising that communication involves shared meaning; (ii) a willingness to provide information and an understanding about what this involves; and (iii) adapting the mode and/or style of delivery in relation to the recipient(s).
3. **Creative thinking** – This relates to the O*NET element Thinking Creatively which is defined in O*NET as 'Developing, designing, or creating new applications, ideas,

relationships, systems, or products, including artistic contributions'. Whilst Thinking Creatively does not appear in the top-10 highest ranked skills in 2035, it is expected to enter the top 20 in 2035, and it was ranked the fifth most important future skill in our literature review (by number of mentions), hence its inclusion in the final list of six Essential Employment Skills. It relates closely to critical thinking and problem solving and is the ability to generate, articulate, and apply innovative ideas, techniques, and perspectives, often in a collaborative environment in response to a challenge or issue. It encompasses: (i) developing new/different ideas; (ii) creating something new/different; (iii) applying a fresh perspective to an issue or challenge; and (iv) applying thought in a new/different way.

4. **Information literacy –** This skill is an amalgamation of four O*NET elements that all relate to appraising, dissecting, synthesising, and interpreting information. The four specific O*NET work activities are: Getting Information; Updating and Using Relevant Knowledge; Processing Information; and Analyzing Data or Information, which are projected to be the 5th, 6th, 10th, and 16th most utilised skills in 2035, respectively. Processing Information is projected to enter the top-10 ranking for the first time in 2035, and Analyzing Data or Information is anticipated to experience the fourth largest increase in absolute demand by 2035 of any of the 161 O*NET elements. The four separate O*NET elements are strongly and positively correlated, reinforcing the assertion that they relate to a common latent construct. Figure 25 presents the (4×3/2=) 6 pairwise scatterplots between the four elements for the 412 UK SOC2020 occupations using the skill prevalence metric. Both Spearman rank order and (ordinary) Pearson correlation coefficients are presented at the top of each pairwise scatterplot. The average pairwise Spearman rank correlation is 0.886, while the average Pearson correlation coefficient is 0.881.

   Information literacy involves accessing and examining data or facts to determine appropriate actions or recommendations, discerning and evaluating arguments, and making and defending judgements based on internal evidence and external criteria. Information literacy encompasses the following sub-domains: (i) determining appropriate actions using logic and reasoning; (ii) identifying strengths and weaknesses through reasoning; and (iii) evaluating the credibility and reliability of information. We also conceptualise information literacy as closely related to the meta-skill Critical Thinking, which is defined in O*NET as 'Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems'. Critical thinking was also identified in our literature review as the joint first most important future skill (by number of mentions)

5. **Organizing, planning and prioritising** – This aligns with the O*NET element Organizing, Planning and Prioritizing Work, defined in O*NET as 'Developing specific goals and plans to prioritise, organise, and accomplish your work'. This is projected to be the second most heavily utilised skill in 2035 (and is the skill expected to experience the eighth greatest increase in absolute demand). Whilst this skill did not feature in the top-10 skills in our literature review, self-management and project planning were attributes of 'Leadership/ management' and 'Self-motivation/ learning orientation' respectively. This skill involves developing specific goals, plans and schedules to prioritise, organise and accomplish work, and directing and coordinating the activities of groups and individuals to complete these objectives on time and

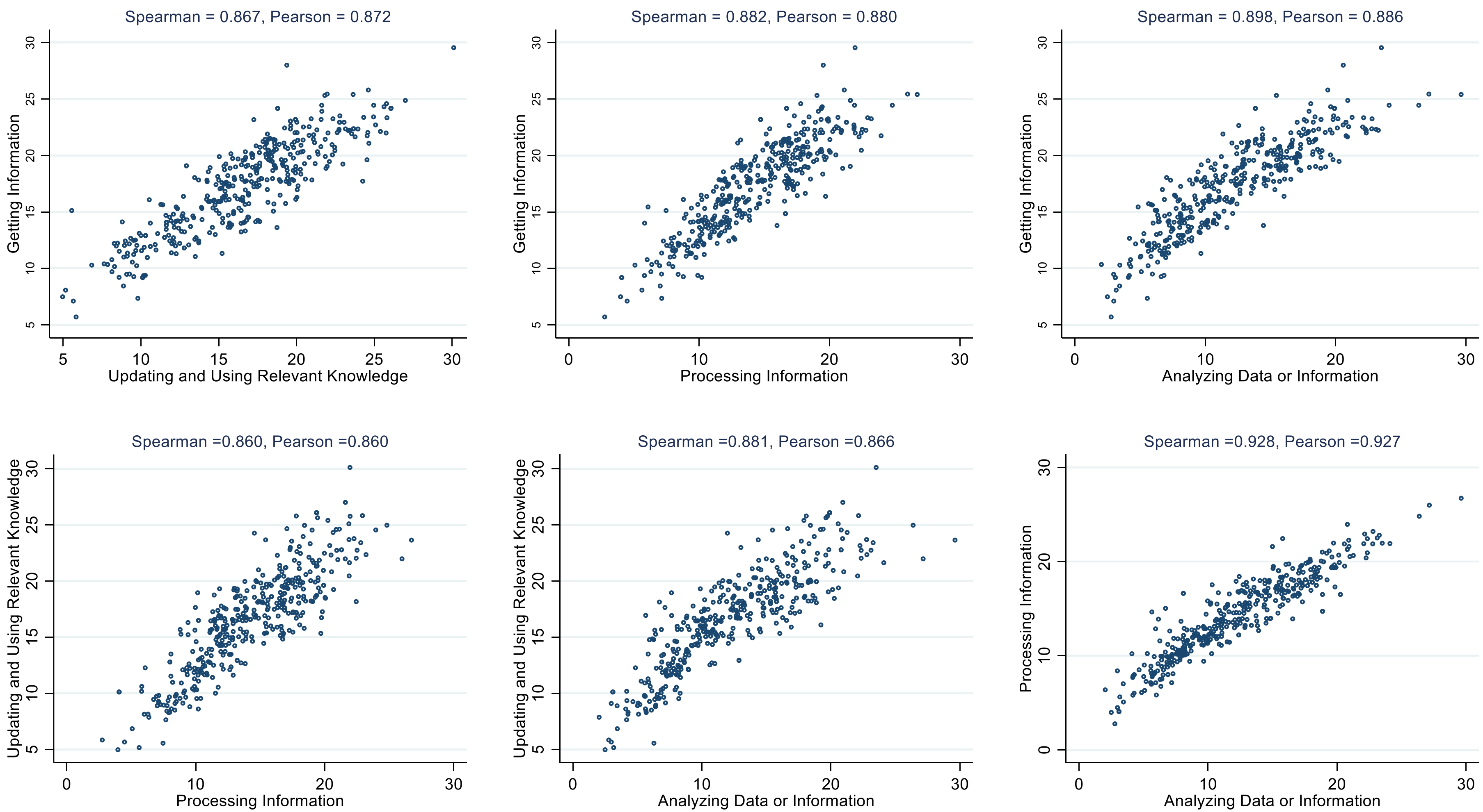
within budget. It encompasses: (i) developing a goal/plan to prioritise something; (ii) developing a goal/plan to organise something; and (iii) developing a goal/plan to complete objectives.

6. **Problem solving and decision making –** This is aligned to Making Decisions and Solving Problems, defined in O*NET as 'Analyzing information and evaluating results to choose the best solution and solve problems'. This is projected to be the fourth most utilised skill in 2035 (and is expected to experience the seventh greatest increase in absolute demand). It was also identified by our literature review as the joint most important future skill (based on frequency of mentions). It involves diagnosing problems, identifying solutions to address these problems, choosing between the alternative courses of action available, planning and carrying out the solution(s) and monitoring and evaluating the progress of the solution(s). It encompasses: (i) analysis of information for problem solving; (ii) identification of problems and associated risks and benefits of solutions; (iii) using effective strategies for identifying solutions and solving problems; (iv) evaluation of information for decision making; and (v) using effective strategies for choosing between options.

Taken together, our six Essential Employment Skills cover seven of the ten highest-scoring O*NET elements for 2035, excluding only Customer and Personal Service (rank 7), Identifying Objects, Actions, and Events (rank 8), and English Language (rank 9). They also cover the top 5 skills identified by our literature review (by number of mentions). The six skills we have identified are all generic and transferable skills which are used widely in a large number of jobs and which are expected to be in high demand across the whole occupational distribution in 2035.

Our set of six Essential Employment Skills largely reinforce the consensus highlighted in our literature review about the skills that will be most essential in employment in 2035. They also share notable similarities with the skills identified as most important by other 'essential skill' taxonomies such as the Australian Skills Classification (ASC) (and, in particular, their list of '10 core competencies') and the framework developed by Skills Builder (Ravenscroft and Barker, 2020). Our definitions of the six Essential Employment Skills lend further weight to this consensus in the literature and existing practice.

Figure 25: Pairwise correlations between Information literacy O*NET elements – Skill Prevalence metric



6 Conclusions and next steps

The analysis presented in this report uses a purely data-driven approach to produce a ranking of the most important skills that are used in employment today, and are projected to be used most intensively in employment in the future. Using a set of occupational skills profiles derived from mapping 161 skills indices extracted from the US O*NET system to 4-digit UK SOC2020 occupations, together with data on occupational employment, we have shown that it is possible to clearly identify a set of skills that are most utilised in employment. While there is some re-ranking of these skills over time, a similar set of skills appear at the top of the distribution of the 161 skills in both 2010 and 2020. We then look to the future using the new IER/CE occupational employment projections for 2035 specifically developed for *The Skills Imperative 2035* programme (Wilson *et al.*, 2022b, 2022c), together with our own projections of the future use of skills within occupations, to provide an assessment of the most important skills that will be in use in the labour market in England in 2035. We find that the skills that are anticipated to be most in demand in the labour market in 2035 are very similar to those that are most important today.

We test the robustness of our conclusions to a number of variants. First, we examine the implications of two *Alternative scenarios* for occupational employment in 2035 which assume an acceleration in the take-up of new technologies such as automation and AI relative to the *Baseline projections*. Second, we repeat our main analysis, which uses a composite measure of skill prevalence, separately for its two constituent components of skill importance and skill level. Finally, we examine some alternative methods for projecting future skill use within occupations. We find that the set of skills projected to be most utilised in employment in 2035 is robust to all these variants.

These top ranked skills are used across many jobs which is a key reason that they remain dominant despite changes in the occupational distribution of employment. While there are also some comparatively large projected changes in a number of specific and specialised skills, particularly associated with new technologies, these more specialised skills, by their nature, are used in relatively few jobs. They therefore still do not rank highly in the overall distribution of skill utilisation.

Our methodology is designed to identify the skills that are most widely utilised in employment, and hence it is unsurprising that we identify a set of generic and transferable skills as being the most prevalent. The particular strength of our O*NET-based methodology is that it is atheoretical and data-driven, and considers an extremely wide range of cognitive and non-cognitive skills, physical skills, broad and specific subject knowledge, individual abilities, areas of knowledge and work activities, i.e., we do not limit our analysis to any particular or restrictive definition of ‘skill’ in advance. Moreover, we would argue that we bring rather greater methodological rigour and testing than many other attempts to classify a set of essential employment skills have utilised.

Having produced a robust ranking of the skills anticipated to be most utilised in employment in 2035, we use this ranking together with the conclusions of *The Skills Imperative 2035* literature review (Taylor *et al.*, 2022), to define a set of six ‘Essential Employment Skills’ for employment in 2035. Listed in alphabetical order, these are anticipated to be:

- Collaboration
- Communication
- Creative thinking
- Information literacy

- Organising, planning and prioritizing
- Problem solving and decision making

These are clearly all generic and transferable skills. They also correlate strongly with the sets of skills identified in other academic and policy-focussed research which has attempted to assess the essential skills and competencies required in employment both today and in the future. This is a significant finding – despite the differences in methodological approaches used, the same kinds of skills are identified as being the most important in employment from the very large and extensive set of skills and attributes that we consider in this report.

It is also significant that a similar set of skills found to be most important today is projected to still be important in 2035. It suggests that the skills 'ecosystem' – the education and training system, together with work experience – needs to re-focus its attention and endeavours on better equipping individuals with these skills and core competencies. That the same/similar skills remain important in the future suggests greater emphasis needs to be directed on understanding how these skills can be further developed and improved in order to better equip individuals for the future world of work. In this, it will be important to recognise the differences between skills that are used and enhanced in the workplace, and the formative skills that need to be developed while in education.

The focus of The Skills Imperative 2035 programme now turns to the next three research questions. These are concerned with the likely *supply* of these Essential Employment Skills in 2035:

- RQ2: What Essential Employment Skills are likely to be available in the future?
- RQ3: Which workers may be affected by the changing demand for these skills?
- RQ4: How do pupils' Essential Employment Skills develop during their formal education?

To answer these questions, *The Skills Imperative 2035* programme will draw on several sources of data, including the Longitudinal Education Outcomes (LEO) dataset and data from the second cycle of the OECD's International Survey of Adult Skills, commonly called PIAAC (OECD, 2016). *The Skills Imperative 2035* programme is also collecting its own data via a new 'Essential Employment Skills Survey', in development by NFER, and which will be administered to 11,500 residents of England between the ages of 15 and 65. Participants' responses will be a unique source of information about the current skills landscape in England.

In conclusion, in this report we have developed a methodology to assess future skills demand by combining information on skills taken from the US O*NET system matched to UK SOC2020 occupations together with projections of future employment. We have used this methodology to identify a set of six Essential Employment Skills that we anticipate will be used most intensively in employment in 2035. These Essential Employment Skills are generic and transferable, reflecting the fact that they are widely used across all employment. While these skills are used intensively in employment today, their utilisation is projected to increase still further in the future. Moreover, employment in the occupations that use these skills most intensively is also projected to increase.

Given the focus of the next stage of *The Skills Imperative 2035* programme, our data analysis is for England only. However, we anticipate that the findings presented in this report – and in particular, the Essential Employment Skills identified as being the most significant for future employment – will also be broadly applicable to the other nations of the UK.

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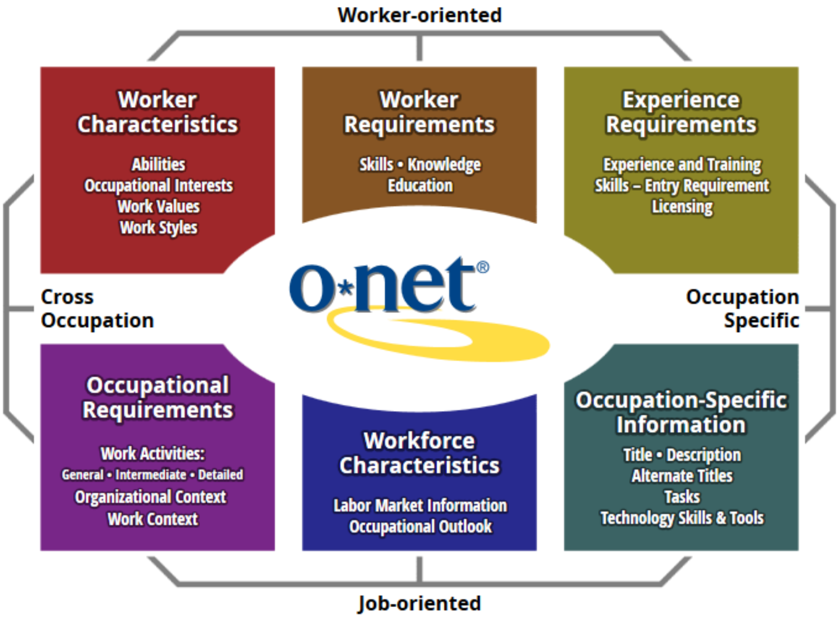
Appendix A: The US Occupational Information Network (O*NET) database

The Occupational Information Network (O*NET) system (https://www.onetcenter.org/) is administered by the US Bureau of Labor Statistics (BLS) and is the largest source of occupational competency data in the US. It was almost 20 years in development as a replacement to the original DOT (Dictionary of Occupational Titles) system which was first published in 1939. O*NET contains information on a wide range of occupational descriptors with a total of 239 measures of skills, abilities, subject-specific knowledge, training, educational and experience requirements, work activities, work contexts and work styles. A comprehensive description of the development of the O*NET system can be found in Peterson *et al*., (1999), and Tippins and Hilton (2010), while Handel (2016) provides a review.

Figure A1: The O*NET content model



Source: https://www.onetcenter.org/content.html

Figure A1 shows the O*NET content model which describes the data structure. O*NET comprises worker-orientated and job-orientated characteristics at both an occupation-specific level and across occupations. Information is collated into six broad areas which include qualifications required, indicators of practical and technical skills, a wide range of 'soft skills' such as communication skills, stamina etc, and details of the tasks involved in the job. Most descriptors are comparable between occupations, although tasks are occupation-specific.

O*NET information is gathered from job incumbents through postal and online questionnaires administered by the BLS, and from professional assessments by job evaluation analysts and occupational experts. Survey respondents are only asked to complete a random selection of the questionnaires in order to avoid survey fatigue. In addition, all respondents provide some background demographic information (which is not released) and are also asked to indicate from a wide range of occupation-specific tasks those that apply to their particular job. Information is published at the 'O*NET-SOC' occupation level, which is a slightly more detailed version of the US SOC. O*NET data collection began in 2001 and is being continually updated on a rolling basis, with approximately 100 occupations updated each year (larger occupations are more regularly updated than the smaller occupations). Indeed, one of the main strengths of the O*NET design is that it is being constantly updated so that changes in skills utilisation *within* occupations over time can be discerned.

The four O*NET 'domains' we make use of in this report – Abilities, Knowledge, Skills, and Work Activities – have elements which: (i) are all measured using a common basis and therefore comparable between all occupations; and (ii) all use both Importance and Level scales to record the utilisation of each element. The domain definitions as provided by the O*NET content model are as follows:

- Abilities: defined as the 'attributes of the individual that influence performance' and include cognitive, psychomotor, physical and sensory abilities;
- Knowledge: comprises descriptors of 'organised sets of principles and facts applying in general domains';
- Skills: include basic skills (which are 'capacities that facilitate learning or the more rapid acquisition of knowledge') as well as cross-functional skills (which are 'developed capacities that facilitate performance of activities that occur across jobs'); and
- Work Activities: are general activities that are 'common across a very large number of occupations'.

For the four O*NET domains that we use, the sources of the data are presented in Table A1 below:

Table A1: Respondent types for the O*NET domains

Domain	No. Elements	Respondents
Abilities	52	Job Analysts
Knowledge	33	Job Incumbents & Occupational Experts
Skills	35	Job Analysts
Work Activities	41	Job Incumbents & Occupational Experts
TOTAL	161	

These 161 O*NET elements are listed in Table 1. As noted by Handel (2016), the divisions between these four domains are imprecise and there is a degree of overlap and potentially some repetition. Arguably, some of the Abilities elements are not 'skills' but, rather than arbitrary pre-selection, we allow the data to determine whether these attributes are highly prevalent or important in employment. In this report, we refer to these 161 O*NET elements

collectively as ‘skills’. Where we reference the O*NET elements explicitly, we underline the element names, and retain the American spelling conventions as used in O*NET.

The other (239=161=) 78 occupation-specific elements comprise Work Contexts (57 items, mainly capturing differences in physical working conditions), Work Styles (16 items, reflecting personal characteristics, including persistence, cooperation, adaptability etc), plus 5 measures of Education and Training requirements (which do not have direct comparability within the UK/English education and training systems).

Most O*NET data for the Knowledge and Work Activities domains comes from a survey of establishments, and then from sampled workers – job incumbents – within those establishments. A targeted approach is used such that establishments in industries and size categories are sampled in which the occupations being targeted for updating are most prevalent. An alternative method of data collection – using occupational experts (OEs) – is also used for around one fifth of occupations:

> *‘… to improve sampling efficiency and avoid excessive burden, as when it is difficult to locate industries or establishments with occupation incumbents; employment is low; or employment data are not available, as is the case for many new and emerging occupations.’*
>
> O*NET Data Collections Program – Supporting Statement B, 2021, p.B-2

Sources of OEs include membership lists of professional or trade associations where these provide good coverage of the occupation. OEs are defined as:

> *‘someone who has worked in the occupation for at least 1 year and has 5 years of experience as an incumbent, trainer, or supervisor. Additionally, an occupation expert must have had experience with the occupation within the most recent 6 months.’*
>
> O*NET Data Collections Program – Supporting Statement B, 2021, p.B-2

OEs use exactly the same questionnaires as job incumbents to record the importance and level of Knowledge and Work Activities. Increasingly, respondents of both types are using on-line web-based questionnaires rather than paper-based questionnaires (they are given the choice).

Job analysts are used to populate the O*NET data for the Skills and Abilities domains. This is essentially because ‘abilities’ and to a lesser extent ‘skills’ are somewhat abstract concepts. Originally, skills data had been provided by job incumbents. (Tsacoumis and Van Iddekinge, 2006, compared job incumbents and job analyst ratings and found no clear evidence that one source provides more valid or accurate data than the other across a large sample of O*NET occupations. Although some mean differences between incumbents’ and analysts’ ratings were observed, there were only minimal differences between the two systems of obtaining skills information.)

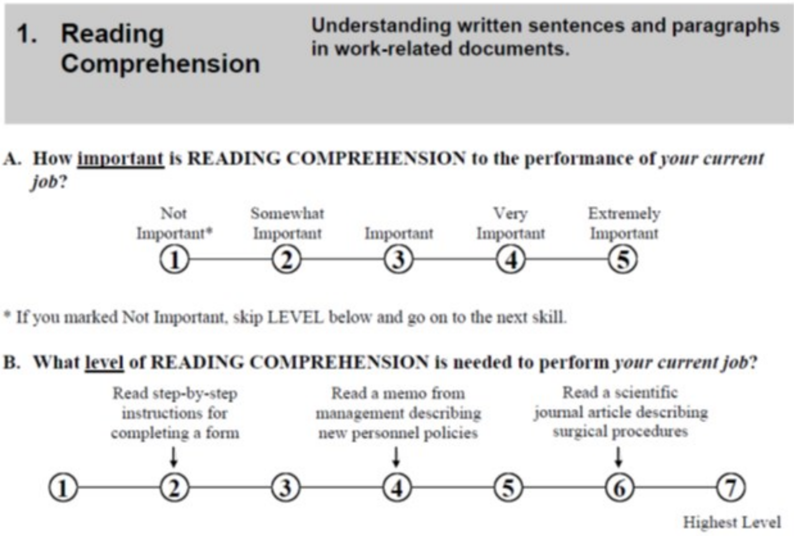
Job analysts must have at least two years of work experience (full or part time work, but not internship, summer job, etc). The work experience requirement was set to ensure that the analysts were highly familiar with a work environment and job responsibilities. They must also have completed two years of graduate education in either Industrial or Organisational Psychology, Vocational Psychology, Human Resources (business department), or Industrial

Relations. Finally, they must have completed courses in both job analysis and in research methods. The analysts are also given O*NET-specific training. They are provided information from job incumbents on the job title, definition, job zone (a 5-point measure of the education, training and work experience required in the job), plus a list of the most important tasks, knowledge, work activities and work context items. Multiple analysts evaluate the data for each occupation. The analysts' rating are then compared statistically and summary measures published in the O*NET database (see, for example, update report December 2022 for the 80 occupations updated in the latest cycle).

In O*NET, each of the Abilities, Skills, Knowledge and Work Activities elements is given both an 'importance' score' and a 'levels' score. The job incumbents and job analysts are first asked how important the skill is to the performance of the job using a Likert scale coded as: 1 – Not Important, 2 – Somewhat Important, 3 – Important, 4 – Very Important and 5 – Extremely Important. They are then asked what level of the skill is required to perform the job. Skill level is recorded on a seven-point scale ranging from 1 (low) to 7 (highest level). In order to help the respondents to give an accurate and comparable measure of the required level of skill, the levels scale information is accompanied by 'scale anchors' – short descriptions or examples specific to the skill at a number of points on the scale to indicate what a given value means in terms of the respective skill.

An example is presented in Figure A2 for the 'Reading Comprehension' skill. As well as the short title of the skill being assessed, respondents are provided with a more detailed description and context (including a reminder that the skill is being assessed in relation to its use in their work). First, there is the Likert scale for the skill's importance. If their response is '2' (Somewhat Important) or above, they are then asked what level of the skill is needed to perform their current job. Here, a skill level of '2' is described as 'Read step-by-step instructions for completing a form' while level '6' is described as 'Read a scientific journal article describing surgical procedures'. Respondents are not asked to provide a skill level rating if they previously rated the importance of the skill at '1' (Not Important). In our analysis, we assign a level score of '0' to occupations with an importance score of '1'. Clearly, given the commonality of the skill importance Likert scale for all 161 skill elements, skills can be legitimately compared across occupations by their importance. For the skill levels, while the scale anchor descriptors are necessarily specific to each skill, they have been calibrated to be comparable and we therefore treat them as such in our analysis. (The middle scale anchor for the level scale 'Read a memo from management describing new personnel policies' has recently been updated to 'Understand an email from management …'. This is an example of the updating to the scale anchor descriptions that are currently being rolled out across the various O*NET elements – see Crawford *et al.,* (2021a, 2021b).

Figure A2: Example question from the O*NET skills questionnaire



1. Reading Comprehension — **Understanding written sentences and paragraphs in work-related documents.**

A. How important is READING COMPREHENSION to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
1	2	3	4	5

* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What level of READING COMPREHENSION is needed to perform *your current job*?

	Read step-by-step instructions for completing a form		Read a memo from management describing new personnel policies		Read a scientific journal article describing surgical procedures	
1	2	3	4	5	6	7
						Highest Level

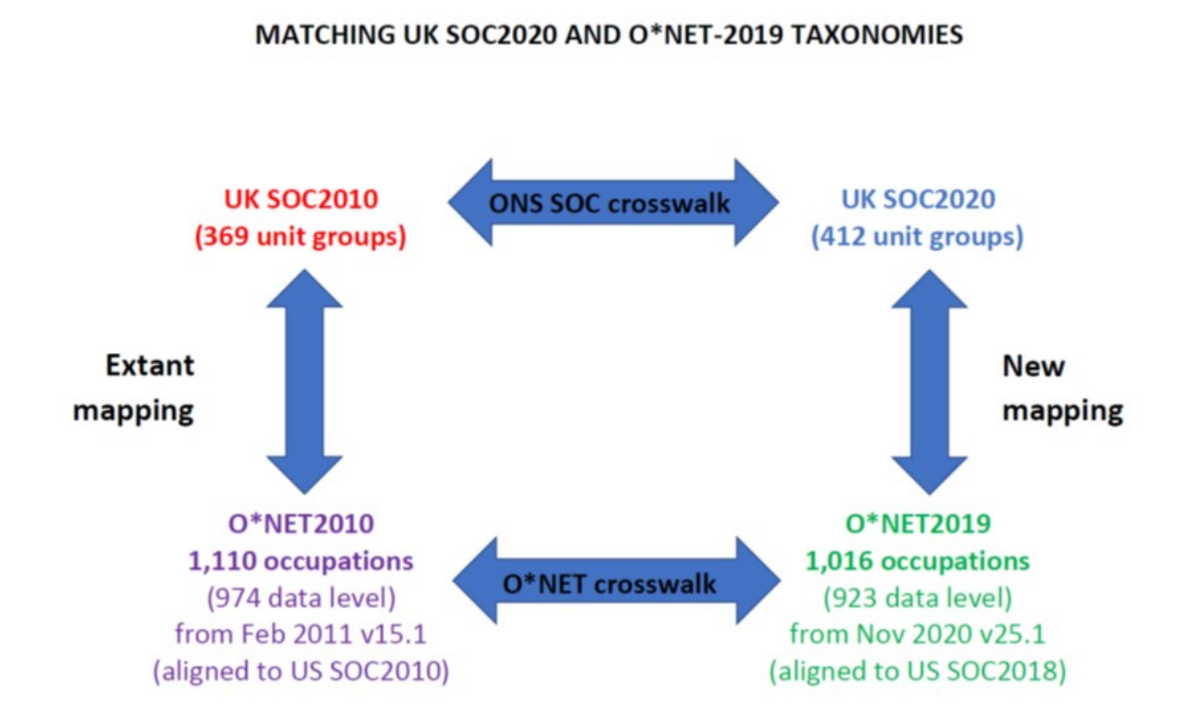
Source: https://www.onetcenter.org/questionnaires.html

Appendix B: Mapping O*NET2019 to UK SOC2020

B.1 Mapping O*NET2019 to UK SOC2020

In this section of the Appendix, we provide a brief description of our O*NET2019 to UK SOC2020 mapping strategy. O*NET2019 is the current classification structure for the O*NET data. It was first used for O*NET v. 25.1 (November 2020), and closely matches US SOC2018 which is the current SOC in the US. UK SOC2020 is the latest occupational classification for the UK and is administered by ONS. We employ two different approaches to matching these classifications. We refer to the first as the ‘new mapping’ while the second is the ‘reverse mapping’. The latter has two variants, ‘complete’ and ‘restricted’. Figure B1 illustrates the linkages that these different mappings exploit.

Figure B1: Mapping O*NET to UK SOC



The ‘new mapping’ is produced by an expert CASCOT coder at IER. In this mapping, each UK SOC2020 4-digit occupation is matched to at least one occupation within O*NET2019, based on the suggestions that the CASCOT software produces and the expert judgement of the coder. This is illustrated on the right-hand-side of the grid in Figure B1. As an example, Table B1 shows that five O*NET2019 occupations have been mapped to UK SOC2020 1123 Production Managers and Directors in Mining and Energy. On average, for each 4-digit UK SOC2020 occupation, the new mapping has 2.7 O*NET2019 occupations, with a minimum of 1 and a maximum of 38 O*NET2019 occupations for one occupation in SOC2020. There are 181 1:1 mappings (44% of all UK SOC2020 occupations) and a total of 951 of the 1,016 O*NET2019 occupations are used to match to the 412 UK SOC2020 occupations.

For the ‘reverse mapping’, we start from the UK SOC2020 to UK SOC2010 relationship tables (the SOC crosswalk as shown at the top of the grid in Figure B1). From there, we link the 369 4-digit occupations in UK SOC2010 to the 1,110 O*NET2010 occupations by means of the extant O*NET-SOC mapping (Bimrose *et al.*, 2013, 2015; Dickerson and Wilson,

2012) as shown on the left-hand-side of the grid in Figure B1. Finally, we use the O*NET2010 to O*NET2019 crosswalk at the bottom of the grid in Figure B1 to map to O*NET2019. This 'reverse' process provides an alternative mapping between UK SOC2020 and O*NET2019 by moving anticlockwise around the grid in Figure B1.

The outcome of this 'reverse mapping' exercise is a many-to-one correspondence between O*NET2019 and UK SOC2020. Furthermore, we obtain two variants of this mapping, based on the UK SOC2020 to UK SOC2010 correspondence used. In the first step of our procedure, we find that each UK SOC2020 is matched to a number of SOC2010 occupations. For example, for UK SOC2020 1123 Production Managers and Directors in Mining and Energy, there are two corresponding UK SOC2010 codes: UK SOC2010 1121 Production Managers and Directors in Manufacturing; and UK SOC2010 1123 Production Managers and Directors in Mining and Energy (Table B2). As shown in Table B2, in terms of employment shares, the former (1.8%) is much smaller than the latter (98.2%). In turn, UK SOC2010 1121 links to 4 O*NET2010 occupations, which each link uniquely with O*NET2019 occupations, while UK SOC2010 1123 links to 5 O*NET2010 occupations and each of these also links to a single O*NET2019 code as shown in Table B2.

We produce two UK SOC2020 to O*NET2019 mappings from this information. The first is a 'complete mapping' which retains all of the UK SOC2010 occupations that link to each of the UK SOC2020 codes. Thus, in our example in Table B2, we will have eight unique O*NET2019 codes linking to UK SOC2020 1123 (While there are nine O*NET2019 codes listed in Table B2, O*NET2019 11-3051.03 Biofuels Production Managers matches to both UK SOC2010 codes, and we only include this once in the overall mapping). On average, for each 4-digit UK SOC2020 occupation, the complete mapping has 11.0 O*NET2019 occupations, with a minimum of 1 and a maximum of 93 O*NET2019 occupations for one occupation in SOC2020. There are 27 1:1 mappings (6.6% of all occupations) and, in total, the complete mapping makes use of 1,012 of the 1,016 O*NET2019 occupations.

The second mapping is a 'restricted mapping' because, for each UK SOC2020 occupation, we only include the UK SOC2010 occupation with the largest employment share. In the example in Table B2, this is UK SOC2010 1123 Production Managers and Directors in Mining and Energy with a share of 98.2%. Ultimately, this matches with five O*NET2019 occupations as shown at the bottom of Table B2. (The restricted 1:1 UK SOC2020 to UK SOC2010 correspondence captures an average (median) of 93% (99%) of employment in each UK SOC2020 occupation). On average, for each 4-digit UK SOC2020 occupation, the restricted mapping has 5.7 O*NET2019 occupations, with a minimum of 1 and a maximum of 35 O*NET2019 occupations for one occupation in SOC2020. There are 41 1:1 matches (10.0% of all occupations) and, in total, the restricted mapping makes use of 1,006 of the 1,016 O*NET2019 occupations.

Note that in this particular example, the 'restricted mapping' and the 'new mapping' are identical since they both match UK SOC2020 1123 Production managers and directors in mining and energy to the same five O*NET2019 occupations. Clearly, this does not necessarily have to be the case.

B.2 Unmatched and non-data level occupations

Despite the fact that all 412 UK SOC2020 occupations have at least one match within O*NET2019 in all three of our mapping variants, we are not able to use all of the 412 UK SOC2020 occupations in our analysis. This is because some of the UK SOC2020 occupations match to O*NET2019 occupations for which no data are collected.

For the reverse mapping, our final sample is comprised of 407 occupations. The five 'missing' UK SOC2020 occupations are:

- 1112 Elected officers and representatives
- 1161 Officers in armed forces
- 3231 Higher level teaching assistants
- 6112 Teaching assistants
- 6113 Educational support assistants

The first two of these (1112 and 1161) match uniquely to 'non-data-level' occupations in O*NET. There are a number of occupations in O*NET for which no data are made available – often because these are small in employment terms and so representative data would be difficult to compile. And no data are collected for any military occupations in O*NET, and UK SOC2020 1161 matches to military occupations only. The remaining three occupations do match to data-level occupations in O*NET2019, but no data have yet been collated and processed (as of O*NET2019 v. 27.1 (November 2022)). However, these five missing occupations only comprise 1.5% of all jobs in England in 2020.

For the new mapping, there are 22 UK SOC2020 matches to O*NET2019 occupations for which no O*NET data are available (resulting in 390 occupations for which data are available). The reasons for these missing occupations is the same as for the reverse mapping described above. However, given that the new mapping matches each UK SOC2020 occupation to fewer O*NET2019 occupations on average, the likelihood of those matches being to non-data level occupations only is higher than for the reverse mappings. In total, these missing occupations constitute about 4% of all jobs in England in 2020.

In both cases, it would be possible to assign data-level O*NET2019 occupations for all of the missing UK SOC2020 occupations using weaker matches than those selected by the expert coder or generated by the reverse mapping procedure. However, given that our primary interest is in assessing the overall utilisation of skills (not skill utilisation in each occupation), the small number of jobs left uncovered by these missing occupations was not deemed sufficient to warrant using less satisfactory mappings to ensure complete coverage of all occupations in UK SOC2020.

Table B1: Example of 'new mapping' for UK SOC2020 1123 Production Managers and Directors in Mining and Energy

SOC2020	SOC2020 Title	O*NET2019	O*NET2019 Title
1123	Production managers and directors in mining and energy	11-3051.02	Geothermal Production Managers
		11-3051.03	Biofuels Production Managers
		11-3051.04	Biomass Power Plant Managers
		11-3051.06	Hydroelectric Production Managers
		11-9199.09	Wind Energy Operations Managers

Table B2: Example of 'complete' and 'restricted mapping' for UK SOC2020 1123 Production Managers and Directors in Mining and Energy

ONS SOC crosswalk				**O*NET crosswalk**			
SOC2020	SOC2020 Title	SOC2010	SOC2010 Title	O*NET2010	O*NET2010 Title	O*NET2019	O*NET2019 Title
1123	Production managers and directors in mining and energy	1121	Production managers and directors in manufacturing SOC2010-2020 share: 0.018	11-1021.00	General and Operations Managers	11-1021.00	General and Operations Managers
				11-3051.00	Industrial Production Managers	11-3051.00	Industrial Production Managers
				11-3051.03	Biofuels Production Managers	11-3051.03	Biofuels Production Managers
				11-9041.00	Architectural and Engineering Managers	11-9041.00	Architectural and Engineering Managers
		1123	Production managers and directors in mining and energy SOC2010-2020 share: 0.982	11-3051.02	Geothermal Production Managers	11-3051.02	Geothermal Production Managers
				11-3051.03	Biofuels Production Managers	11-3051.03	Biofuels Production Managers
				11-3051.04	Biomass Power Plant Managers	11-3051.04	Biomass Power Plant Managers
				11-3051.06	Hydroelectric Production Managers	11-3051.06	Hydroelectric Production Managers
				11-9199.09	Wind Energy Operations Managers	11-9199.09	Wind Energy Operations Managers

Appendix C: Skills projections methodology

A change in the utilisation of any particular skill over time can occur for three reasons: (i) a change in the employment shares for occupations using that specific skill; (ii) a change in the measure of that skill's utilisation within occupations; and (iii) both (i) and (ii) simultaneously. Whilst IER/CE provide us with employment projections for 2035 at the 4-digit UK SOC2020 level, measures of skills utilisation for 2035 are not available. For this reason, we need to generate our own projections of future skills utilisation.

Our projections are obtained as follows. Consider the simple equation:

$$Y_{it}^{j} = f_i^{j}(t) + \varepsilon_{it}^{j} \qquad \text{(C1)}$$

where Y_{it}^{j} is the measure of utilisation for skill j in occupation i at time t. The right-hand side of the equation depends on two terms, i.e. $f_i^{j}(t)$ which is an arbitrary function of time, and ε_{it}^{j}, namely an idiosyncratic occupation, time and skill-specific component. We observe data on skills utilisation in 2010, 2015 and 2020. We treat time as a continuous variable measured in years elapsing since 2010. Hence, t takes values $t = \{0, 5, 10\}$. Estimating equation (C1), separately for each occupation i and skill j and each skill metric (skill importance, skill level, as well as skill prevalence (a composite score, resulting from the product of skill importance and skill level), we obtain:

$$\hat{Y}_{it}^{j} = \hat{f}_i^{j}(t)$$

which is the portion of Y_{it}^{j} predicted by time, i.e. after we remove any occupation-specific effect. We can therefore project this forward to 2035, i.e. for $t = \{25\}$ and our prediction becomes:

$$\hat{Y}_{i,2035|2020}^{j} = \hat{f}_i^{j}(t)$$

where $\hat{Y}_{i,2035|2020}^{j}$ is the estimated measure of skill j for occupation i, which we forecast in 2035, based on the information we have up to 2020.

Our predictions are determined by the choice of functional form $f_i^{j}(t)$, which defines the degree to which skill utilisation changes over time. We discuss four different alternatives below.

C.1 Linear projections

If we assume that skills utilisation changes linearly over time, then any upward or downward trend between 2010 and 2020 will be projected up to 2035 with a constant gradient. The model we estimate is:

$$Y_{it}^{j} = \beta_{0,i}^{j} + \beta_{1,i}^{j} t + \varepsilon_{it}^{j} \qquad \text{(C2)}$$

In other words, for each skill j and for each occupation i (and for each skill metric), we fit a straight line (using Ordinary Least Squares regression) with intercept $\beta_{0,i}^{j}$ and slope $\beta_{1,i}^{j}$ using the three data points for 2010, 2015 and 2020. Intuitively, $\beta_{0,i}^{j}$ represents the baseline level of skill utilisation in 2010 (when $t = 0$), whilst $\beta_{1,i}^{j}$ captures the average annual change in skill. While this forecast method is easy to implement, it comes with the strong ('naïve') assumption that the rate of change is constant. In other words, if a skill experiences a strong increase/decrease in utilisation within the first 10 years of our sample, this functional form will keep projecting a strong increase/decrease into the future, at the risk of hitting the bounds of our skill metrics. Even absent this bounds issue, it might not be realistic to assume that skills utilisation keeps evolving at the same constant rate over time. Rather, utilisation might be expected to increase or decrease at a diminishing rate. For this reason, we propose three alternative functional forms for our projections.

C.2 Logarithmic projections

An alternative functional form for $f(t)$ is the Inverse Hyperbolic Sine (IHS) function. This is given by:

$$Y_{it}^{j} = \beta_{0,i}^{j} + \beta_{1,i}^{j}\tilde{t} + \varepsilon_{it}^{j}$$
$$\tilde{t} = \sinh^{-1} t = \ln\left(t + \sqrt{t^2+1}\,\right)$$

Unlike the linear projections, the change in skill utilisation over time is not constant:

$$\frac{\partial Y_{it}^{j}}{\partial t} = \beta_{1,i}^{j}\frac{1}{\sqrt{t^2+1}}$$

In other words, the IHS functional form implies that skills utilisation increases/decreases at a diminishing rate. Note that the IHS functional form is equivalent to $Y_{it}^{j} = \beta_{0,i}^{j} + \beta_{1,i}^{j}\ln(t) + \varepsilon_{it}^{j}$ for large t, but unlike the logarithmic functional form, it is able to accommodate $t = 0$. When this is the case, the IHS function is still defined as $\tilde{t} = \ln(1) = 0$. Essentially, however, the IHS functional form is equivalent to specifying skill change as a function of log(t).

C.3 Scaled Logistic projections

All our three skill metrics are technically bounded between a minimum (lower) and maximum (upper) boundary value, i.e. from 1 to 5 for skill importance, from 0 to 7 for skill level, and from 0 to 35 for skill prevalence. To ensure that the projections keep within these boundaries, we can transform the observed data Y_{it}^{j} using a scaled logistic transformation which maps $(a, b) \to \mathbb{R}$:

$$Y_{it}^{jT} = ln\left(\frac{Y_{it}^{j} - a}{b - Y_{it}^{j}}\right)$$

where *a* is the lower bound and *b* is the upper bound for the skill metric. We can then (linearly) forecast on the logistic scale, as in equation (2), by estimating the equation:

$$Y_{it}^{jT} = \beta_{0,i}^{j} + \beta_{1,i}^{j}t + \varepsilon_{it}^{jT}$$

and convert back to the actual skill scale using the inverse transformation:

$$\hat{Y}_{it}^{j} = \frac{a + b \times e^{\hat{Y}_{it}^{jT}}}{1 + e^{\hat{Y}_{it}^{jT}}}$$

where $\hat{Y}_{it}^{j}$ is the forecast of the skill using the logistic projection.

C.4 Fractional Logit projections

The previous method cannot handle the boundary values of a or b, i.e. Y_{it}^{jT} is not defined when the skill metric is at its lower or upper boundary value. This can be an issue particularly at the lower bound, since when skill importance = 1 (Not Important), skill level = 0, by construction (and skill prevalence = 0). One solution sometimes used in the literature is to add (subtract) half of the minimum value of Y_{it}^{j} whenever the value is equal to a (b). A more satisfactory solution is to use a fractional logistic model specifically developed for the situation when the dependent variable can take values only within a bounded range, including the bounds (Papke and Wooldridge, 1996). This specification is related to the standard binary logit model except the dependent variable can also take values within the unit interval. Estimation is by quasi-maximum likelihood – see Papke and Wooldridge (1996) for details.

To illustrate, Figure C1 to Figure C6 present the projections obtained for each of the four alternative functional forms as described above, for UK SOC2020 1111 Chief Executives and Senior Officials (Figure C1 to Figure C3), and UK SOC2020 9269 Other Elementary Occupations n.e.c. (Figure C4 to Figure C6), which are the first and last occupations in the UK SOC2020 unit group (4-digit) classification respectively. We illustrate projections for four of our eight exemplar skills, namely Establishing and Maintaining Interpersonal Relationships, Interacting with Computers, Making Decisions and Solving Problems and Mathematics, and for all three skills metrics (skill importance, skill level and skill prevalence) respectively.

It can be noted that the naïve linear projections approach generates the most 'extreme' projections for 2035 by maintaining the upward/downward trend over the whole of the observation period. Indeed, the linear projection for Interacting with Computers for UK SOC2020 1111 Chief Executives and Senior Officials exceeds the upper bound of '5' for skill importance for 2035 (see top right quadrant of Figure C1). In practice this happens very infrequently and, when it does, we simply cap the skill measure at the boundary value. In contrast, the logarithmic (IHS) projections tend to smooth any trend, conferring it a diminishing rate of change (and, interestingly, the boundary issue for Interacting With Computers for the skill importance for SOC2020 1111 does not arise).

As anticipated, the scaled logistic and fractional logit projections are not distinguishable from the linear projections in general, unless the skill metric is close to either the lower or upper boundary. In our main analysis, we therefore focus on the linear projections for skills in 2035, while also investigating the sensitivity of our findings when we use the logarithmic projections (i.e. IHS specification).

Figure C1: Skill Importance projections for UK SOC2020 1111 Chief Executives and Senior Officials

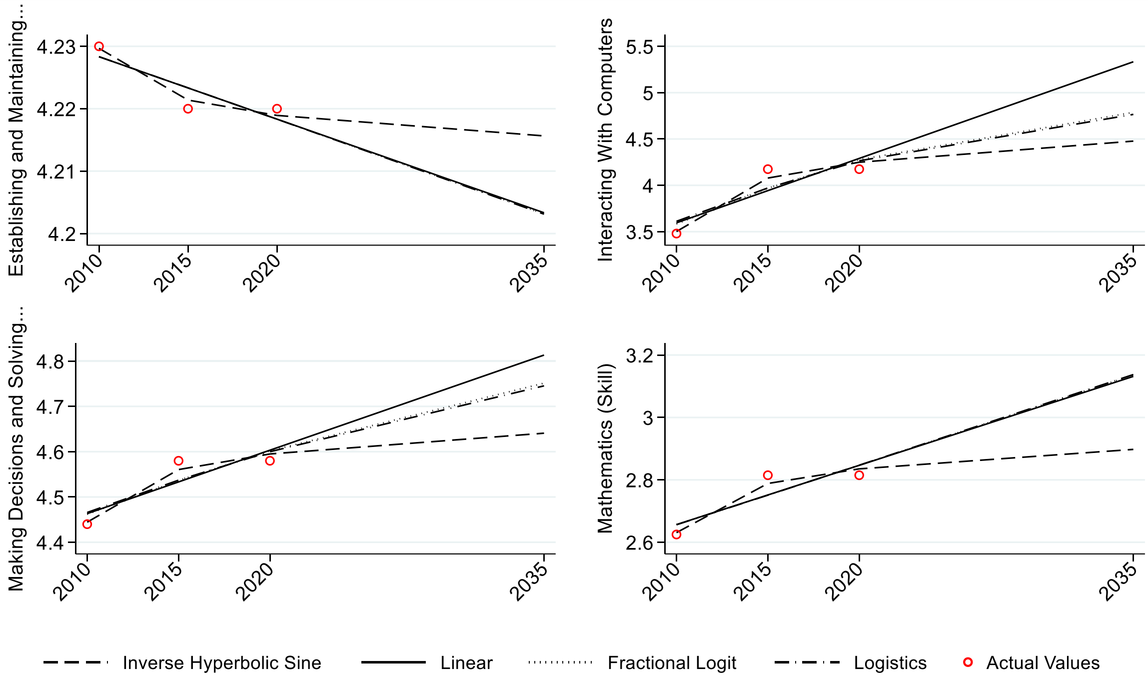


Figure C2: Skill Level projections for UK SOC2020 1111 Chief Executives and Senior Officials

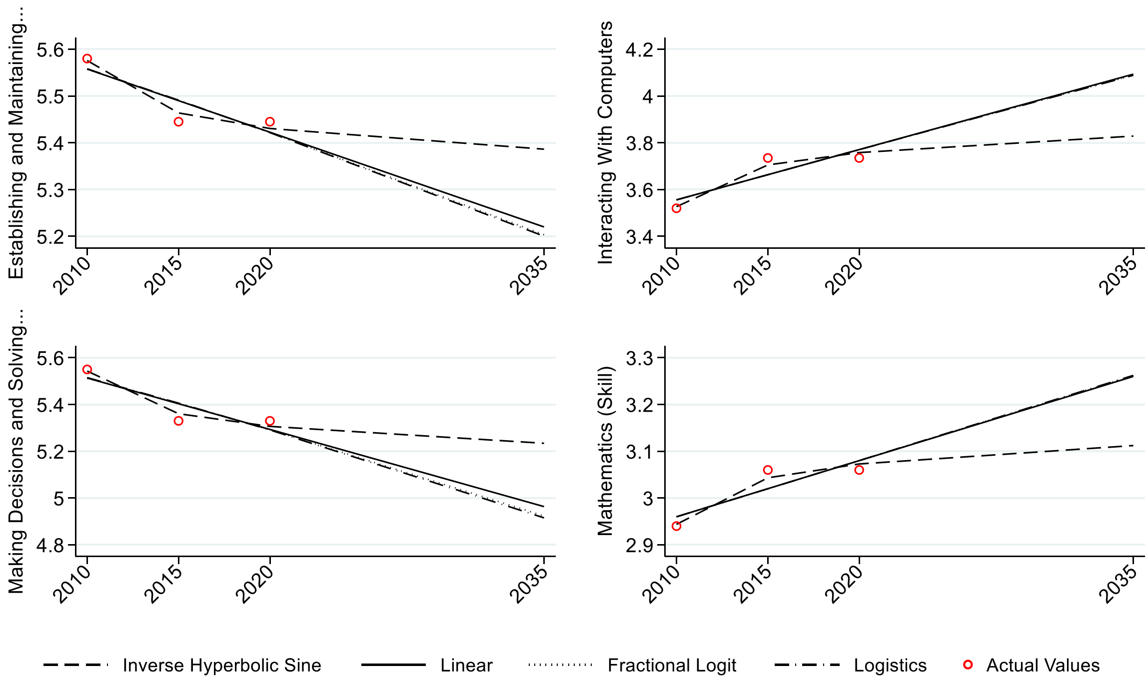


Figure C3: Skill Prevalence projections for UK SOC2020 1111 Chief Executives and Senior Officials

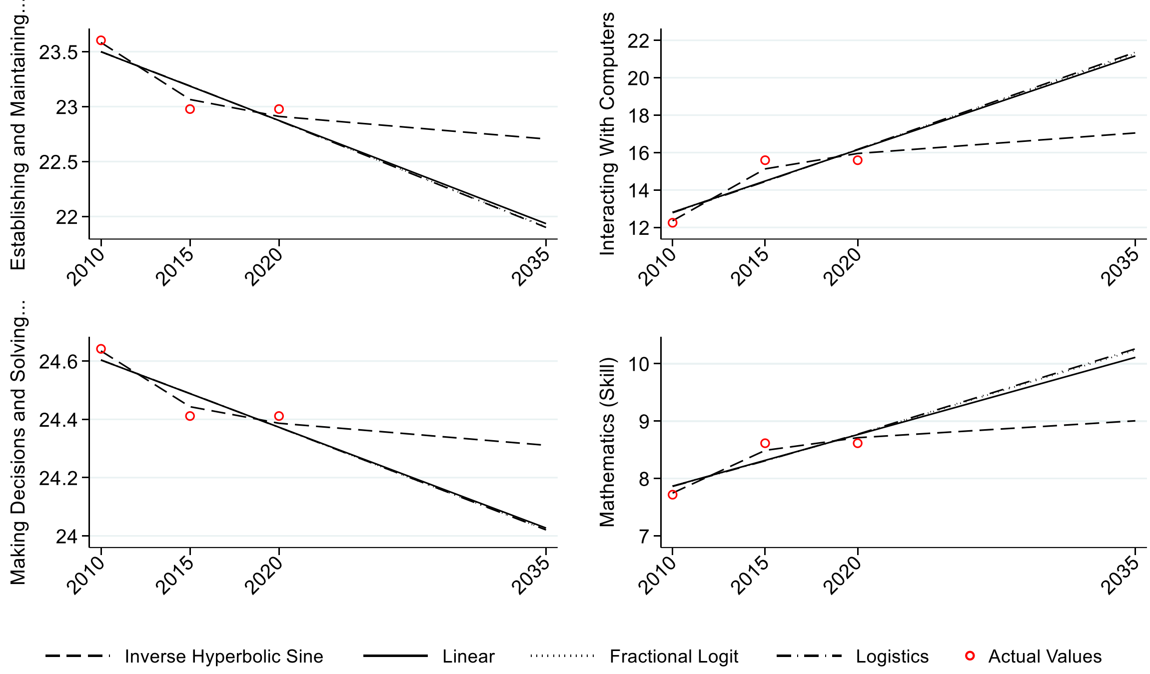


Figure C4: Skill Importance projections for UK SOC2020 9269 Other Elementary Ocupations n.e.c.

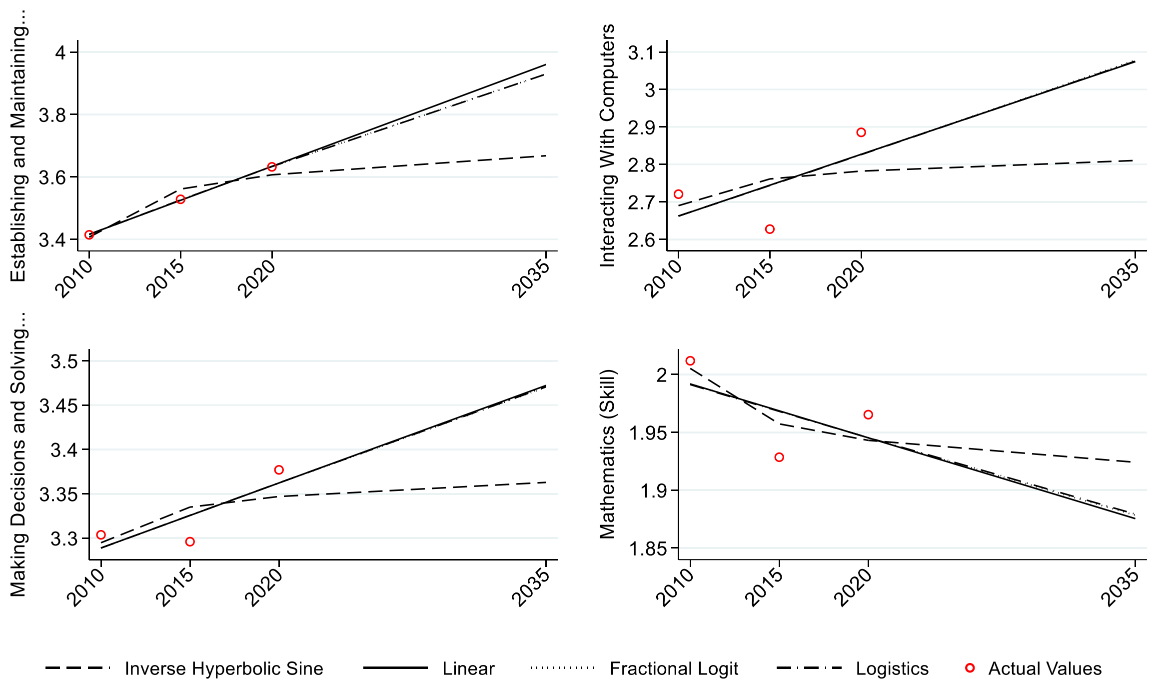


Figure C5: Skill Level projections for UK SOC2020 9269 Other Elementary Ocupations n.e.c.

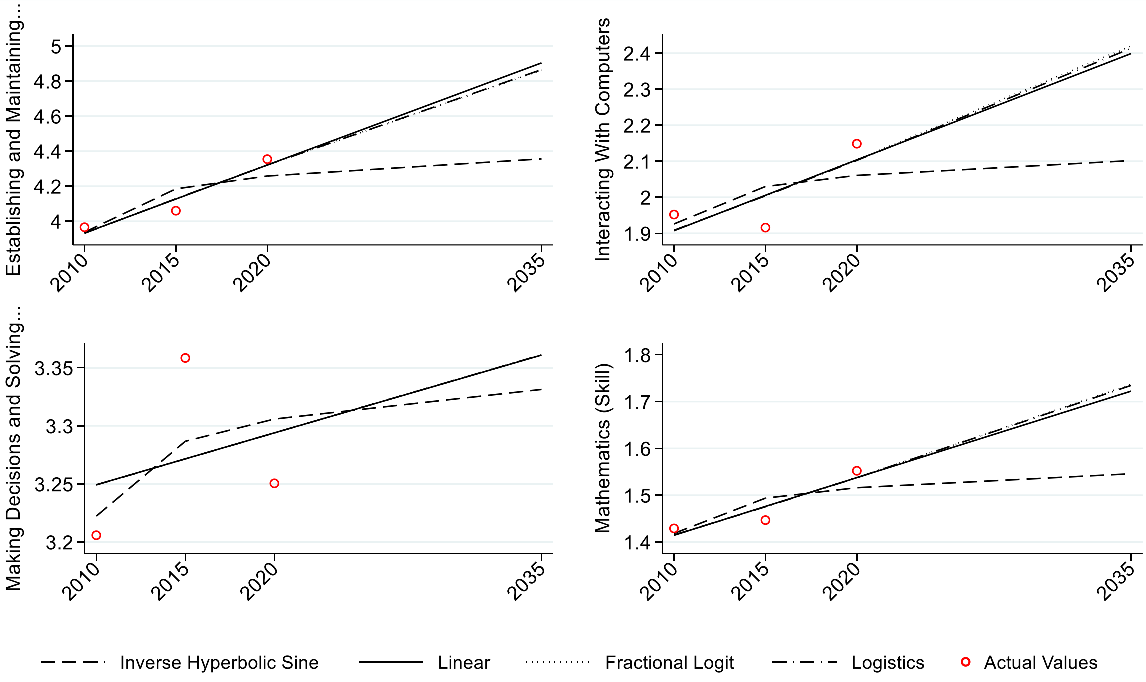
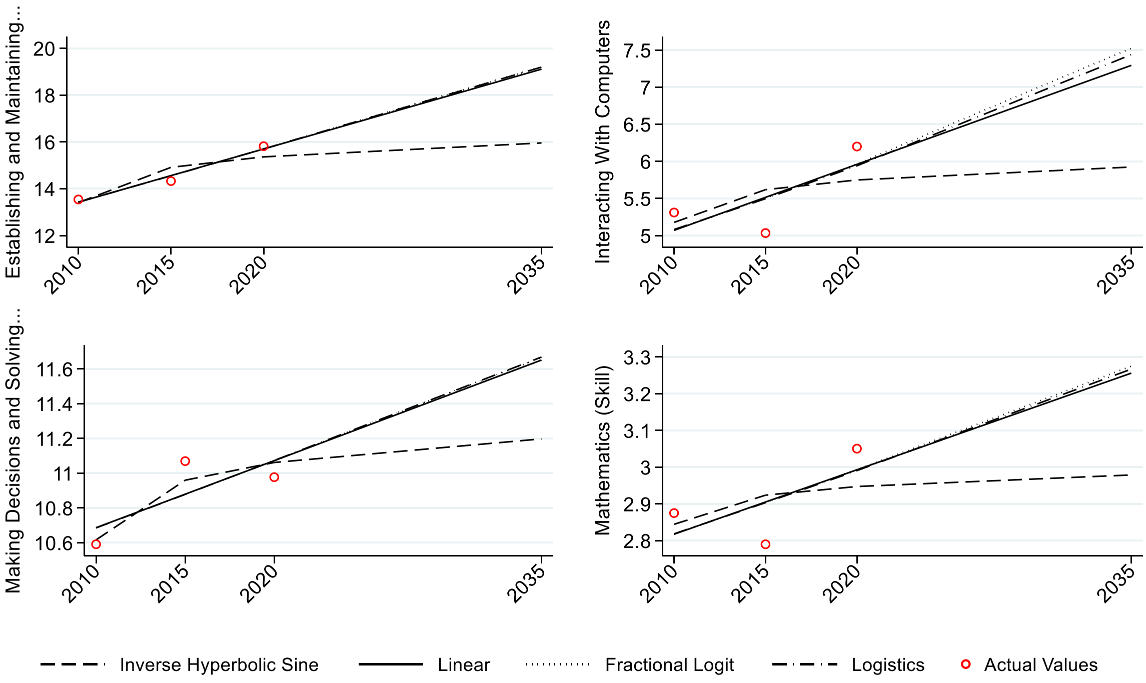


Figure C6: Skill Prevalence projections for UK SOC2020 9269 Other Elementary Ocupations n.e.c.



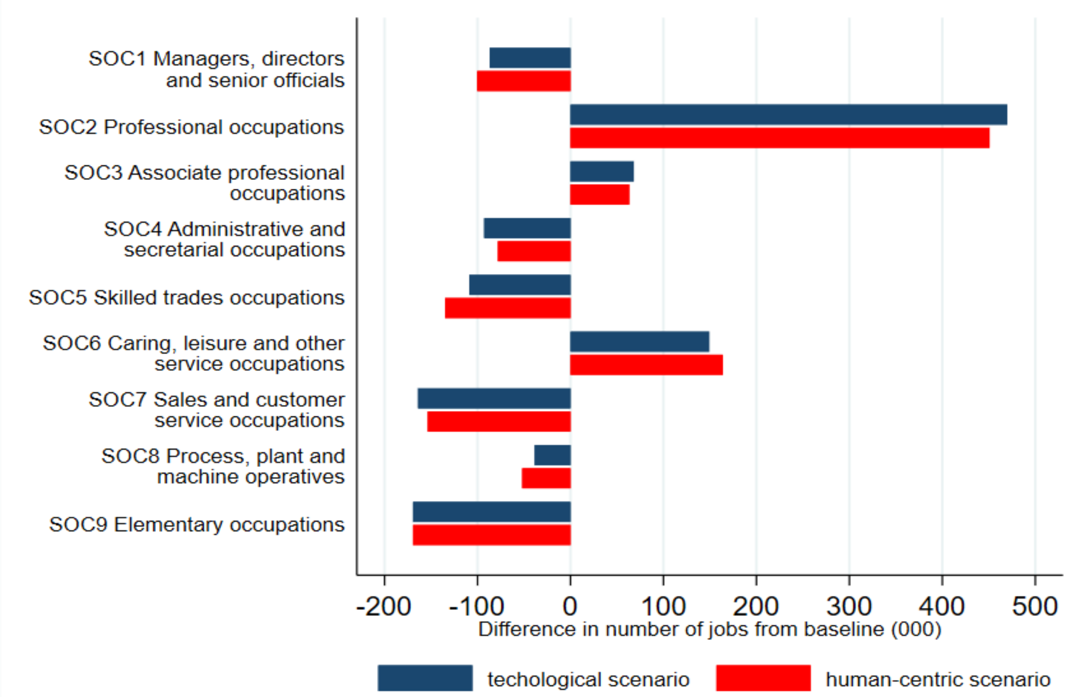
Appendix D: How robust are the findings to the assumptions we have made?

In this Appendix, we examine the robustness of our main conclusions as presented in Section 3 to the different assumptions that we make and the variants that we consider. **Appendix D.1** considers the two *Alternative scenarios* for employment that IER/CE have also generated together with the *Baseline projections* that we have used for the core results presented above. In **Appendix D.2**, we investigate the skills importance and skills level metrics separately and compare the findings with those presented above using the skill prevalence index (defined as the product of skill importance and skill level). The impact on our findings from using the different mappings between O*NET and SOC that we constructed (as explained in **Appendix B**) is examined in **Appendix D.3**. Finally, in **Appendix D.4** we investigate the differences on our results of using alternative methods for the skills projections (as described in **Appendix C**).

D.1 Alternative employment scenarios

Our first set of variations relate to the *Alternative scenarios* for employment that IER/CE have constructed for the future patterns of occupational employment. These are described in detail in Wilson *et al.,* (2022c). The two main *Alternative scenarios* that have been produced – a *Technological opportunities scenario* and a *Human-centric scenario* – produce estimates for total employment in England in 2035 identical to that under the *Baseline projections* assumptions that we have used in our main results presented in the previous section. However, this aggregate disguises some significant redistribution of occupational employment. For UK SOC2020 major groups (1-digit), Figure D1 presents the difference in occupational employment from the *Baseline projections* under the two *Alternative scenarios*.

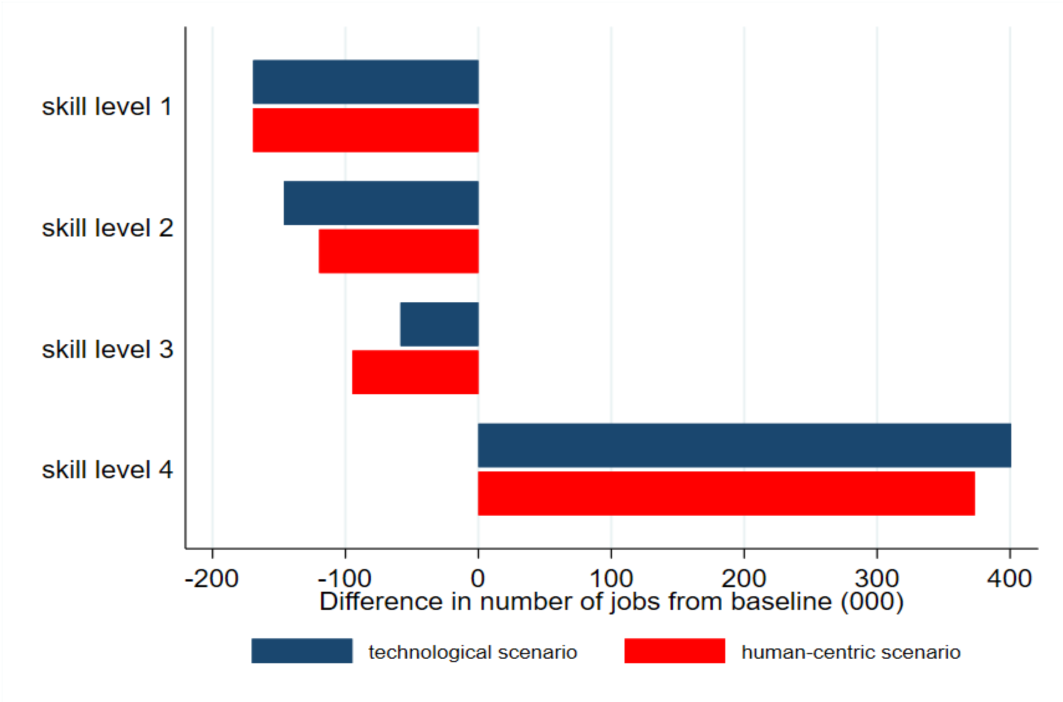
Figure D1: Differences in occupational employment under the *Alternative scenarios*



As can be seen, the *Alternative scenarios* imply significantly greater employment in SOC2: Professional occupations (+6% greater than under the *Baseline projections* for the *Technological opportunities scenario*; +5% greater than under the *Baseline projections* for the *Human-centric scenario*) and in SOC6: Caring, leisure and other service occupations (+5%; +6%). This is balanced by significantly less employment in SOC5: Skilled trades occupations (–4%; –5%), SOC7: Sales and customer service occupations (–7%; –6%) and SOC9: Elementary occupations (–6%;–6%). For the other UK SOC2020 1-digit occupational groups, the differences in the number of jobs between the *Technological opportunities scenario* and the *Human-centric scenario*, and the *Baseline projections*, are all 3 percent or less.

In terms of SOC broad skill levels, the differences between the *Baseline projections* and the two *Alternative scenarios* are presented in Figure D2. Both *Alternative scenarios* imply around 400,000 more jobs at SOC Skill level 4 (highest), with correspondingly fewer jobs at Skill level 3, Skill level 2 and Skill level 1 (lowest) as compared to the *Baseline projections*. The magnitude of this increase (400,000 against the *Baseline projections* total of 10.5 million jobs at this level – see Figure 17) is relatively modest however (an increase of 4 percent).

Figure D2: Differences in employment by SOC Skill level under the *Alternative scenarios*



These occupational employment and skill level differences relative to the *Baseline projections* imply some comparatively large differences in the demand for certain skills. For example, relative to the *Baseline projections*, the demand for Science skills (using the prevalence metric) increases by +7.1% (+6.9%) under the *Technological opportunities scenario* (*Human-centric scenario*). There are similarly comparatively large increases in the demand for Programming skills (+5%) under both of the *Alternative scenarios*. There are also decreases in skill demand of up to 5 percentage points relative to the *Baseline projections* in a number of physical and sensory characteristics.

However, none of these changes impact significantly on the top 20 skills ranking. The ranking of the top 20 skills under the *Technological opportunities scenario* and the *Human-centric scenario* is identical to that obtained with the *Baseline projections*. This is not unexpected. While the demand for certain specific technical and scientific skills will be enhanced under the two *Alternative scenarios*, these skills are not used intensively across the whole of employment, and therefore they are typically ranked quite low in the distribution of all skills (e.g. both Science and Programming are in the bottom quintile of the ranked skills in 2035 under the *Baseline projections*, so even a comparatively large percentage increase in their utilisation under the two *Alternative scenarios* is not sufficient to propel them into the top 20 skills). In addition, the top 20 skills are used more intensively in higher skill jobs. Thus, the overall 'uplift' in the skill composition of employment evident in Figure D2 under the two *Alternative scenarios* only serves to increase the dominance of the top 20 skills in the overall ranking.

While there is some re-ranking of skills further down the distribution under the two *Alternative scenarios*, the skills that dominate the top 20 ranking are generic and transferable skills used in many/most jobs. Hence, the top 20 skills are little impacted by the changing occupational and skills distribution of employment under the *Technological opportunities scenario* and the *Human-centric scenario*.

D.2 Alternative skill metrics

The analysis thus far has focussed mainly on our prevalence measure of skill, which is the product of the skill importance and skill level metrics from O*NET. Our rationale for this composite measure of skills is that it arguably captures the overall 'pervasiveness' or 'primacy' of the skill for each occupation. It is, however, an artificial construct and, despite their high correlation in the data, skill importance and skill level are intended to capture different dimensions of skills use. We have therefore also undertaken the analysis presented in Section 3 for these two measures of skills separately.

Figure D3 and Figure D4 present the top 20 skills ranking for the skills importance and skills level measures respectively, using the *Baseline projections* for employment and the linear skills projections. These can be contrasted with Figure 19 for the skill prevalence metric. The top 3 most significant skills in 2035 as measured by their skill importance are anticipated to be Getting Information, Communicating with Supervisors, Peers, or Subordinates and Making Decisions and Solving Problems, while the top 3 according to the skill level metric are expected to be Organizing, Planning, and Prioritizing Work, Establishing and Maintaining Interpersonal Relationships and Updating and Using Relevant Knowledge. As can be seen, there is a considerable degree of overlap in the top 20 skill importance and top 20 skill level lists in 2035, and hence it is not surprising that there is a high correlation of both these rankings with the skill prevalence top 20 list for 2035 too. For example, Communicating with Supervisors, Peers, or Subordinates is rank 2 for skills importance and rank 4 for skills level in 2035, and hence it is unsurprising that it is rank 1 for skill prevalence.

There are notable differences too, however, between skill importance, skill level, and skill prevalence. For example, the increasing importance of Interacting with Computers which enters the top 20 skill prevalence list in 2035 can be seen to result from its increasing *importance* as a skill – it was rank 20 in 2010, rank 12 in 2020 and projected to rank 5 in the top 20 skills by skill importance in 2035. It does not, however, appear in the top 20 skills by *level* (it is rank 33 on the skill level metric in 2035). In contrast, the appearance of Thinking Creatively in the top 20 skills using the skill prevalence metric can be seen to be the outcome of its rank 14 position in 2035 when measuring skills by level (Figure D4); it does not appear in the skills importance top 20 ranking (it is rank 31 in skills importance in 2035). Moreover, the appearance of Analyzing Data or Information in the top 20 skills prevalence (rank 14 in 2035 as shown in Figure 19 and Table 4) can be seen to be the result of both the increasing importance of this skill (from rank 38 in 2010, to rank 31 in 2020, and projected to rise to rank 24 in skills importance by 2035) *and* the increasing level to which it will need to be utilised (from rank 36 in 2010, to rank 27 in 2020 and projected to rise to rank 16 in 2035 as shown in Figure D4).

Figure D3: Top 20 skills ranking – Skills Importance measure, linear skills projections

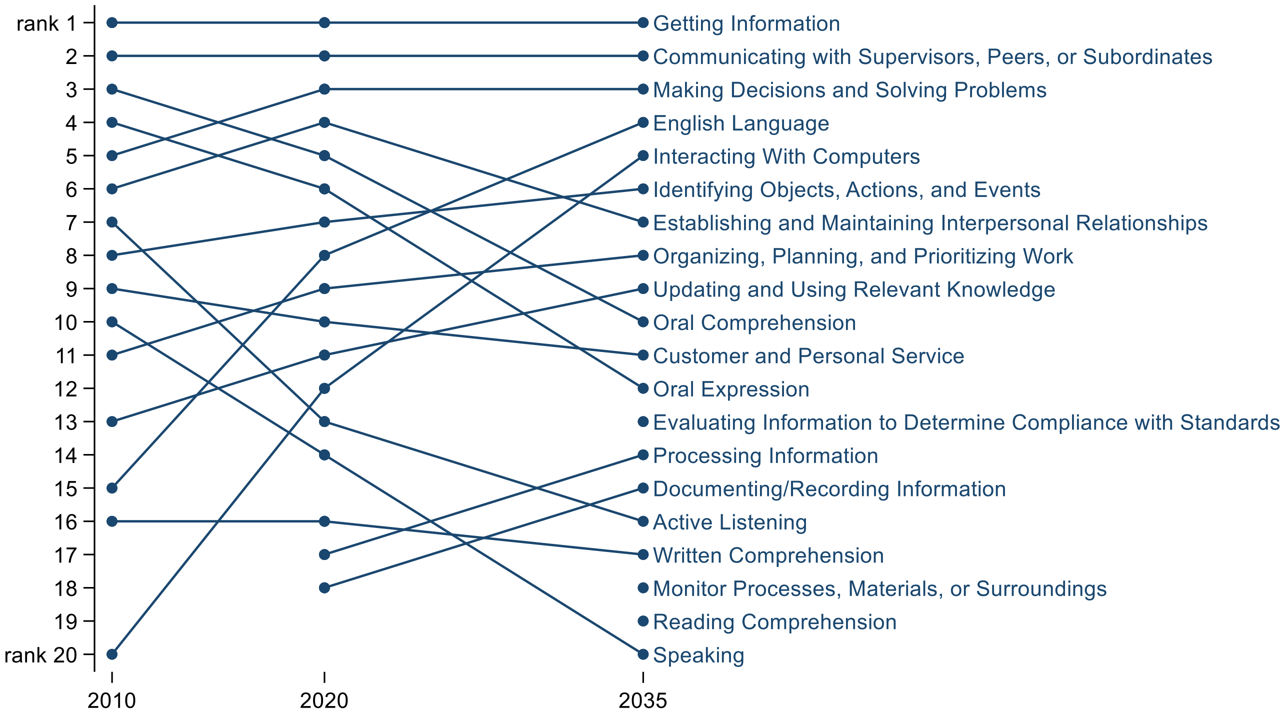
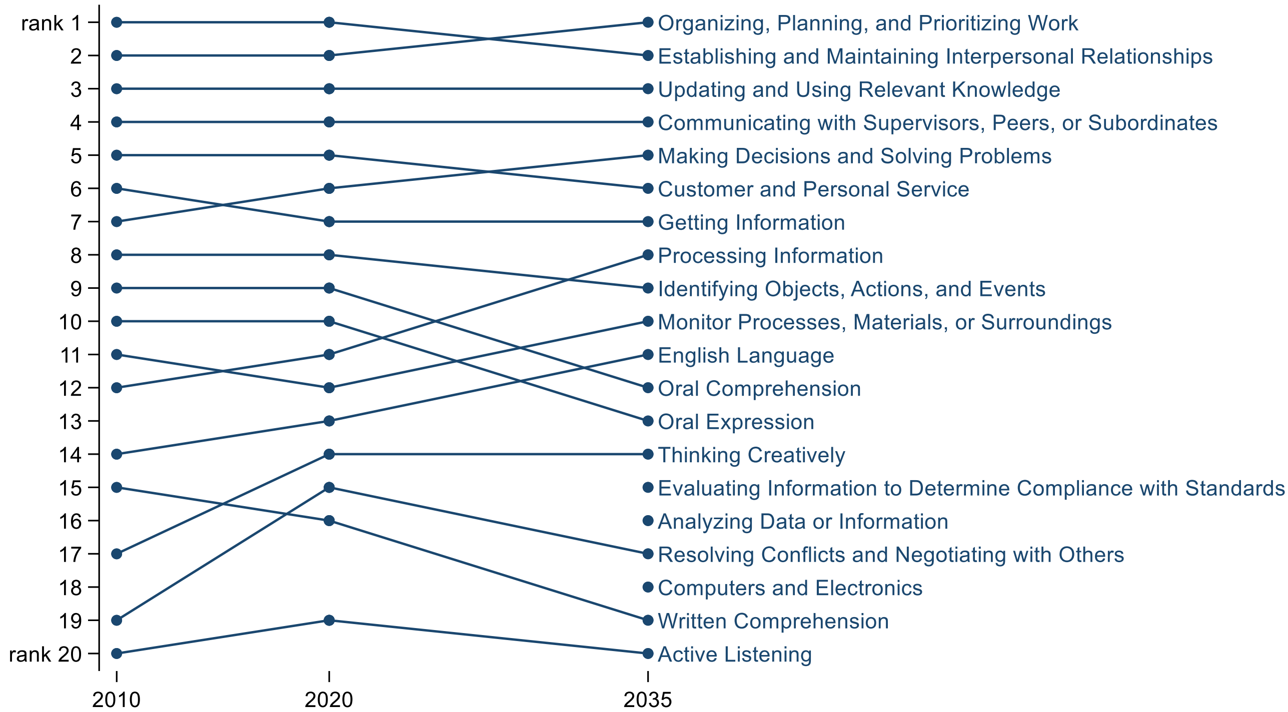


Figure D4: Top 20 skills ranking – Skills Level measure, linear skills projections



However, in general, the findings using the skills prevalence measure as reported in Section 3 also reflect the most significant skills in terms of their importance and their level. Our general conclusions on the skills we have identified will be utilised most in employment in 2035 are not conditional on having focussed on the skill prevalence metric.

D.3 Alternative skill mappings

The third set of variants that we consider relate to the way in which the mapping between O*NET and UK SOC has been compiled. We examine the implications for our occupational skills profiles of the choices we have made in compiling the mapping. As explained in Subsection 2.1.1. above and in detail in **Appendix B**, we consider three main variants. First, there is the mapping produced by using the existing O*NET2010 to UK SOC2020 mapping and extending this to O*NET2019 and UK SOC2020 by using the two crosswalks. The two variants we have are the 'complete mapping' which uses all of the SOC2010 codes that match to each UK SOC2020 occupation (this is the version of the mapping that we have employed in our main analysis), and the 'restrictive mapping' which only uses the largest (by employment) SOC2010 code to match to each SOC2020 occupation. Second, there is the 'new mapping' between O*NET2019 and SOC2020 generated by the expert CASCOT coder from scratch. Figure D5 to Figure D12 present the skills profiles using these three different mappings for the skill prevalence measure for our eight exemplar skills. As can be seen, the skills profiles are very similar in all three cases. The average (Pearson) correlation between the new mapping and the restricted mapping for the values of the eight skills is 0.906, while the average (Spearman) rank order correlation for the eight skills is 0.894, demonstrating a close correspondence as is evident from Figure D5 to Figure D12. The corresponding average Pearson and Spearman correlations between the complete and restricted mappings are 0.931 and 0.933 respectively. Updating the old mapping with the crosswalks in order to construct the mapping between O*NET2019 and SOC2020 therefore seems to work well. It has the added advantage that we can also use it at an intermediate stage to exploit historic O*NET2010 data (as used to generate the skills projections as discussed in Subsection 2.1.2 and **Appendix C**).

Figure D5: Comparison of mappings – Establishing and Maintaining Interpersonal Relationship

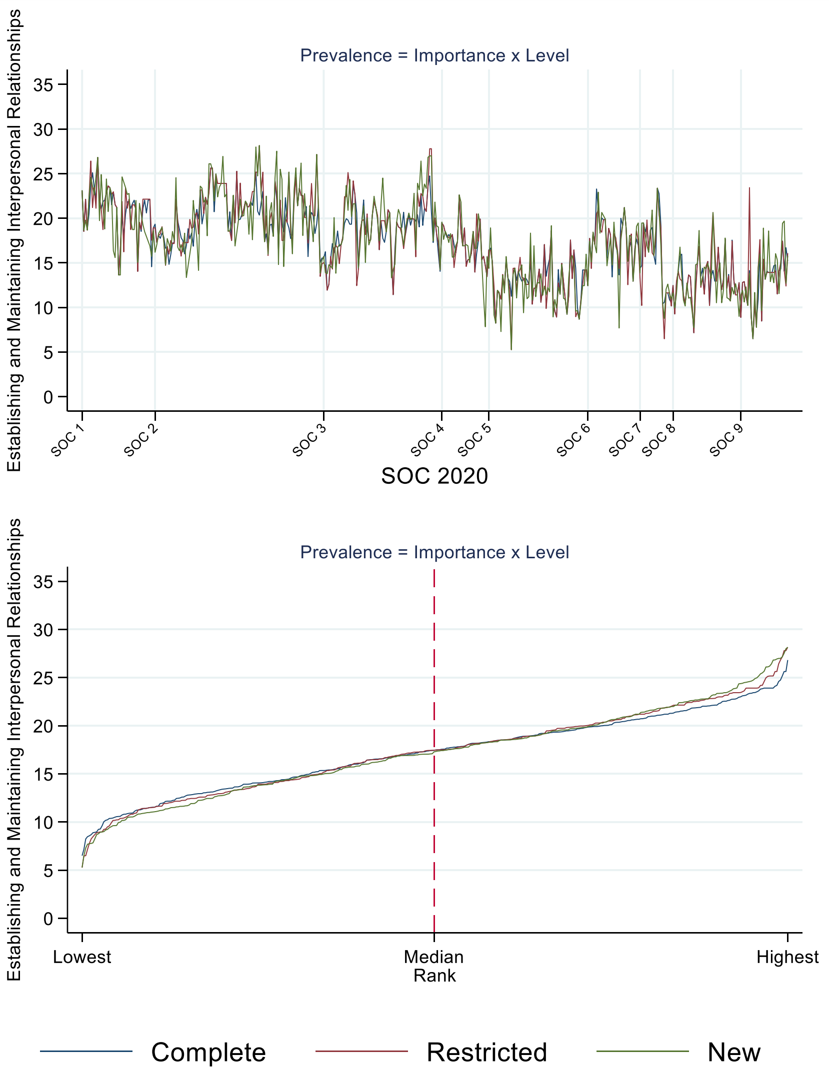


Figure D6: Comparison of mappings – Interacting with Computers

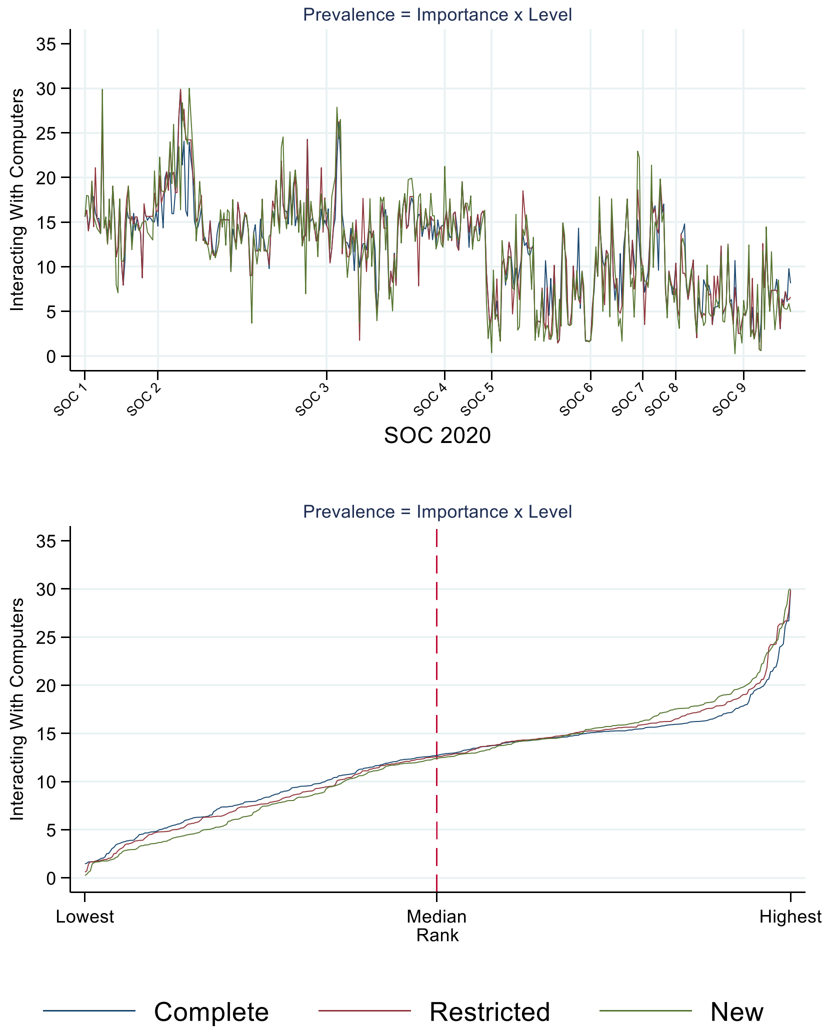


Figure D7: Comparison of mappings – Making Decisions and Solving Problems

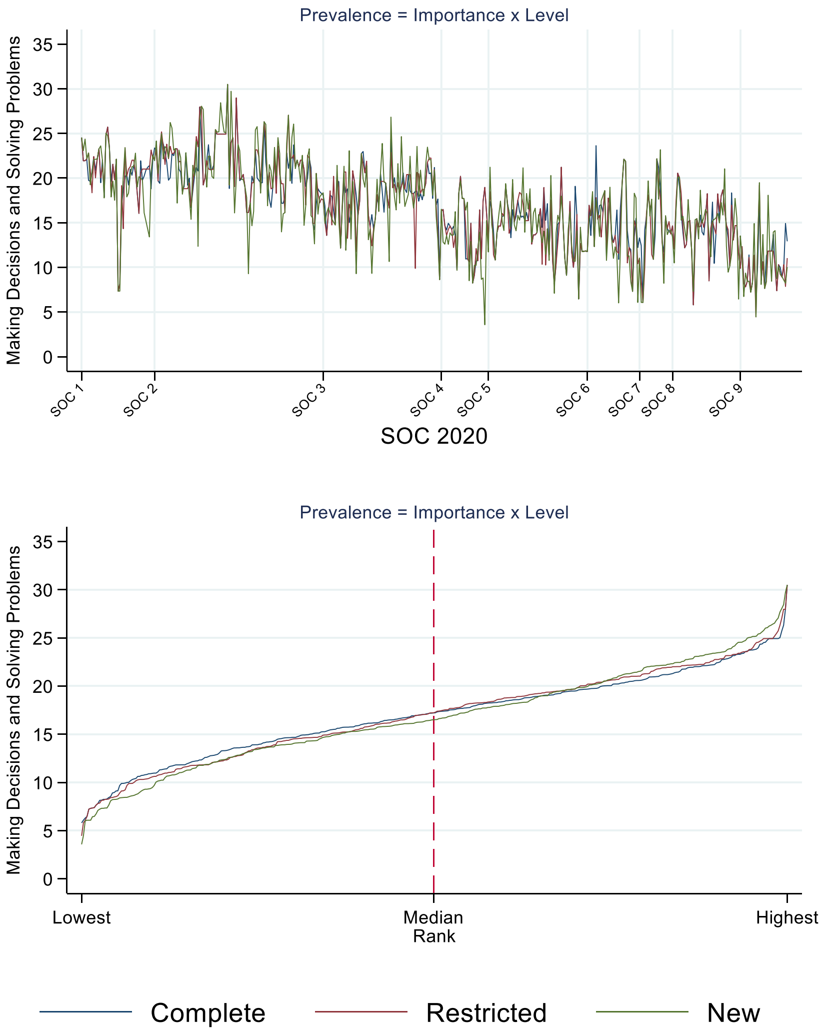


Figure D8: Comparison of mappings – Mathematics

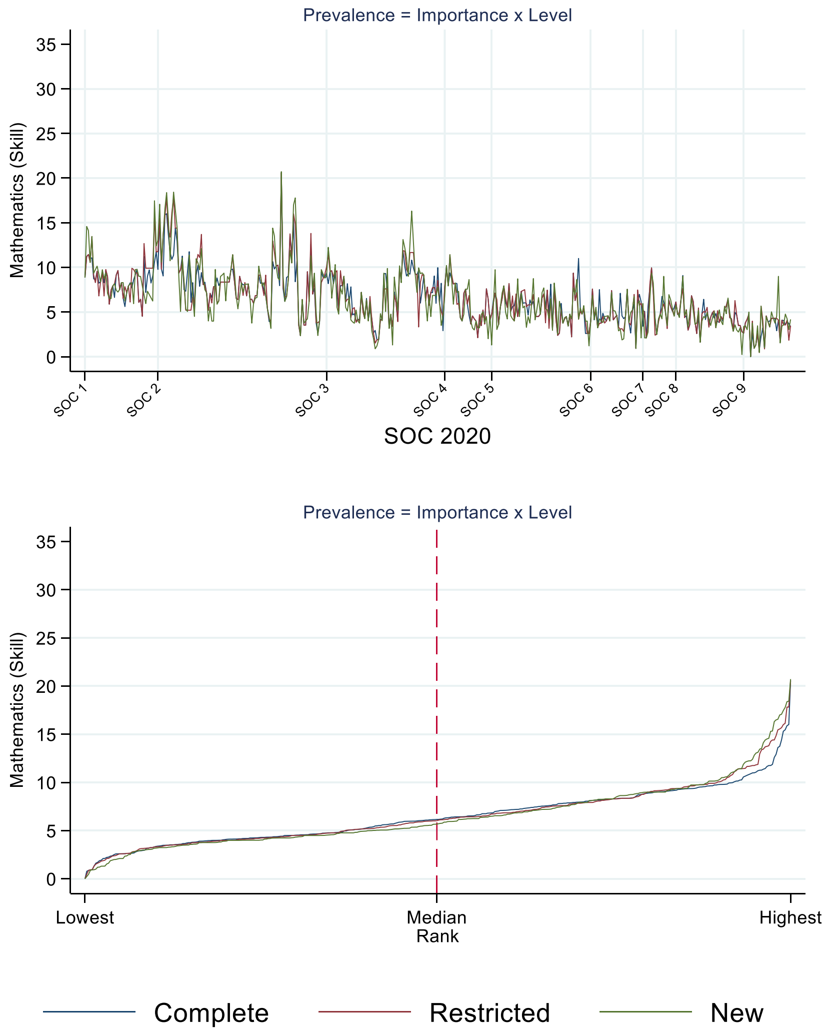


Figure D9: Comparison of mappings – Programming

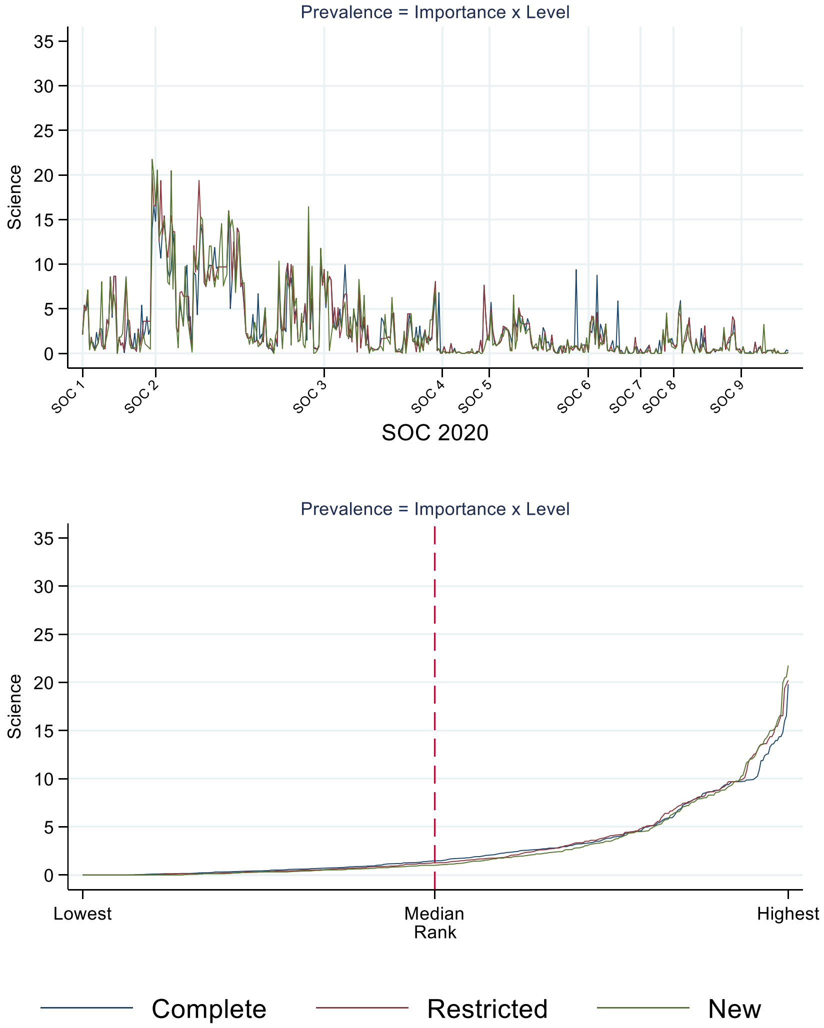


Figure D10: Comparison of mappings – Science

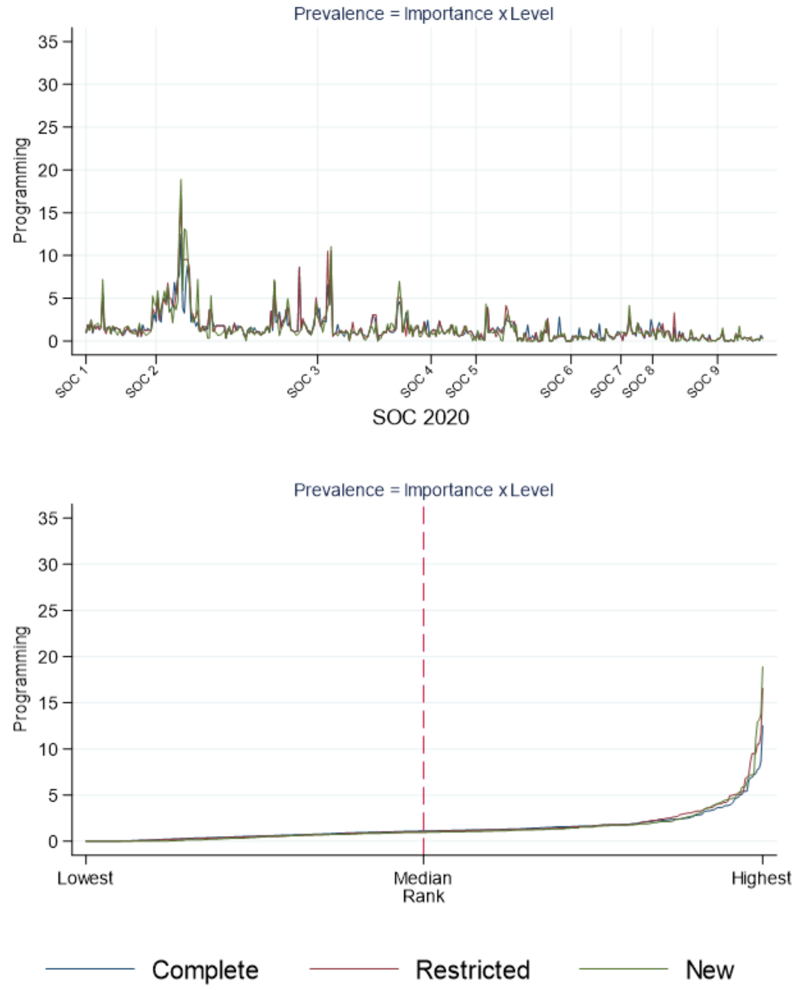


Figure D11: Comparison of mappings – Service Orientation

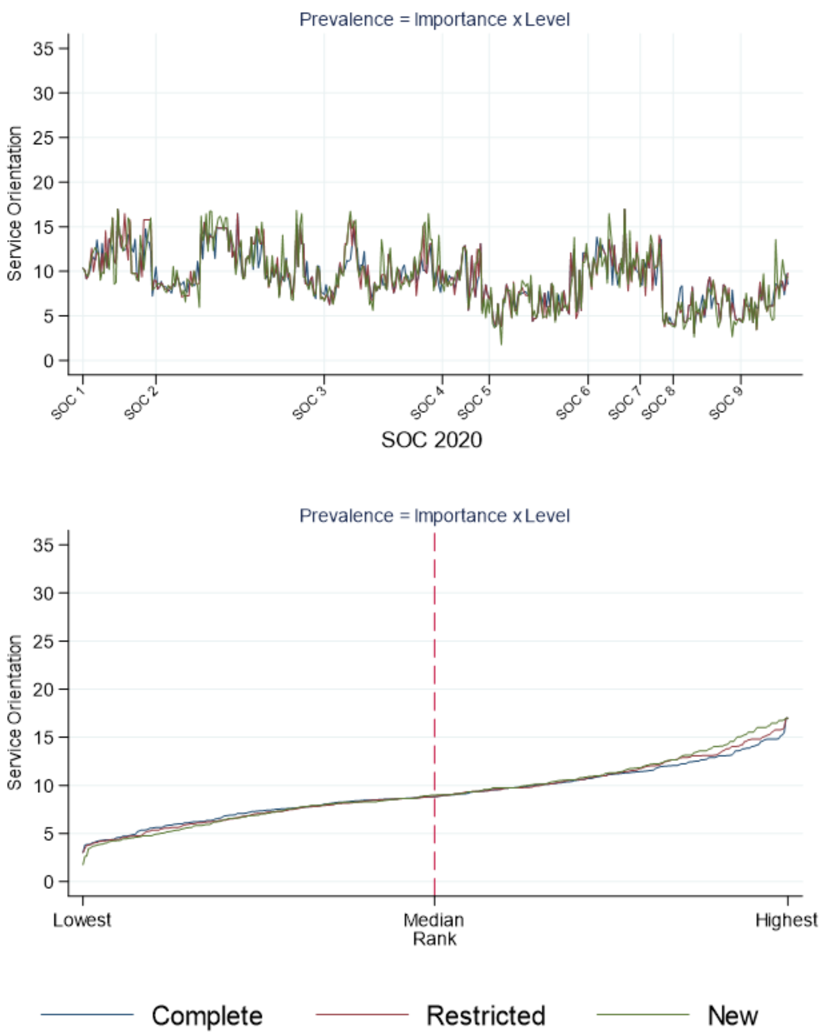
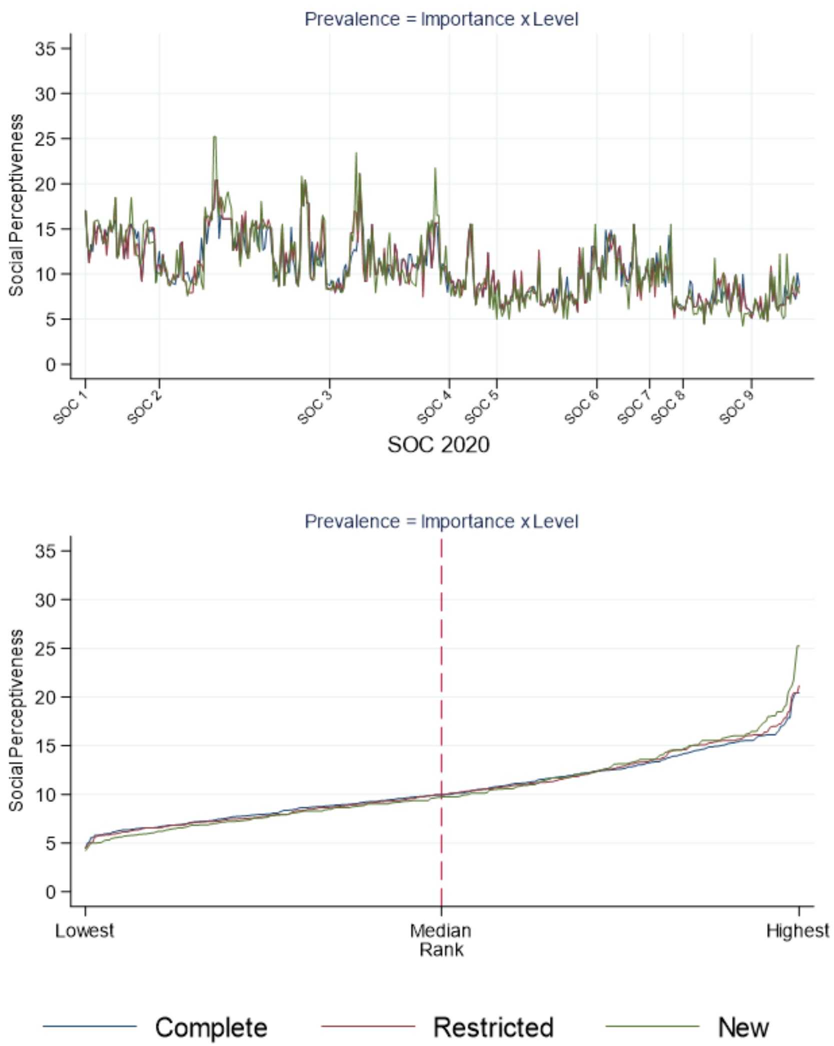


Figure D12: Comparison of mappings – Social Perceptiveness



D.4 Alternative skill projections

Our final set of comparisons relate to the method we have used to generate the skills projections for 2035. The main results as presented in Section 3 use the linear projections method as described in **Appendix C**. It is noted there that these are the most 'naïve' in that they simply assume that past increases/decreases in skills continue at the same rate indefinitely into the future. The limited range for the skill importance measure (from 1 to 5), and for the skill level measure (from 0 to 7) (and hence for the skill prevalence measure from 0 to 35) means that for our data, this is both infeasible and improbable (although the number of instances where the projections reach the bounds is limited). In this subsection, we therefore examine the sensitivity of our main results to changing the assumption regarding the future trend in skills. In particular, we examine the implications for the top 20 skills in 2035 from assuming a logarithmic future trajectory for skills as produced by the IHS specification. This formulation assumes that skills increase or decrease into the future (according to their historic trend), but do so at a diminishing rate. Such projections are therefore more 'conservative' than the linear projections.

Figure D13: Top 20 skills ranking – Skills Prevalence measure, logarithmic skills projections

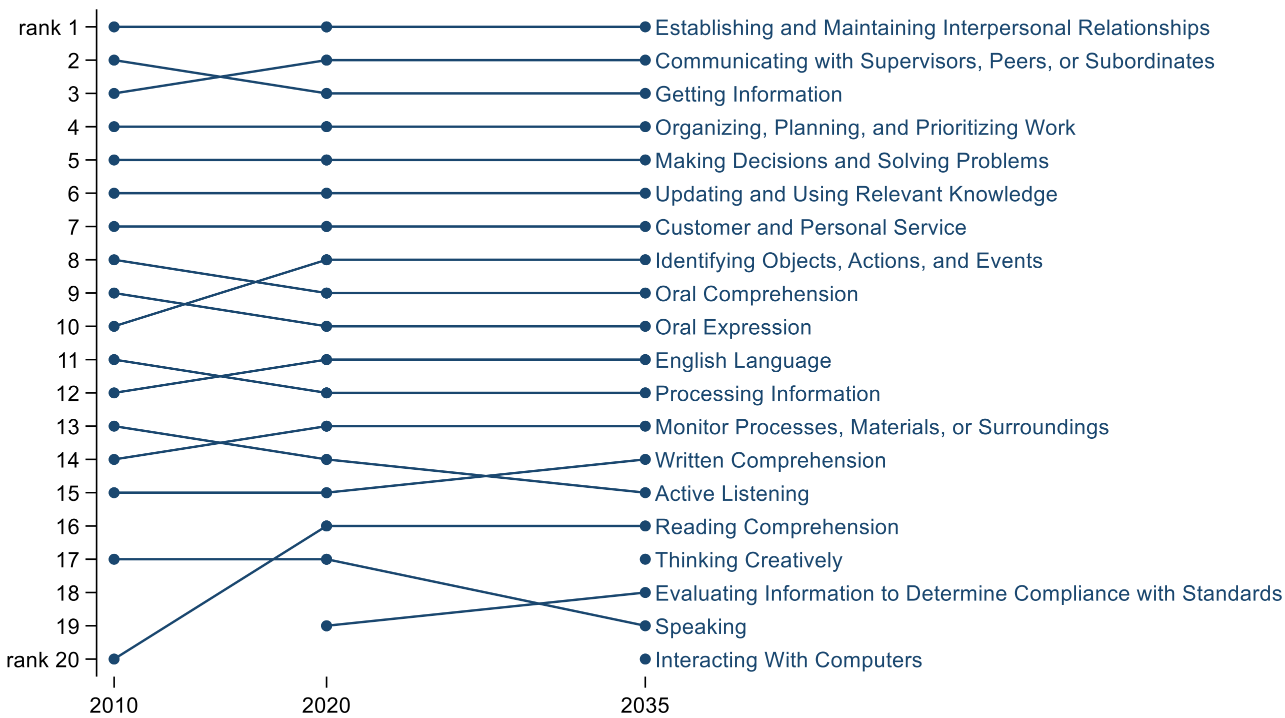


Figure D13 presents the top 20 skills ranking for the skill prevalence metric using the logarithmic skills projections, and can be compared directly to the main results for the top 20 skills utilisation presented in Figure 19 using the linear projections. As can be seen, there is much less re-ranking of the top 20 skills when using the logarithmic projections – indeed, the top 10 ranked skills in 2035 are exactly the same as the top 10 in 2020. Despite this greater inertia in the skills rankings over time when using the logarithmic projections, it is interesting to note that Thinking Creatively and Interacting With Computers still enter the top 20 skills in

2035 when using the logarithmic projections just as they do when using the linear projections.

This greater ‘inertia’ in the skills rankings when using the logarithmic projections is apparent in both the skills importance and skills levels metrics. Figure D14 and Figure D15 present the top 20 skills using the skills importance and skill level metrics for 2010, 2020 and 2035 using the logarithmic projections. Again, it is apparent that the more ‘conservative’ logarithmic specification for projecting future skills leads to rather less re-ranking in the top 20 skills as measured by their importance (and also less re-ranking further down the ranked distribution), although Interacting With Computers still moves up the distribution in 2035. Similarly, there is greater constancy in the rank order of skills levels when using the logarithmic projections for future skills (cf Figure D4 and Figure D15), although Analyzing Data or Information still enters the top 20 in 2035.

The more moderate basis for the future trajectories of skills using the logarithmic projections is also reflected in the corresponding between-within decomposition of the total change in skill use over the forecast period. For the logarithmic projections, this decomposition is presented in Table D1. Over the forecast period 2020-2035, the average proportion of the total change in skills demand which is due to changes *between* occupations is 65%, while the average proportion due to changes *within* occupations is 35%. This compares with 10% and 90% respectively when using the linear projections as shown in

Table 7. With the logarithmic projection method, a greater proportion of the change is attributed to the changing occupational distribution of employment (i.e. changes in skills demand due to changes between occupations), rather than to changes of skills within occupations. The magnitudes of the between-within decomposition shares using the logarithmic projections are also more similar to the observation period 2010-2020. However, it is important to emphasise that the identity of the top ranked skills in demand in 2035 are almost unchanged whichever of the two methods of skills projections are used.

Table D1: Between-Within decomposition of total skill change – Skills Prevalence, logarithmic projections

Skill elements:	Observation 2010-20 % between : % within	Forecast 2020-35 % between : % within	Whole period 2010-35 % between : % within
All 161 skill elements	58 : 42	65 : 35	61 : 39
Abilities (52)	65 : 35	70 : 30	65 : 35
Knowledge (33)	39 : 61	52: 48	53 : 47
Skills (35)	77 : 23	77 : 23	74 : 26
Work Activities (41)	42 : 58	47 : 53	47 : 53

Note: The pairs of numbers in the table are the median between : within shares of the total change in skill demand over the period in the column heading. Hence for 2010-2020, calculated across all 161 skill elements, the average ‘between’ share was 58% and the average ‘within’ share was 42%. The interpretation is that, on average, 58% of the total change in skills demand was due to changes in skill utilisation *between* occupations, while 42% was due to changes *within* occupations.

Thus, in terms of our assessment of which are the most important skills in use in employment in 2035, our conclusion is that the method of projecting future skills use in each occupation is relatively unimportant. While the magnitude of the changes may differ, and the precise ranking within the top 20 may change, it is still primarily the same skills that are ranked most highly in terms of their utilisation in 2035 whichever of the two main projection methods we employ.

Figure D14: Top 20 skills ranking – Skills Importance measure, logarithmic skills projections

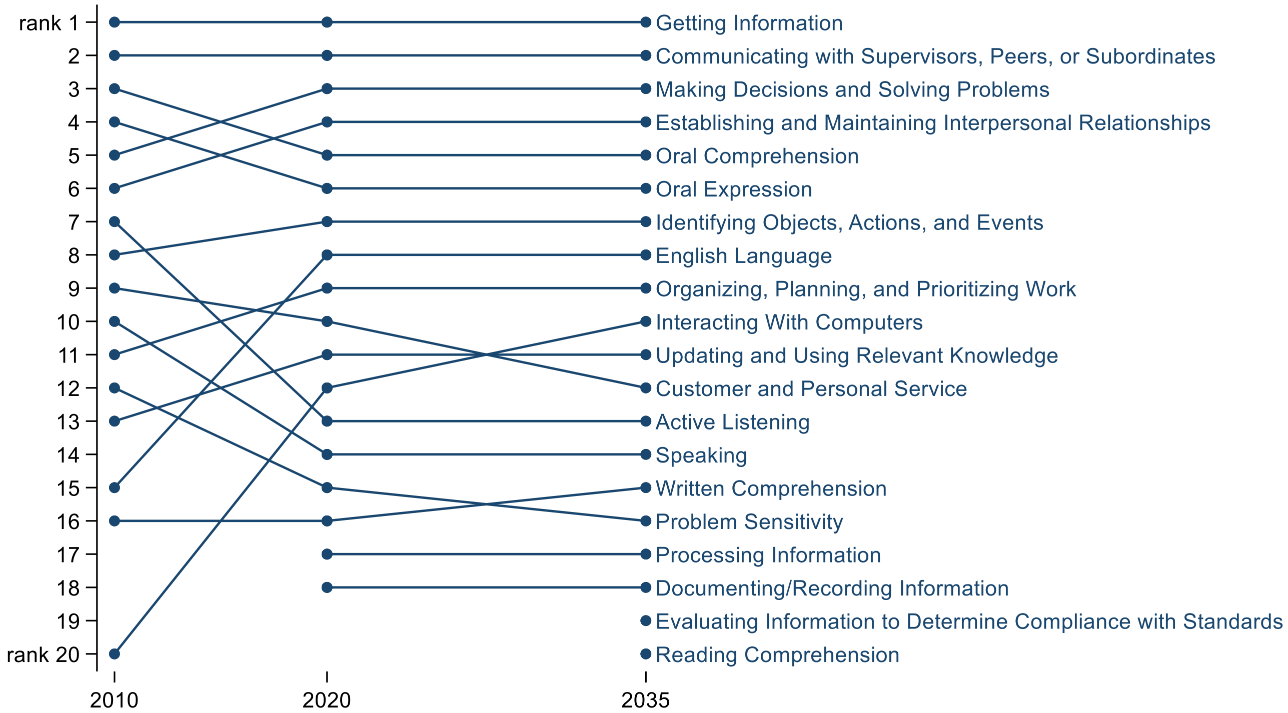
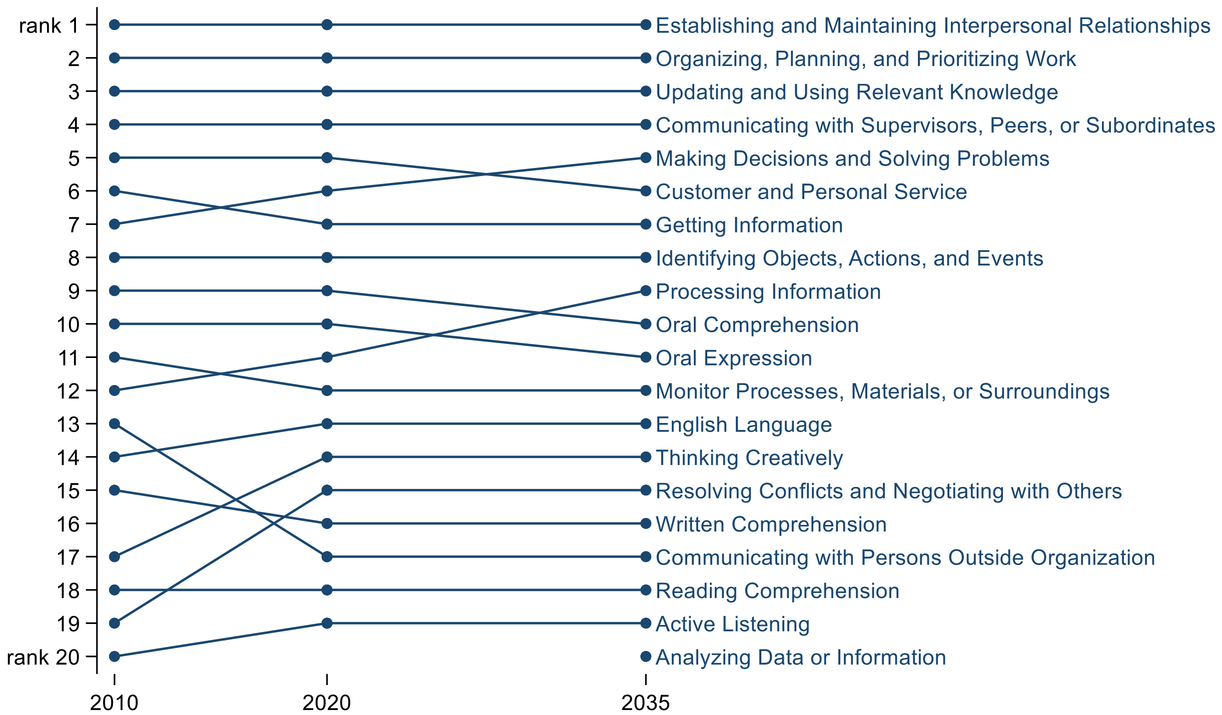


Figure D15: Top 20 skills ranking – Skills Level measure, logarithmic skills projections



Appendix E: ONS Skill Level definitions

The ONS classifies jobs in SOC2020 into groups according to their 'Skill Level' and 'Skill Specialisation' (ONS, 2020). Skill levels are distinguished by the length of time required for a person to become fully competent in the performance of the tasks associated with a job. This is a function of the time taken to gain necessary formal qualifications, or the required amount of work-based training. As well as formal training and qualifications, some tasks require experience for acquiring competence. ONS defines four skill levels, from Skill Level 1 (lowest) to Skill Level 4 (highest), as described in Table E1.

Table E1: ONS SOC2020 Skill Level Classification

Skill Level	Description
Skill Level 1 (lowest)	The first skill level equates with the competence associated with a general education, usually acquired by the time a person completes his/her compulsory education and signalled via a satisfactory set of school-leaving examination grades. Competent performance of jobs classified at this level will also involve knowledge of appropriate health and safety regulations and may require short periods of work-related training. Examples of occupations defined at this skill level within the SOC 2020 include postal workers, hotel porters, cleaners and catering assistants.
Skill Level 2	The second skill level covers a large group of occupations, all of which require the knowledge provided via a good general education as for occupations at the first skill level, but which typically have a longer period of work-related training or work experience. Occupations classified at this level include machine operation, driving, caring occupations, retailing, and clerical and secretarial occupations.
Skill Level 3	The third skill level applies to occupations that normally require a body of knowledge associated with a period of post-compulsory education but not normally to degree level. Several technical occupations fall into this category, as do a variety of trades occupations and proprietors of small businesses. In the latter case, educational qualifications at sub-degree level or a lengthy period of vocational training may not be a prerequisite for competent performance of tasks, but a significant period of work experience is typical.
Skill Level 4 (highest)	The fourth skill level relates to what are termed "professional" occupations and high-level managerial positions in corporate enterprises, or national or local government. Occupations at this level normally require a degree or equivalent period of relevant work experience.

Source: SOC2020 Volume 1: structure and descriptions of unit groups
https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume1structureanddescriptionsofunitgroups

Skill specialisation is defined as the knowledge required for 'competent, thorough and efficient' delivery of the tasks that comprise a job. It can also distinguish the type of work performed, the materials worked with, tools used, and so on.

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