Department for Education

Future skills projections and analysis

Research report

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Abbreviations

ARIMA – Autoregressive integrated moving averages (econometric technique)

BEIS – Department of Business, Energy and Industrial Strategy

CEDEFOP – European Centre for the Development of Vocational Training

COPS – Canadian Occupational Projection System

DBT – Department for Business and Trade

DESNZ – Department for Energy Security and Net Zero

DfE – Department for Education

EP – Employment Projections

ESCD – Employment and Social Development Canada

ESWDT – Exponential smoothing with dampened trend (econometric method)

ETAP – Evaluation and Trial Advice Panel

GDP – Gross Domestic Product

IFATE – Institute for Apprenticeships and Technical Education

ISCED – International Standard Classification of Education

KSBs – Knowledge, Skills and Behaviours

LAs – Local Authorities

LEP – Local Enterprise Partnerships

LFS – Labour Force Survey

LMI – Labour Market Information

LSIPs - Local Skills Improvement Plans

LSOA – Lower Layer Super Output Areas

MAC – Migration Advisory Committee

MCA – Mayoral Combined Authorities

MGI – McKinsey Global Institute

NFER – National Foundation for Educational Research

NOS – National Occupational Standards

O*NET – Occupational Information Network

OBR – Office for Budget Responsibility

ONS – Office for National Statistics

PIAAC – OECD Programme for the International Assessment of Adult Competencies

RAG – Red-Amber-Green (assessment structure)

RQFs – Regulated Qualification Framework

SIC – Standard Industrial Classification

SOC – Standard Occupation Classifications

SSC – Sector Skills Councils

SSDA – Sector Skills Development Agency

UFS – Unit for Future Skills

UKCES – UK Commission for Employment and Skills

WF – Working Futures

Executive summary

Background

Understanding the economy's skills needs now and in the future is crucial for planning, both centrally and at local and sector levels.

There are a range of skills forecasts used in the UK, which vary according to both their level of coverage of different sectors and the purpose for which they are intended. The most well-known and widely used economy-wide skills forecast is Working Futures (WF).[1] The latest version of WF is the Skills Imperative 2035 programme.[2] A variety of segment-level forecasts also exist and are commissioned on an independent basis by relevant sector bodies. At a regional level, employer groups supported by Chambers of Commerce produce Local Skills Improvement Plans, reconciling existing data with the needs of employers and authorities locally.

Motivation for this work

Whilst significant effort is put into producing skills forecasts, it is less clear what best practice in such forecasts looks like and also whether or not it is being applied by forecast commissioners, developers and users in the UK. There is currently no best practice framework or formal process of engagement across sectors/regions or with central bodies such as the Unit for Future Skills (UFS).[3] The extent to which current forecasts meet users' needs at both the economy-wide and the segment-level is also unclear.

Against this backdrop, the UFS commissioned Frontier Economics and Sheffield Hallam University to review and assess leading and emerging methodologies for analysis of future skills needs, in order to prepare the UFS to produce (or commission) economy-wide skills projections and support its various stakeholders to improve the quality and reliability of their own analysis.

This report adds to the evidence base on UK skills forecasting by providing a detailed assessment of the benefits and limitations of current methods used in the UK and internationally (at both the economy-wide and segment-level). It also recommends areas of focus for encouraging best practice and improving cohesion in the UK skills forecasting landscape in the future.

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[1] https://warwick.ac.uk/fac/soc/ier/researchthemesoverview/researchprojects/wf/

[2] https://www.gov.uk/government/publications/labour-market-and-skills-projections-2020-to-2035

[3] The Unit for Future Skills (UFS) is an analytical and research unit within the Department for Education. It has been set up to improve the quality of jobs and skills data, working across government to make this available and more accessible to policy makers, stakeholders and the general public. https://www.gov.uk/government/groups/unit-for-future-skills

The work will support the UFS in its mission to become a centre of expertise on skills forecasts, helping it to commission high quality forecasts to inform its own work, and to advise on best practice for other parties involved in skills forecasts (Local Authorities, skills bodies, employers etc.).

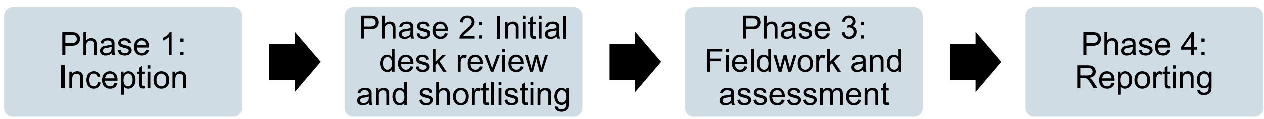
Approach

Based on a structured search for current skills forecasting techniques, we reviewed over 70 skills forecasting reports. From this list, we selected 18 case studies (9 economy-wide and 9 segment level forecasts) which were reviewed in detail using a combination of detailed desk-based review and 22 interviews with users, developers and commissioners.

This review informed a conceptual framework summarising how skills forecasts are created and the inputs and methods that can be used at each stage ('building blocks', explained in more detail in Section 3: Categorising approaches to skills forecasting).

In parallel, we set out the criteria that can be used to consider best practice in skills forecasting. We assessed the methods used in the 18 case studies against these criteria and summarised the benefits and limitations of these methods, as well as how methods and inputs can be combined. Throughout the project, findings were tested in workshops with the UFS Steering Group.

Figure 1: Overview of methodology



Findings from assessment

Given the range of use cases and their needs, it is appropriate to have multiple forecasts

Despite the large volume of skills forecasts and methodological differences in approaches, **there are commonalities in the design of skills forecasts**. Most skills forecasts involve several steps which usually happen sequentially:[4]

- The first step involves constructing a view of the macroeconomy and how this is likely to evolve over the near and medium term (e.g. GDP forecast to grow at Z%

[4] While the majority of forecasts reviewed follow this process, there are exceptions e.g. foresighting which does not link to employment outcomes. We discuss this approach further in Sections 3 and 5.

per year) and what this means for the labour market (e.g. wages and employment expected to grow by X% per year).

- The second step involves linking the expected state of the macroeconomy to employment outcomes (e.g. in 10 years the economy will need Y thousand engineers, Z thousand nurses etc).
- The third step involves linking employment outcomes to specific skills (e.g. the economy will need X thousand people with advanced machine learning skills etc.)

Different skills forecasts use different methods to inform these three steps. These methods vary in complexity and rigour and can range from relatively light touch qualitative assessments (e.g. to establish the general direction of travel for specific sectors) through to complex statistical modelling (e.g. to project economic performance at sub-national level taking into account flows of goods and services).

Precisely what method is appropriate will clearly depend on the context and research question. **We provide a detailed assessment of the advantages and disadvantages of different methods reviewed in Section 4:** Assessment of approaches to skills forecasting including Red-Amber-Green (RAG) assessment summaries (see pages 42, 44, 72 and 74). Overall, there is no “silver bullet” method and, because there are different users with different needs, there is a role for a range of forecasts. We have categorised users into four representative user types, and our RAG assessment includes ratings for each of these user types.

There are important limitations that are common across many forecasts

We found three notable gaps that were common to a large number of forecasts:

1. **Skills as a unit of analysis.** Forecasts typically encounter difficulties linking from macroeconomic trends or employment forecasts to skills i.e. producing a *skills* forecast, rather than forecasts at an employment level. The UK currently lacks a skills taxonomy which can be used as a central reference point: work is currently underway to address this issue.[5]
2. **How skills change within occupations.** Most forecasts produce outputs at Standard Occupational Classification (SOC) level, but few currently attempt to understand how the specific skills within occupations may change (e.g. will the changing nature of work mean that more digital skills are required in the future in a given occupation?). An understanding of within-occupation skill changes is crucial to understanding the impact of key labour market trends such as automation and AI. This issue could be partially addressed with data improvements, such as

[5] A Skills Classification for the UK (publishing.service.gov.uk)

additional survey evidence from employers as is gathered in the US.[6] It is also likely that alternative or expanded approaches to forecasting will be needed to fully address this gap. Foresighting is a good example of a new approach which tackles within-occupation changes, although it is not clear this method could be applied at an economy-wide level because it requires a detailed understanding of the impacts of technology at a very granular sub-sector level.

3. **Granularity to meet range of user needs**. Some users will need more granular information than is available from outputs at the SOC level. For example, those designing industry standards need forecasts at a detailed qualification level. Sector bodies are typically interested in granularity at a lower SOC or SIC (Standard Industrial Classification) level, and in some instances standard classifications (SOC and SIC) do not match up to their own understanding of their industry. This is another gap which is predominantly driven by data limitations, for example a lack of consistent data collection from employers, as well as a lack of suitable methods that can be applied without detailed granular data.

The fragmentation of the landscape creates challenges

The skills forecast landscape in the UK is diverse and fragmented. Multiple skills forecasts are produced by different organisations, at different intervals, levels of complexity and granularity and for different purposes. There are good reasons for this fragmentation and it is clear that no single forecast/approach can meet the needs of all users. The fragmentation does, however, present some challenges.

The landscape is hard to navigate. There is currently no single repository where skills forecasts are stored and easily accessible. As such, users (and potential users) may not know what is available already. This could lead to unnecessary duplication of effort and also prevent learning from experience.

Skills forecasts are not easy to digest. Disparate sources providing different skills forecasts and using different approaches mean that the findings are not easy to assimilate. As a result, users/commissioners may not know what approach to choose, how to interpret results, or how to assess the quality of a forecast.

Lack of guidance on best practice. There is currently no guidance on what constitutes best practice in conducting/commissioning skills forecasts and how existing forecasts can be used for different purposes, which could contribute to forecasts of varying quality. One potential form for such guidance is a decision tree. One way to implement this could be to create an expert panel – similar to the Evaluation and Trial Advice Panel (ETAP)[7] – to

[6] Quarterly Census of Employment and Wages: https://www.bls.gov/cew/
[7] The Evaluation and Trial Panel (gov.uk)

provide tailored advice to commissioners, developers and users. Guidance could include, but is not limited to:

- How best to identify and engage with stakeholders and experts.
- How to assess and improve the performance of difference methods.
- How developers can frame outputs and results, and how these should be interpreted by users.
- How to tailor the sophistication of the selected method appropriately, especially given user's needs and data limitations.

We discuss this in further detail in Section 6: Findings and recommendations.

There is a key role for a central economy-wide forecast

A single, respected foundational forecast at a national level provides a focus for expert input and debate and enables cohesion across government. If consensus is built around this central forecast it can act as a 'starting point' that others can use and build on (e.g. sectoral bodies; regions; LSIPs).

At the moment this role is filled by Working Futures. This forecast has a degree of trust and consensus around it as a central reference point and has users at the economy-wide and segment level. It is being developed as part of the Skills Imperative 2035 programme, for example to build in a more detailed skills taxonomy. The methodology is in line with similar forecasts produced internationally, such as the US[8] and Germany.[9]

Whilst there is no single alternative skills forecasting approach that appears superior in all dimensions to Working Futures, **gaps have been identified that could improve Working Futures going forward**. Some of these gaps could be developed as builds or add-ons without substantively changing the current approach, such as building in a process for stakeholder engagement and developing additional scenario analysis (see Section 6: Findings and recommendations for more detail).

Other gaps in Working Futures are the common limitations across the UK evidence base described above (including a skills taxonomy, forecasting changes within occupations, and developing granularity). Addressing these gaps would likely require more substantive development such as new data collection and/or investigating the potential to use new or more innovative approaches and techniques at certain stages to complement the central model.

[8] Employment Projections (EP) program.
[9] The QuBe project.

Recommendations flowing from our work

Facilitating cohesion and information sharing

Recommendation 1: Create a central repository for skills forecasts and related documentation and information, including signposting to relevant methodologies and datasets.

Recommendation 2: Provide synthesis and associated commentary summarising the latest skills forecasts, and highlighting key gaps in the evidence base.

Recommendation 3: Develop best practice guidance for how skills forecasts should be commissioned, developed and/or used. This could include guidance on: engagement with experts and incorporating this into a forecast; assessing accuracy; and the framing of results and how to use and interpret outputs.

Deepening the role of Working Futures

Recommendation 4: Develop Working Futures to address the current gaps. This could involve developing add-ons to the current approach (e.g. stakeholder engagement and scenarios). This could also involve investigating the potential to use new methods and inputs at certain steps of the overall approach (e.g. using vacancy data and data from employers and/or using new methods alongside the core model, for example dynamic skills taxonomies). This would build further on Working Futures' existing position as a trusted central forecast.

Recommendation 5: If Working Futures cannot feasibly be adapted to close key gaps, then an alternative new forecast method could be considered. User needs may be better met by a forecast method that can deliver on some of the evidence gaps we have highlighted in our Findings. These benefits should be weighed against the time and resource costs, and the risk that having multiple economy-wide forecasts could reduce cohesion.

Recommendation 6: Develop a process for knowledge sharing and diffusion of information on the central forecast, for both segment-level and economy-wide users. Combined with recommendations 1-3, this will build consensus and encourage best practice use.

Section 1: Introduction

Background to this study

The skills, knowledge and attributes required by the UK labour market are evolving rapidly. On top of existing trends such as an ageing population and increased digitisation, events like the Covid-19 pandemic and the UK's exit from the EU will inevitably affect the skills required by the labour market in the future. The significant risk of mismatches between the skills requirements of the past and those required to service established and emerging sectors in the future make it increasingly important to ensure that training and qualification programmes are well targeted.

Predicting future skills needs is notoriously difficult and there are different approaches for doing so. Some rely on detailed modelling, such as macroeconomic and econometric models, accounting for (where possible) significant events. Other studies take a more qualitative approach using surveys, workshops or interviews to get insights from sector experts, employers and others. No approach is likely to be able to answer all possible questions that interest central government, as well as those that interest other users such as local planners and those involved in workforce planning. The resources needed to construct a forecast also need to be proportional to its use.

Aims and objectives

Against this backdrop; the Unit for Future Skills (UFS)[10] at The Department for Education (DfE) commissioned Frontier Economics and Sheffield Hallam University to review and assess existing approaches to skills forecasting.

The overarching aim of this project was to support UFS in becoming a centre of expertise on skills projections or forecasts. The outcomes of this project, including this report, will support UFS in commissioning high quality forecasts to inform its own work, as well as to advise on best practice for other parties involved in skills forecasts (Local Authorities, skills bodies, employers etc.).

Our assessment of different approaches to skills forecasting involved considering their strengths and limitations in different contexts, identifying examples of best practice, and identifying evidence gaps and possible improvements.

[10] The Unit for Future Skills (UFS) is an analytical and research unit within the Department for Education. It has been set up to improve the quality of jobs and skills data, working across government to make this available and more accessible to policy makers, stakeholders and the general public. Unit for Future Skills (gov.uk)

We reviewed approaches taken to forecasting future skills at the whole-economy level (referred to as 'economy-wide' throughout this report), as well as those used to produce results for individual industries, sectors or local areas (referred to as 'segment-level').

The skills forecasting landscape in the UK

Understanding and improving skills to make the UK more productive and more competitive internationally has been a focus of governments for decades.

UK Commission for Employment and Skills and Sector Skills Councils

The Leitch Review of Skills in 2006[11] brought a series of changes in the UK skills landscape, including the establishment of the UK Commission for Employment and Skills (UKCES)[12] which replaced the Sector Skills Development Agency (SSDA)[13] in 2008. UKCES had responsibility for research including the employer skills survey[14], skills forecasting (Working Futures) and for the 18 Sector Skills Councils (SSC) that had been established in 2002.

The SSCs and UKCES developed and updated National Occupational Standards (NOS)[15] and used NOS alongside other research to produce labour market information and skills forecasts at national, regional and sectoral levels. The interaction between the SSCs and UKCES was two-way. UKCES commissioned economy-wide forecasting, while SSCs were responsible for identifying skills gaps and shortages in relevant sectors.

UKCES was responsible for commissioning the UK's central economy-wide skills projection from 2002 until 2016. This forecast was the Working Futures model (WF), and it was developed by the Institute for Employment Research at the University of Warwick and Cambridge Econometrics.[16] It was produced every 2-3 years relying on a macroeconomic model, similar to other economy-wide forecasts produced globally.

SSCs, in developing reports for their sectors, typically used employer groups, surveys of employers and workers, and other in-depth qualitative and quantitative methods to develop a clear picture of the current and future state of labour demand supply in their sectors. The SSC sectoral reports would go to UKCES, who would be able to link the intelligence to the current version of Working Futures or use it to help inform the commissioning of the next iteration.

[11] Leitch Review of Skills (gov.uk)
[12] UK Commission for Employment and Skills (gov.uk)
[13] Sector Skill Development Agency
[14] Employer skills survey: 2022 (gov.uk)
[15] National Occupational Standards (gov.uk)
[16] Working Futures (Warwick Institute for Employment Research)

At a local level, Regional Development Agencies used Working Futures and evidence from SSCs to direct funding to develop skills that were needed in the region. These organisations were closed in 2012, and Local Enterprise Partnerships were developed, although with limited capability to use skills forecasts in this way.

The UKCES and SSC approach created a structured skills forecasting and labour market infrastructure, that supplemented official statistics like the Labour Force Survey. The UKCES closed in 2016.

Post-2016: Economy-wide forecasts

Since 2016, DfE commissioned Working Futures, most recently in 2020 covering the period 2017-2027. The most recent publication, Skills Imperative 2035[17], was commissioned by the Nuffield Foundation and produced by a consortium led by NFER.[18][19] Alongside this, DfE has recently commissioned Horizon Scanning[20] to supplement Working Futures; this uses a qualitative, scenario-based approach to understand what the labour market could look like in the future. Other central government forecasts are typically developed or commissioned to focus on specific issues (examples include a PwC report[21] on the impact of automation and a Migration Advisory Committee[22] report on shortage occupations); these may be updated regularly or produced as one-off forecasts.

Post-2016: Local-level forecasts

As part of the response to the Skills for Jobs white paper in 2021, it was decided to support employer groups to develop Local Skills Improvement Plans (LSIPs).[23] These LSIPs were mostly developed by Chambers of Commerce and their initial articulation of employer needs was expected to be based on existing data analysis by UFS and where applicable by local or mayoral combined authorities.[24] As such, much of the LSIP analysis was qualitative in nature, engaging with employers, local and/or mayoral combined authorities, and post-16 skills providers. The LSIPs set out the key skills needs of the area, and post-16 skills providers must ensure they provide education and training that meets those needs. As such, they have some value as skills forecasts, particularly in

[17] Labour market and skills projections: 2020 to 2025 (gov.uk)
[18] The Skills Imperative 2015 (NFER)
[19] Throughout this report we use ‘Working Futures’ to refer to the general approach, methods and models used to produce this economy-wide forecast since 2016, including the recent publications under the Skills Imperative 2035 programme. Where appropriate we refer to ‘Skills Imperative 2035’ to discuss the recent developments made to the forecast and ongoing research under this programme.
[20] RAND Europe (2022) Labour market and skills demand horizon scanning and future scenarios
[21] PwC (2021) The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills.
[22] MAC (2020) Review of the shortage occupation list
[23] Skills for jobs: lifelong learning for opportunity and growth (gov.uk)
[24] Local Skills Improvement Plans. Statutory Guidance for the Development of a Local Skills Improvement Plan

the way they reconcile existing data with the needs of employers and authorities locally, but they were not designed to produce new quantitative skills forecasts.

In addition to this, some government office regions commission their own region-specific forecasts, such as the East of England forecasting model.[25]

Post-2016: Sector-level forecasts

Since the closure of the SSCs, sector-level forecasts are commissioned on an independent basis by the relevant sector bodies. Some of these organisations are the remaining SSCs supported by employers, while others are older organisations such as those with royal charters or industry training boards, or membership organisations in specific sectors. Examples identified as part of this report include the engineering sector and the screen industries. Whilst there is sometimes consistency within sectors, for example the Workforce Foresighting Hub produces forecasts for a number of sub-sectors within high-value manufacturing,[26] segment-level forecasts are usually produced from scratch each time with a high level of fragmentation. There is no best practice framework or formal process of engagement across sectors/regions or with central bodies such as UFS.

These sector-based organisations allow for the involvement of industry experts beyond central government in skills forecasting. Those with skills expertise can also be involved in regional skills forecasting, explicitly through LSIPs or as part of advisory groups to local or regional authorities. Skills expertise is also explicitly required for the process adopted by the Workforce Foresighting Hub. In most other cases however, skills expertise is required only at the point of developing the qualifications or training identified as a future need by skills forecasting, rather than being part of the forecast development process.

The language of skills forecasts

There are a number of terms used in the skills forecasting landscape. For the purpose of this report, terms are defined as:

- **Forecast:** We use this as a 'catch all' term for any view produced of future skills needs.[27]

[25] East of England Forecasting Model (EEFM)
[26] Workforce Foresighting (InnovateUK)
[27] We note that the term 'forecast' is not always used in the same way as we have used it in this report. For example, foresighting and projection methods can sometimes distinguish as different from a 'forecast', on the basis that they are not necessarily predicting what skills will actually look like in the future, for example being instead a 'what if' scenario based on continuation of a given trend. We do not apply this definition

- **Method:** A methodological approach used to arrive at a view of future skills needs. This could be an 'end to end' method, which would be a way of getting all the way from inputs (e.g. data or expert views) to outputs (data or information on future skills). Or it could be one single 'method' used as part of an entire skills forecasting process – e.g. a time series projection of historical data.
- **Case studies:** We reviewed a large number of 'studies' which comprised published descriptions of methods used to arrive at future skills 'forecasts'. From our initial search we then selected a shortlist ('case studies'), as discussed in Section 2: Methodology.
- **Use case:** The application of a future skills forecast to a research question. Each case study is typically designed for one or more specific use cases, although may be used as an input, alongside other forecasts, for additional use cases. Examples of high-level use cases are policy design or understanding the direction of the labour market.

As an example, we have discussed in the Section 'The skills forecasting landscape in the UK' the widespread use of Working Futures as a view on future labour market trends in the UK; we selected this as one of our shortlisted *case studies*. It uses multiple *methods and inputs* (published labour market data, macroeconomic models, econometrics and qualitative expert input) to arrive at a *forecast* of future occupational employment and skills (qualifications). It has a large number of *use cases*, including workforce planning and understanding the direction of the labour market, and is typically combined with other forecasts by a range of users.

Structure of this report

The remainder of this report is structured as follows:

- **Section 2: Methodology:** This section describes the phases of research undertaken by the Frontier/Sheffield Hallam team to arrive at the conclusions set out in this report.
- **Section 3: Categorising approaches to skills forecasting** This section summarises the types of methods found in our review of existing approaches to skills forecasting and projections. These approaches can be broken down into the inputs and methodological 'building blocks' that are used to produce a view on future skills.
- **Section 4: Assessment of approaches to skills forecasting:** In this section we summarise the methods found in our review and assess their strengths and

when we talk about 'forecasts' and instead intend it as a general catch-all term: we instead discuss 'projections' and 'foresighting' as different examples of 'methods' to produce 'forecasts'.

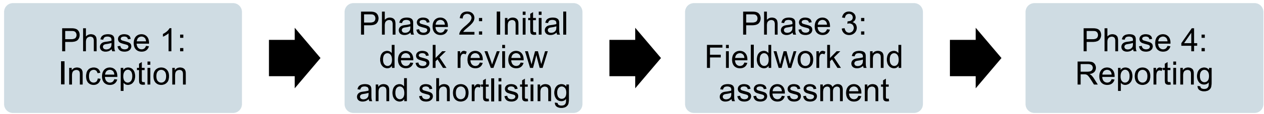
limitations across our five assessment criteria and their suitability across different contexts. We provide examples based on the shortlisted applications we have assessed. The aim of this section is to provide a clearer view of best practice in the skills landscape and what works when; this will provide a starting point for delivering guidance and provide tools for other users of this report.

- **Section 5: Combining building blocks:** Based on the findings from Section 4 we provide some general guidance around three main questions: (1) are all building blocks equally relevant?, (2) is there a correct ordering of the building blocks?, and (3) how should methods across building blocks be combined?.
- **Section 6. Findings and recommendations:** This section brings together a summary of the overall findings from our detailed assessment set out in Sections 4 and 5. We set out some recommendations flowing from our assessment findings.
- **Section 7. Conclusions:** This section draws together our findings and provides a statement of how this research adds to the evidence base on future skills.

Section 2: Methodology

This study was divided into four key phases. Figure 2 provides an overview of the approach; each individual stage is described in more detail in this section.

Figure 2: Overview of methodology



Source: Frontier Economics

Phase 1: Inception

At the outset of the study, we agreed the proposed methodology with the UFS Steering Group, which included UFS team members and representatives from government departments and bodies involved with skills forecasting, among them: the Institute for Apprenticeships and Technical Education (IFATE), HM Treasury, the Office for National Statistics (ONS), Department for Energy Security and Net Zero (DESNZ) and Department for Business and Trade (DBT).

We held scoping interviews with users and developers of skills forecasts to inform our approach to categorising studies in the desk review stage. These interviews included representatives from IFATE, the Workforce Foresighting Hub, DESNZ, DBT and DfE.

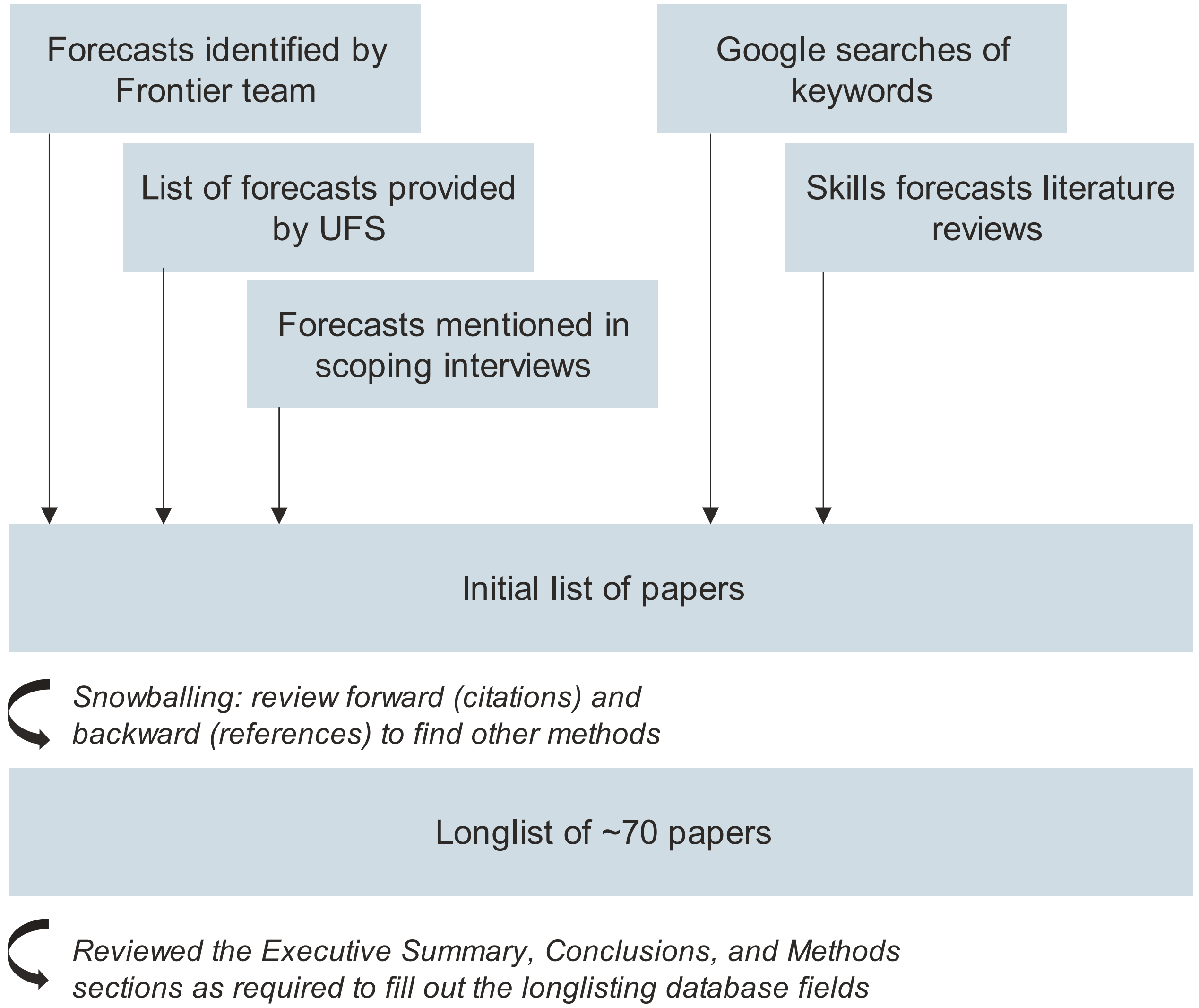
Phase 2: Initial desk review and shortlisting

In the second phase we produced a shortlist of ‘case study’ examples of skills forecasting, which we then reviewed in detail and used the results to develop our assessment and guidance around skills forecasting approaches. To arrive at a shortlist, we first identified a longlist of around 70 studies with a broad coverage of example applications of skills forecasting. We then used criteria to select case studies from the longlist which together covered a range of different sectors and methodological approaches.

Review of longlist

We identified an initial list of examples of skills forecasts based on studies known to Frontier/Sheffield Hallam, UFS, and scoping interviewees. We identified additional papers using searches of keywords, skills and employment forecasting literature reviews, and snowballing using citations and references, as shown in Figure 3.

Figure 3: Longlisting process



Source: Frontier Economics

The final longlist included around 70 studies. We reviewed all studies and produced a database across the following dimensions:

- **Upfront information:** Document category (e.g. journal article, discussion or working paper, other report, blog post, etc); Title; Associated institution(s); Author(s); Publication date; Web link;
- **High-level description**: Two-sentence description of purpose and contents of the study;
- **Type of forecast**: Whether the forecast covered skills demand or supply (or both); Whether the forecast was at economy-wide or segment level; If at segment level, which industries or sectors were covered;

- **Unit of analysis**: The key variable(s) forecasted, e.g. skills, employment, occupations; Whether the outputs were quantitative or qualitative; The level of granularity e.g. at occupational or geographical level; The frequency of forecast (for forecasts produced and updated regularly); The timescale and horizon of forecast (e.g. how many years into the future);
- **Method detail**: A detailed description of the methods used to arrive at the forecast;
- **Method category / categories**: A grouped description of the type of method used category (e.g. time series analysis, exponential smoothing);
- **Data sources**: Sources used to produce forecast e.g. published datasets;
- **Use case:** Detail of the application of the forecast, i.e. what the forecast was used for, if described in the study; Country of application.

Shortlisting

The objective of shortlisting was to produce a sample of studies which we would assess through a detailed desk review and focussed interviews.

From the 70 longlisted studies, we first excluded studies which did not meet minimum levels of robustness and/or transparency. This did not involve applying a formal threshold to the study, but instead excluding studies which would not give us insight into best practice applications, for example excluding studies which did not publicly report methods and inputs in sufficient detail to allow us to conduct our assessment, and excluding studies with very limited citations or that had significant methodological flaws referenced in our scoping interviews.

We divided the remaining studies into economy-wide and segment-level examples.

From the economy-wide studies, we selected a shortlist of examples which together covered:

- High profile examples of UK applications (widely used and trusted forecasts, and outputs applied and/or commissioned by central government to inform policy decisions);
- A breadth of:
    - international applications (United States, Canada, EU, Germany);
    - method types (both complex models and simpler or lower resource methods); and

- use cases (i.e. applications to different research questions).

We considered a group of forecasts with a more specific local or regional focus but excluded these as either being difficult to assess effectively[28] or lacking robustness.

We considered including examples of nowcasting studies, which produce estimates of current employment and/or skills incorporating more timely information than that available from published statistics (which may be published with significant time lags).[29] In discussion with UFS, we decided that these studies lie outside the key focus on methods for *future* skills specifically.

From the segment-level studies, we selected examples which together covered a breadth of:

- sectors (including: construction; advanced manufacturing; engineering, health, digital; technology; creative sectors; hospitality; green sectors and emerging high-growth sectors);
- method types and use cases, as above.

We tested the draft shortlist with the Steering Group in a workshop. The shortlist which includes 18 case studies was finalised based on interviewee availability, so that we had at least one interview per shortlisted case study for the fieldwork stage. The shortlisted studies are listed in Table 1 and Table 2.

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[28] This included Local Skills Improvement Plans (LSIPs), which we longlisted as an example of producing views on future skills in local areas. However, as the methods employed to produce LSIPs differ in each local area, we concluded these could not be assessed as a single methodological example of producing a skills forecast. However, we spoke to users and commissioners of local skills forecasts as part of the interview stage and we discuss findings from these interviews in later sections of this report.

[29] For example: Bank of England (2018). Using online job vacancies to understand the UK labour market from the bottom-up; Jobs and Skills Australia (2023). Nowcast of Employment by Region and Occupation (NERO).

Table 1: Shortlisted economy-wide studies covered in our assessment

Study	Commissioner	Developer	Country
The Working Futures model (WF)	Department for Education (DfE), Nuffield Foundation, National Foundation for Educational Research (NFER)	Cambridge Economics, University of Warwick, Institute for Employment Research	UK
The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills	Department of Business, Energy and Industrial Strategy (BEIS)	PwC	UK
Labour market and skills demand horizon scanning and future scenarios	Department for Education (DfE)	RAND Europe	UK
UK Skills Mismatch in 2030	Industrial Strategy Council	McKinsey	UK
Employment Projections (EP) Programme	US Bureau of Labour Statistics	US Bureau of Labour Statistics	US
CEDEFOP	European Union, CEDEFOP	Cambridge Economics, University of Warwick, Institute for Employment Research, and others	EU
Project QuBe (*Qualifikation und Beruf in der Zukunft*)	Federal Ministry for Education and Research	Institute for Employment Research and the Federal Institute of Vocational Education	Germany
3 year Employment Outlooks	Labour Market Information Council	Employment and Social Development Canada (ESCD)	Canada
Australia’s National Skills Commission	Department of Employment and Workplace Relations	National Skills Commission / Jobs and Skills Australia	Australia

Table 2: Shortlisted segment-level studies covered in our assessment

Study	Commissioner	Developer	Sector covered
Green Jobs Taskforce: Report to Government, Industry and the Skills sector	The Green Jobs Delivery Group	The Green Jobs Delivery Group	Green sector
CSN Industry Outlook 2023-2027	Construction Industry Training Board (CITB)	Experian	Construction
UK Commission for Employment and Skills (CES) insights	UK CES	UK CES	Various
Workforce Foresighting Hub - Emerging skills project	High Value Manufacturing Catapult	Workforce Foresighting Hub	Various
Engineering skills needs - now and into the future	Engineering UK	Lightcast	Engineering
NHS Projections	The Health Foundation	REAL Centre	Healthcare
Preparing for a changing workforce: A food and drink supply chain approach to skills	Food & Drink Sector Council (FDSC)	Food and Drink Federation (FDF) and Sheffield Hallam University	Food and drink
Technology industry skills forecast based on AI-mined public data	Various	Headai	Various
Skills Forecast Service and Quarterly Screen Skills Barometer	ScreenSkills	ScreenSkills	Creative screen industries

Phase 3: Fieldwork and assessment

In the fieldwork stage we undertook a detailed desk review and assessment of the shortlisted case studies, and held 22 interviews with commissioners, users and developers of skills forecasts, of which 10 were with users and commissioners, and 12 were with developers. The fieldwork was designed around the assessment criteria used to assess different approaches to skills forecasting.

Assessment criteria

The purpose of assessing the shortlisted case studies was to identify the strengths and limitations of the forecasts in different contexts. To this end we developed a list of five 'assessment criteria' to capture the desirable features of a skills forecast. The assessment criteria were based on the requirements identified by stakeholders in scoping interviews and were tested with UFS team members. The five criteria are: (1) relevance, (2) accuracy, (3) versatility, (4) data availability and requirements, and (5) resources and ease of use. The assessment criteria are set out in Table 3 and explained in more detail in the text beneath.

Table 3: Assessment criteria

Criteria	Explanation
Relevance	Does the output of the forecast meet the user's needs and answer the user's research question?
Accuracy	Is the forecast internally and externally valid?
Versatility	Can the forecast be used to test different assumptions or to test the impacts of differing future trends, e.g. through scenarios?
Data availability and requirements	How much data or other inputs are required to produce the forecast and how easily available are these inputs?
Resources and ease of use	What resources are required (time and skills) to develop, update, or use the forecast?

Source: Frontier Economics

We used this framework to collect information consistently across studies, using it for both the desk review and fieldwork (interviews), focussing on collecting evidence to answer the questions under each of the criteria, and thinking about trade-offs between different criteria.

Relevance: This criterion captures the extent to which a skills forecast meets the intended needs and priorities of stakeholders, including the extent to which outputs can be used for policy and other decision-making. The relevance of a forecast to a particular user will be defined by features including: timeframe, granularity, unit of analysis (skills, employment or occupations) and sector coverage.

The 'relevance' of one forecast will depend on the use case. For example, one user might require a forecast focussed on results for the next 2 years. Another user might be interested in detailed results for a single sector. From our scoping interviews we identified four representative 'types' of forecast users. These are the key user groups who we understand the UFS are considering when producing best practice guidance. Each of these user groups might have different assessments of the relevance of a single forecast. These four representative types are:[30]

- **Central planners**, who use skills forecasts for policy and strategy, as an input for other analyses and for discussion and debate. Central planners are typically government departments, for whom the required features can vary depending on the use of the forecast. Long-term, economy-wide skills and employment forecasts are typically useful, alongside other forecasts with more specific focuses.

- **Local users** interested in detail at a regional level, for example those involved in producing Local Skills Improvement Plans (LSIPs). Again, the timescale and granularity required will vary depending on the type of local user, for example LSIPs cover three year periods.[31] Developers of LSIPs often build on economy-wide information such as the Working Futures forecast by including more specific local information, for example from qualitative engagement with employer groups. Working Futures only provides regional breakdowns so local users may want to use additional modelling for a more detailed breakdown (for example to LEP, mayoral combined authority or LSOA level).

- Users engaged in **workforce planning**, using the forecast for training and recruitment, such as employers and training providers. These users are often interested in replacement demand and industry growth, typically at a segment-level and potentially including detailed sectoral breakdowns. In many cases, they are interested in bespoke sector definitions which do not necessarily align with SIC or SOC codes, such as the screen sector or detailed advanced manufacturing sectors. These users are often interested in changing skills within jobs, for example increased demand for digital skills.

- Those **designing qualifications and standards**, including higher and further education and apprenticeships such as IFATE. This requires a high degree of granularity at a skills and qualification level. These users are most often interested

[30] We note that this list of users is a simplification and that there is a diversity of user types that fall under each of these categories. We use this list only as a framework to structure our assessment of the relevance of different skills forecasts to different users. There may also be other user types who do not fall directly into these categories, such as those who use skills forecast for their own career purposes, but we expect these four types to cover the majority of users of interest to UFS for the purpose of this work. Additionally, whilst these groups do not overlap, one individual may do two roles and so fall into multiple user groups.
[31] Local Skills Improvement Plans. Statutory Guidance for the Development of a Local Skills Improvement Plan

in shorter timeframes, around three years, to align with the time required to rollout new qualifications or standards.

In our assessment, we considered the relevance of a forecast separately for each of these user types.

Accuracy: This criterion captures the degree to which a skills forecast can be depended on to perform consistently well. To assess accuracy, we considered:

- Internal validity: Are the estimated relationships in the model valid and does the approach account for potential bias? Has the model undergone a degree of scrutiny, e.g. has it been tested or peer-reviewed?

- External validity: Does the model accurately reflect the real world? Can the results be generalised?

Versatility: A versatile forecast is one which is able to account for a range of possible future outcomes. For example, this could include scenario analysis to model the range of impacts of labour market events such as the UK's exit from the European Union, or alternatively to model the range of future technology trends such as the rate of automation. A successfully 'versatile' forecast should go beyond simple 'low' and 'high' outcomes (which are more like sensitivities), but instead reflect the impacts on the labour market for a range of different outcomes or trend rates.

Data availability requirements: A forecast will perform well against these criteria if the inputs it uses are publicly available and regularly published, and/or likely to be available in the future in the granularity and volume required by the skills forecast. Data inputs could include qualitative information that informs key assumptions, for example survey data.

Available resources and ease of use: This criterion captures both the resources needed to develop the forecast and those needed to use and understand its outputs. Some models require advanced software (such as Python or machine learning techniques) to develop, or an advanced technical understanding (for example relating to econometrics); these models would perform less well against the criteria. Forecasts which are transparent, and those where stakeholders can understand the model outputs and the key drivers of the results would perform well. This would involve not just publishing detailed technical reports to describe the methods and inputs used, but also presenting results in ways which are easy to use, and presenting the methods and limitations of the forecast in a way that can be easily understood by non-technical users.

There is a clear trade-off between some of these criteria.[32] For example, forecasts which are complex are likely to be ranked highly on accuracy requirements if they capture lots of valid relationships between variables, but will likely be ranked poorly on ease of use if it makes it difficult to explain. Different users will place different weightings on different criteria. For example, some users may have very limited data and resources and so prioritise forecasts with low data requirements and resource needs at the expense of other criteria such as accuracy. In addition, there are links between some criteria. For example, there might be a link between relevance and versatility. Policy users might value forecasts that are more versatile as these allow them to test scenarios to assess the impact of different policies.

Desk assessment of studies

We conducted a desk-based review of the shortlisted forecasts to assess each study against each of the criteria. We used published documentation of each study, including output reports, online tools and technical annexes. Where necessary, the assessment (including understanding details of the method applied and its use cases) was supplemented with input from interviews.

Interviews

We developed a topic guide for interviews with input from the UFS. The topic guide was developed around the assessment criteria, with a particular focus on questions that could not be answered through desk assessment.

We held 22 interviews with commissioners, users and developers of the shortlisted case studies, of which 10 were with users and commissioners and 12 were with developers. The interviewees were identified through a combination of UFS, Frontier and Sheffield Hallam contacts. Interviews were conducted by the Frontier/Sheffield Hallam team.

This interview stage allowed us to gain insights from a range of different individuals. In ‘developer’ organisations, we were typically able to speak to those involved in both the hands-on building of forecasts, such as analysts, and/or more senior team members who built or directed the approach and conceptual framework. We were typically able to speak to those who commissioned and used forecasts within organisations such as Local Skills Improvement Plans, government departments and sector organisations. We were able to discuss why specific forecasting approaches were commissioned and the benefits of the skills forecasts used. Where the developing and commissioning organisation were the same, these groups were also able to discuss the use of their forecast.

[32] A survey was sent to interviewees to collect quantitative evidence on the weighting of criteria by different user types. The sample size from the survey is small and therefore not representative, so we have not drawn any conclusions from this.

Assessment of skills forecasting methods

Typically, a number of different methods are combined together to produce a skills forecast. We found the majority of case studies conducted the same three stages to produce a forecast from start to finish – but employed different methods at each of these stages.[33] We defined each of these stages (termed 'building blocks') by their purpose in producing a forecast, and categorised the methods used at each step among the studies we had reviewed. It is more meaningful to consider best practice at a building block and method level (rather than at a forecast level) because forecasts are in practice combinations of multiple inputs and methods.

Breaking the stages of forecasting down in this way allows us to consider the strengths and weaknesses of individual methods (instead of case studies), as well as ways of combining methods according to their strengths. Section 3 provides more detail on this building blocks approach and categorisation.

We triangulated evidence from the desk assessment and interviews to assess each type of method against our assessment criteria. We also assessed how these methods are combined to produce a skills forecast. The results of the assessment are summarised in Sections 4 and 5.

Phase 4: Reporting

We synthesised our findings from desk review, workshops and interviews into our overall conclusions and recommendations for the UFS, summarised in Sections 6 and 7.

[33] For example, one forecast might use: (1) interviews to understand the directions of future macroeconomic trends, (2) time series analysis to understand the impacts of macroeconomic trends on employment, and (3) a standardised skills classification to link changes in employment to changes in skills. Another forecast might use the same two methods for the first two stages, but at stage (3) instead use jobs postings data to link changes in employment to skills clusters.

Section 3: Categorising approaches to skills forecasting

In this section, we first describe our general findings on the approaches used to produce skills forecasts, as found from a desk review of around 70 skills forecasts. We then describe the framework developed to categorise the methods used into the ‘building blocks’ that are used to put together a complete forecast. In Section 4, we use this framework to assess approaches to skills forecasting in different contexts.

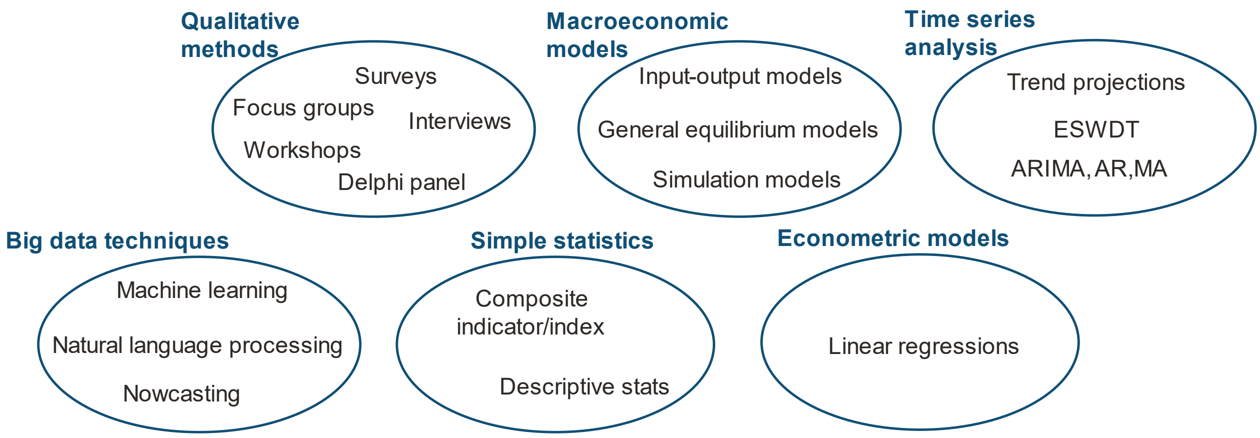
Longlisted skills forecasts

The longlist of skills forecasts, compiled as described in the methodology section, included 44 economy-wide and 27 segment-level studies.

Types of methods used

Across all studies reviewed, we found 17 types of methods, which can be roughly grouped into 6 different types as shown in Figure 4.

Figure 4: Methods used in longlist of studies

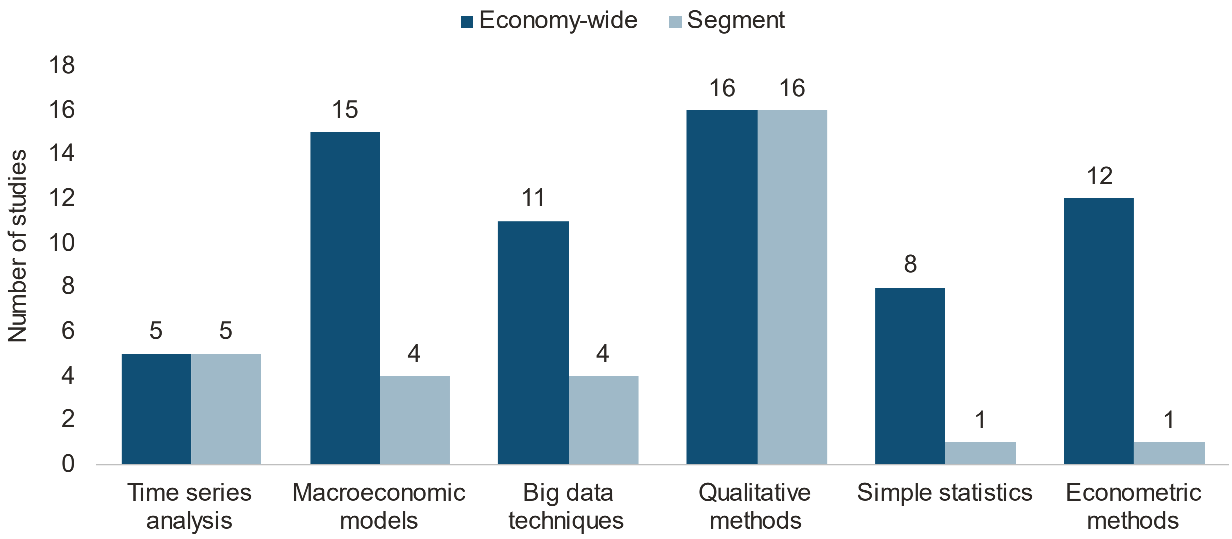


Source: Frontier Economics

Many studies, in particular more robust studies, used a combination of one or more of the methods shown in Figure 4. For example, to arrive at a view on future skills, a study might use both time series analysis of historical data and focus groups with sector experts.

Economy-wide forecasts were more likely to use macroeconomic models, econometric methods, time series and big data models. Segment-level forecasts more often relied on qualitative expert engagements, in particular to bring in sector-specific or local area-specific insight, and typically used methods which were less resource intensive to develop and/or use. Figure 5 sets out the method types used across the economy-wide and segment-level examples.

Figure 5: Distribution of methods by type



Source: Frontier Economics

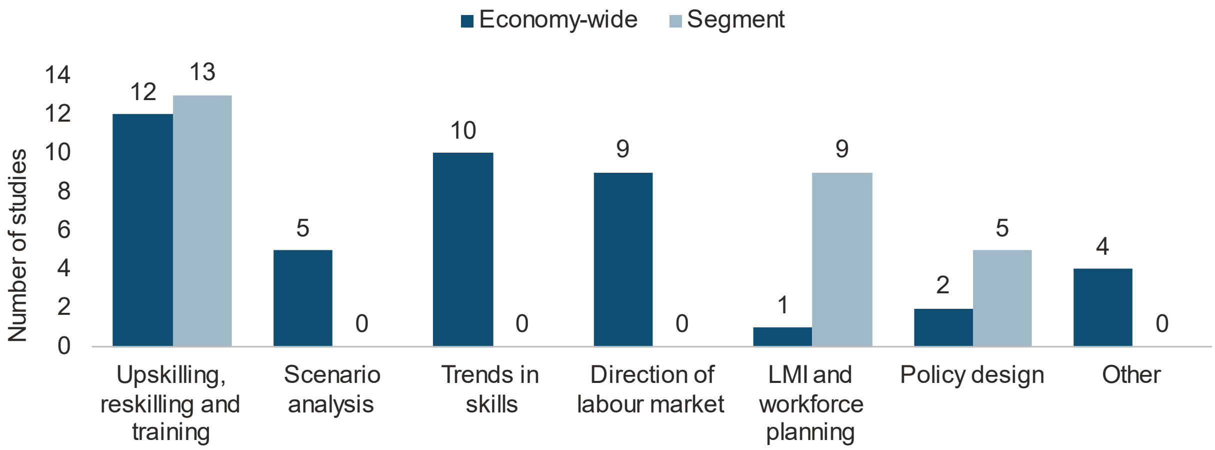
Note: We assigned up to two methods to each study because many studies used multiple methods.

Use cases of skill forecasts

Forecasting the requirements for upskilling, reskilling and training was the most common use case across the studies reviewed: almost half of all segment studies reviewed are used for this purpose. Segment studies are also typically used for workforce planning and policy design. In contrast, economy-wide studies were mainly used to understand the trends in skills and the direction of the labour market as well as supply gaps in further and higher education. Figure 6 sets out use cases across the economy-wide and segment-level examples. Studies were classified based on their primary use: for example, users might want to know about trends in skills in order to develop upskilling or training programmes, but in this case we would classify the use as upskilling or training programmes.

The segment-level studies reviewed covered a number of different segments, including green jobs, manufacturing, engineering, healthcare and the food and drink sector. In some studies, the same forecasting approach had been applied to multiple sectors, for example work conducted by the UK Commission for Employment and Skills.

Figure 6: Distribution of use cases by type



Source: Frontier Economics

Note: Studies are classified based on their primary use, noting this is likely a simplification of uses. For example, some studies are designed specifically with policy design in mind, whilst others simply identify the trend in skills (noting that this may be taken forward by others for separate purposes such as designing training programmes or workforce planning).

Skills forecast building blocks

Skills forecasts typically combine multiple methods to produce their output, for example a given forecast may combine a macroeconomic model, a skills taxonomy and expert interviews.

As outlined in sub-section Phase 3: Assessment of skills forecasting methods in Section 2, we found three stages (termed ‘building blocks’) that are typically required to build a forecast from start to finish. At each of these stages, developers have a choice of methods to use. This is illustrated under ‘Methods' in Figure 7, where the three building blocks are defined based on their purpose in producing a forecast, as observed in the studies we have reviewed. The three blocks, or the three purposes of the methods used in skills forecasting, are:

- Identifying the future trends in the economy or labour market;
- Linking these trends to employment outcomes;
- Linking trends, or employment outcomes, to skills.

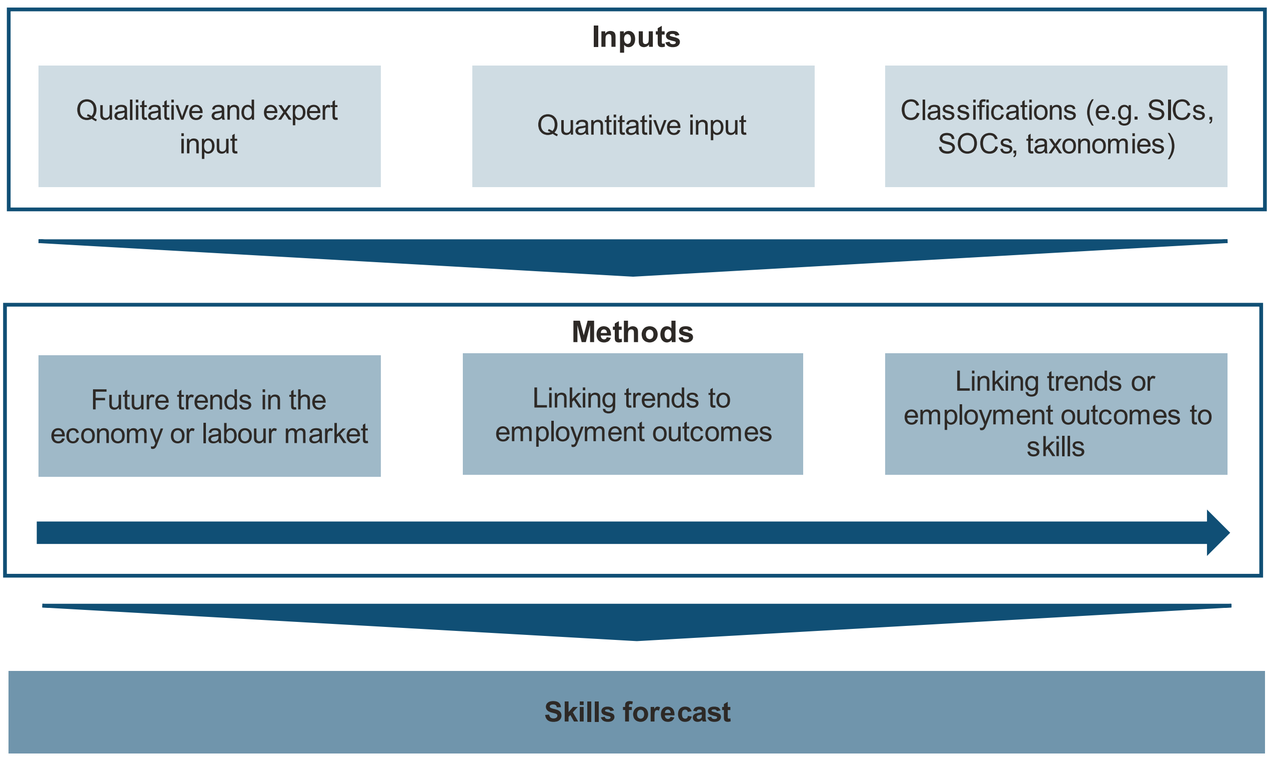
In the majority of studies reviewed, these three stages occur sequentially (as illustrated by the arrow in Figure 7). However, there were some exceptions and some forecasts that did not use every building block.[34] We discuss this in more detail in Section 5: Combining building blocks.

As well as the methodological building blocks, we found three high-level categories of the types of inputs that can go into building a skills forecast. These are:

- Qualitative and expert input;
- Quantitative input;
- Classifications, e.g. SICs, SOCs and taxonomies.

We discuss both methods and inputs in more detail in the following two sub-sections.

Figure 7: Skills forecast building blocks



Source: Frontier Economics

[34] One exception to the typical structure is foresighting, as used by the Workforce Foresighting Hub. Foresighting can be used to understand future trends in the economy, and these trends are linked directly to skills. This approach does not include the ‘Linking trends to employment outcomes’ building block. Unlike the typical approach, this approach is able to capture changes in skills required for a given occupation. Other studies we reviewed do not use every building block. For example, Canada’s 3 year employment projections does not link to skills.

Methods

We found three key stages of building a skills forecast, which in the majority of studies reviewed occur sequentially in the following order:

- **Identifying the future trends in the economy or labour market:** This involves forming a picture of what the future will look like, such as what will happen to economic growth, disruptive technology or demographic trends. An example of a way to form a view on future trends is to use external evidence, for example a forecast of future UK GDP growth, or government targets for offshore wind capacity. This step could also involve using qualitative input such as industry analysts.

  The output of this step will be a view (qualitative or quantitative) of one or more key trends, for example: the rate of population growth up to 2030; the pace of automation of key tasks in a given industry.

- **Linking these trends to employment outcomes:** After forming a view of future trends, the next step is to link these trends to what this means for outcomes in the labour market. These trends are typically linked to employment outcomes, by industry or occupation. Examples of methods used to make this link are time series projections, or by using a macroeconomic model.

  The output of this step will be a view (qualitative or quantitative) of future employment. This could be quantitative (X thousand jobs in occupation Y in region Z by 2030); or qualitative (employment in sector A will grow and employment in sector B will decline in the next 5-10 years).

- **Linking trends, or employment outcomes, to skills:** In order to generate a skills forecast, either trends or employment outcomes must be linked to skills. If a forecast of employment outcomes has been produced, this can be achieved by 'cross-walking' the employment classification with a skills classification (for example SOC codes to qualifications, or SOC codes to O*NET). This 'cross-walk' tends to be static, requiring the (sometimes limiting) assumption that the skills requirements within the employment classification used (for example within SOC codes) does not change over time. Alternatively, a dynamic mapping can be used, or a direct forecast of skills can be produced, which in some cases allows this assumption to be relaxed.

  The output of this step will be a view of future skills. This could be quantitative (e.g. an additional X thousand people with skills in Python will be needed by 2050); or qualitative (e.g. communication and leadership skills will become more important in sector A over the next 5-10 years).

Within each of these building blocks, studies use different methods to arrive at a view on future skills. The building blocks are then combined to make an overall forecast.

Taking the Working Futures forecast as an example:

- **Building block 1: Future trends in the economy or labour market:**

  Method used: Combination of (1) external data from sources like the ONS to define certain parameters such as population projections, (2) existing evidence to inform assumptions such as automation rates; and (3) expert judgement.

- **Building block 2: Linking trends to employment outcomes:**

  Method used: A macroeconomic model developed by Cambridge Econometrics, complemented with simple econometric methods to project forward historical patterns in occupational and qualification structure of employment within industries.

- **Building block 3: Linking employment outcomes to skills:**

  Method used: The macroeconomic model also produces qualification outcomes (an approximation of skills). Separately, additional work is being conducted to map UK SOC with US SOC based on O*NET data.

Inputs

Each building block can use multiple input types. We found three key types of inputs used to build a skills forecast:

- **Qualitative input:** For example, expert interviews about the future trajectory of the sector of interest. Qualitative inputs could be gathered in different ways, such as through focus groups or surveys.
- **Quantitative input:** For example, ONS-published UK historical labour market information, or Lightcast job vacancy data.
- **Classifications:** Of employment, occupations, or skills, for example SIC codes, SOC code, qualifications, O*NET.[35] These could be used to structure quantitative or qualitative inputs or outputs.

Taking the Skills Imperative 2035 as an example:

- **Qualitative inputs:** Expert judgement is used as an input into determining future trends, and in different scenarios (for example for the pace of technological change), but there is no formal process for including qualitative input (e.g. no formal workshop or panel process).

[35] In October 2023 DfE published a report detailing user needs for a UK standard skills classification and plans for its development and maintenance. [A Skills Classification for the UK (publishing.service.gov.uk)]

- **Quantitative inputs:** The main building blocks are all built on quantitative data, using all publicly available UK LMI data.
- **Classifications:** The forecast uses UK SOC and SIC codes, qualification levels and the O*NET skills taxonomy.

Methods used in the shortlisted case studies

Table 4 summarises the methods used by each of the shortlisted case studies, divided into the three building blocks. We provide an initial list here and a more detailed description of each method in Section 4. This list, and the examples provided in Section 4, are our best understanding of methods employed based on the information available.

Table 4: Categorisation of forecasts into methods by building block

Forecast	Approaches to future trends	Linking trends to employment outcomes	Linking trends or employment outcomes to skills
The Working Futures model	Judgements or external forecasts of economic trends	Macroeconomic and econometric models	Direct mapping + Macroeconomic models and econometric models (via qualifications)
Labour market and skills demand horizon scanning and future scenarios	Horizon scanning	No explicit link	Qualitative (high-level skill groupings)
Workforce Foresighting Hub - Emerging skills project	Foresighting	Qualitative (via role groups)	Qualitative and machine learning techniques (via competencies sets)
Canada's 3-year Employment Outlooks	Composite indicators	Time series analysis	No explicit link
The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills	Machine learning techniques	Other - *changes* in occupational employment	Machine learning techniques

Forecast	**Approaches to future trends**	**Linking trends to employment outcomes**	**Linking trends or employment outcomes to skills**
The Working Futures model	Judgements or external forecasts of economic trends	Macroeconomic and econometric models	Direct mapping + Macroeconomic models and econometric models (via qualifications)
Technology industry skills forecast based on AI-mined public data - Headai	Machine learning techniques	Time series analysis and projections	Machine learning techniques / Time series analysis and projections
Engineering skills needs - now and into the future	Projection of past trends	Time series analysis and projections	Machine learning techniques
NHS projections	Judgements and external forecasts	Time series analysis and projections	No explicit link
UK Skills Mismatch in 2030	Judgements and external forecasts	Macroeconomic and econometric models	Macroeconomic and econometric models (via McKinsey Global Institute classification of tasks)
CSN Industry Outlook - 2023-2027	Judgements and external forecasts	Macroeconomic and econometric models	Qualitative (survey)
US Employment Projections Programme	Judgements and external forecasts	Macroeconomic and econometric models	O*NET and other national taxonomies
UK Commission for Employment and Skills (UKCES) insights	External forecasts (Working Futures) and other judgements	External forecasts (Working Futures) + qualitative	External forecasts (Working Futures) + qualitative

Forecast	**Approaches to future trends**	**Linking trends to employment outcomes**	**Linking trends or employment outcomes to skills**
The Working Futures model	Judgements or external forecasts of economic trends	Macroeconomic and econometric models	Direct mapping + Macroeconomic models and econometric models (via qualifications)
Germany QuBe	Judgements and external forecasts	Macroeconomic and econometric models	Direct mapping (via qualifications) + Macroeconomic models
Cedefop	Judgements or external forecasts	Macroeconomic and econometric models	Direct mapping
Australia's National Skills Commission	Projection of past trends	Time series analysis and projections	Time series analysis (via qualifications)
Green Jobs Taskforce: Report to Government, Industry and the Skills sector	Judgements (workshops) or external forecasts	Qualitative (workshops)	Qualitative (via qualifications)
Skills Forecast Service and Quarterly Screen Skills Barometer	Judgements or external forecasts	Qualitative (survey and Delphi process)	Qualitative (survey)
Preparing for a changing workforce: A food and drink supply chain approach to skills	Judgements or external forecasts	Qualitative (survey)	Qualitative (survey)

Motivation for categorising methods

In our assessment we look at the types of methods identified in Table 4 under each building block. This allows us to:

- assess the strengths and limitations of methods instead of studies. For example, we assess the strengths and limitations of macroeconomic models as a tool in skills forecasting, relative to other methods, and not the performance of individual macroeconomic models;
- assess methods for a given purpose, e.g. the strengths and limitations of horizon scanning for the purpose of identifying future trends. Assessing a method which is used as only one element of building a skills forecast is more informative than attempting to assess the ability of a given method to produce an entire forecast.

This approach is better suited to meeting the aims of this research by producing an assessment of how methods are used (across different studies) to produce skills forecasts. This will support UFS in commissioning high quality projections to inform its own work. This approach to categorisation is also useful as we expect that different stakeholders may be engaged at different parts of the forecasting process: by assessing methods at each stage, this will support UFS in engaging with stakeholders at these different points and help users who work at a specific stage.

Section 4: Assessment of approaches to skills forecasting

In this section we describe the ways in which different methods are used to build skills forecasts, and provide an assessment of these methods, including their benefits to users, and their relative strengths and limitations.

Structure and scope of assessment

This section contains the following:

- A detailed assessment of the first two building blocks as outlined in Section 3: **(1) approach to future trends,** and **(2) linking trends to employment outcomes.** The assessment is structured as followed:
    - A comparison of methods within each building block, including: a 'red-amber-green' (RAG) assessment table summarising which methods produce the most relevant outputs depending on different user requirements; and a 'red-amber-green' (RAG) assessment table summarising the strengths and limitations of each method across our other four assessment criteria.
    - More detail on each individual method, covering: a description of each method and how it has been applied in the studies we have reviewed; a discussion of the method's strengths and limitations based on our five assessment criteria[36]; how performance might vary depending on the context and intended purpose; and an indication of what 'best practice' looks like based on the individual studies we have reviewed, supporting the summaries in the assessment tables.
- A discussion of **building block (3): linking trends/employment outcomes to skills**, describing: how this link is typically made in the studies reviewed; the strengths and limitations of different approaches; and describing the cases where classifications are used (such as an industry classification or skills taxonomy). An assessment of different classifications was outside the scope of this study. We discuss recent research detailing user needs for a UK standard skills classification and plans for its development and maintenance (DfE, 2023).[37]
- A discussion of the different ways to include **qualitative inputs** (e.g. surveys, expert groups). We discuss qualitative inputs separately as these can be used to inform each building block and complement quantitative input but cannot be assessed as 'methods' under the framework we use for building blocks 1 and 2.

[36] Relevance, accuracy, versatility, data availability requirements, available resources and ease of use.
[37] A Skills Classification for the UK (publishing.service.gov.uk)

- A discussion of **reconciliation**, which covers ways to combine and align economy-wide with segment-level forecasts, including motivations for doing this and the challenges found across the instances of reconciliation in the studies reviewed.

The assessment covers the methods used in the 18 shortlisted studies listed in Table 4, and is based on our detailed desk review plus 22 interviews with commissioners, users and developers. Where relevant we include specific quotes drawn from our interviews. As discussed in Section 3, we assess methods and not individual studies, although we provide examples throughout this section.

Building block 1 – Approaches to future trends

Future trends can drive changes in employment or skills. Demand for labour is a derived demand[38] and is guided by key developments in the economy and the technologies used to produce goods and services. Therefore, any forward-looking exercise to assess future skills needs should start by understanding the key trends governing the economy, its driving forces and how they interact with each other in different contexts.

> To understand what is happening in the labour market you should understand first what is happening in the economy… unless they [the skill projections] are rooted in some reality it can become very woolly.
> – *Developer*

This building block involves taking a view on how wider trends will develop in the future. Trends could include: economic growth; demographic change; globalisation; the legal and policy landscape; industry growth; industry-specific factors (e.g. green transition, technological change, major infrastructure projects); as well as events such as the UK's exit from the European Union and the Covid-19 pandemic. Some of these trends might be more stable and/or persistent, for example economic and demographic trends, while others are more uncertain, such as understanding the impact of technology on future jobs. Additionally, some trends such as the transition to Net Zero might be more relevant for some sectors than others.

Predicting trends precisely is challenging and there will always be a degree of uncertainty around them. Nonetheless, these trends are important for the forecast to provide a realistic picture of how employment or skills are likely to change over a given time period.

The 'output' of this building block is to provide qualitative and/or quantitative insights on how wider factors are changing over time based on historical information and possible

[38] Derived demand means that the demand for labour comes from the demand for the good or service that the labour produces.

future developments. These insights can then be used in the second building block to assess their effect on employment outcomes; and/or in the third building block to assess their effect on skills.

We found six types of methods used to understand future trends across the studies reviewed:

- Judgements or external forecasts of economic trends;
- Horizon scanning;
- Foresighting;
- Composite indicators;
- Machine learning techniques;
- Projection of past trends.

The following two tables present a summary of the strengths and limitations of each of these methods across our five assessment criteria. (For detail on the definition of each criterion, see Section: Assessment criteria).

Table 5 considers the 'relevance' criterion for each of the four representative user types that we identified during scoping. (For detail on the definition of each representative user type, see Section: Assessment criteria). Table 6 assesses each method across the other four assessment criteria.

In the sections following the Tables we describe each method and provide more detail to support our summary assessments.

Table 5: Building block 1 – Approaches to future trends - relevance assessment

Method	Central planner	Local user	IFATE	Workforce planning
Judgements or external forecasts of economic trends	Green – Can be aligned with central government (or other relevant) forecasts.	Amber – Use of local forecasts or trends is possible but depends on availability/quality of local forecasts which aren't always there.	Amber – Use of granular, qualification trends is possible, but depends on availability/quality of local forecasts which aren't always there.	Amber – Use of detailed/specific sector information is possible but depends on availability/quality of local forecasts which aren't always there.
Horizon scanning	Green – Targeted at understanding the implications of broad policies. Key limitation is that the probability of each scenario is not known.	Amber – Current applications do not provide detail at a regional level. Potentially could be applied regionally in the future but would need an application to confirm feasibility.	Red – Provides high level information, rather than detailed granular information. More useful for looking over a longer time horizon.	Amber - Likely not granular enough to support specific workforce planning but helps to understand how needs might be affected by policy.
Foresighting	Amber – Useful to understand needs for key goals, e.g. different challenges for government departments. Common language allows comparison across different sectors. However, does not provide an understanding of broader changes in the job market and limited reconcilability with other forecasts.	Amber – Current applications do not provide detail at a regional level. Potentially could be applied regionally in the future but would need an application to confirm feasibility.	Green – The forecasts of competencies can be mapped to IFATE qualifications and can be used to understand gaps in qualification standards (see Building block 3).	Green – Focuses on specific sectors and their value chains. Used to support workforce planning and training: understand the skills need and therefore training needs for workers. Engages with industry and so designed to be useful for their purpose.

Method	Central planner	Local user	IFATE	Workforce planning
Judgements or external forecasts of economic trends	Green – Can be aligned with central government (or other relevant) forecasts.	Amber – Use of local forecasts or trends is possible but depends on availability/quality of local forecasts which aren't always there.	Amber – Use of granular, qualification trends is possible, but depends on availability/quality of local forecasts which aren't always there.	Amber – Use of detailed/specific sector information is possible but depends on availability/quality of local forecasts which aren't always there.
Composite indicators	Red – Limitations of this approach (see second RAG assessment against other criteria) mean that this has less use for a central planner, where more data is typically available and so other methods can be applied.	Amber – Could be useful where there is limited data availability in local regions.	Amber – Could be useful where there is limited data availability at the granular level needed for other methods.	Amber – Could be useful for sectors with limited resource and data availability.
Machine learning techniques	Green - Machine learning techniques can be applied in any way to suit any given audience.	Green - Machine learning techniques can be applied in any way to suit any given audience.	Green - Machine learning techniques can be applied in any way to suit any given audience.	Green - Machine learning techniques can be applied in any way to suit any given audience.
Projections of past trends	Amber – A role for past trends in some forecasts but should be supplemented with other methods where past trends are less helpful (e.g. considering technology trends).	Amber – Local trends could be used, useful where data availability might limit other options.	Amber – Shorter time scale makes this application more useful. However, not accounting for changes in the labour force limits usefulness.	Amber – Sector specific trends could be used, useful where data availability might limit other options. More relevant for some industries than others (e.g. stable industries compared to novel/innovative industries).

Table 6: Building block 1 – Approaches to future trends - other criteria assessment

Method	Accuracy	Versatility	Data requirements	Resources and ease of use
Judgements or external forecasts of economic trends	Amber - Assumptions may reduce internal validity, depends on the judgements used.	Amber - Varying degrees to which this will capture external factors - depends on the method use. Scenarios are not a central feature.	Green - Typically low data requirements, depends on the judgement used.	Green - Typically low resource requirements, depends on how judgements are gathered.
Horizon scanning	Amber - A structured approach increases accuracy and trust in method. However, accuracy depends on the quality of qualitative evidence.	Green - Explicitly accounts for future changes (e.g. technology, ageing). Developing appropriate scenarios forms the basis of the model.	Amber - Requires significant qualitative input and evidence review.	Amber - Specialist software used to undertake qualitative engagement. However, results focus on high level implications and are easy to engage with.
Foresighting	Amber - A structured approach increases accuracy and trust in method. However, accuracy depends on the quality of qualitative evidence.	Green - Approach places a heavy focus on accounting for technology changes. Scenarios not necessarily required due to short time frame.	Amber - Requires intensive engagement with industry. No external data so no risks of data availability in the future.	Amber - Proprietary AI model: high resource requirement to develop and difficult for users to understand what drives results. However, results are easy to engage with.
Composite indicators	Red – Captures more detail than using only one figure, but simplistic and unlikely to capture all effects. Particularly limited if it fails to look at forward looking measures.	Red – In theory, could account for future changes (e.g. including indicators for future changes), but no examples found in practice, suggesting limitations in producing. Scenarios can only be developed in a simplistic way.	Amber – Depends on the indicators used: can be built with publicly available data or a larger amount of data. Trade-off with accuracy and versatility.	Green – Easy to understand and typically requires less technical resources than other methods.

Method	Accuracy	Versatility	Data requirements	Resources and ease of use
Judgements or external forecasts of economic trends	Amber - Assumptions may reduce internal validity, depends on the judgements used.	Amber - Varying degrees to which this will capture external factors - depends on the method use. Scenarios are not a central feature.	Green - Typically low data requirements, depends on the judgement used.	Green - Typically low resource requirements, depends on how judgements are gathered.
Machine learning techniques	Amber - A structured approach to bring in novel data. However, results likely depend on assumptions underlying the model and are highly 'black box'.	Green - Significant scope to capture technology and to incorporate scenarios.	Red – Typically high data requirements. The size and ease of accessing inputs vary by the method (e.g. limitations on webscraping).	Red - High resource requirement to develop, typically outsourced. Difficult to explain the drivers of changes to users.
Projections of past trends	Red – Results hinge on a very strong assumption i.e. that the future conditions will follow historical trends.	Red – Does not account for changes, assumes part trends will continue. Scenarios can only be built in a simplistic way.	Amber – Depends on trends projected (e.g. Lightcast use proprietary data). Trade-off with accuracy.	Green - Simpler to implement than other methods. Easy for users to understand the drivers of changes.

Judgements or external forecasts of economic trends

Description of the method

There are several different ways that external forecasts or judgements can feed into forecasts. These include:

- Economic growth or demographic trends used as inputs, for example into macroeconomic models (e.g., Working Futures uses population projections);
- Assumptions or expert insight into labour market trends such as automation (e.g. ‘UK Skills Mismatch in 2030’) or the impact of Brexit/Covid-19;
- Industry or regional growth forecasts based on sectoral/regional variables or project-based information (e.g., CSN Industry Outlook, Green Jobs Delivery Group);
- Targets, typically defined by government, implying an industry growth trajectory, such as Net Zero or targets for offshore wind capacities (e.g., Workforce Foresighting Hub, Green Jobs Delivery Group).

Box 1. Case study – The inputs used for Working Futures

The macroeconomic model (MDM-E3) used for Working Futures relies on a number of exogenous inputs to help form a view about future trends. These include:

- population projections by region;
- government spending and taxes;
- economic conditions in the rest of the world, including GDP growth rates;
- global fossil fuel and commodity prices, and;
- the availability of UK natural resources (e.g. coal, oil and gas) for extraction

Box 2. Case study - UK Skills Mismatch in 2030

The study was produced for the Industrial Strategy Council to understand which qualifications, knowledge and workplace skills are likely to face mismatch by 2030 due to the changing nature of work. The 'changing nature of work' was determined by considering trends in the economy.

Key trend – Automation

Assessing the impact of automation is based on a McKinsey Global Institute (MGI) method used for other papers. The five stages for assessing the potential for automation by 2030 are: (1) technical feasibility, (2) cost of developing and deploying solutions, (3) labour market dynamics, (4) economic benefits and (5) regulatory and social acceptance. The framework is informed by academic research, internal expertise and industry experts.

Other trends

Other trends are captured by a simple variable, for example the ageing population is captured as the share of the population and the number of health care professions per 1,000 people. Each variable comes from a reliable public source.

The trends considered are: the automation of tasks; rising incomes and consumer spending; the ageing population; the development and deployment of new technology; infrastructure investment; residential and commercial buildings; and the energy transition and efficiency. Trends were selected from a shortlist based on the magnitude of their impact on jobs.

Assessment of the method

We do not assess the methods used to produce the external forecasts themselves, but instead discuss the advantages and disadvantages of applying external forecasts to understand future trends in the economy. This method is only as good as the forecast used and developers need to take care that they select appropriate, reliable forecasts.

Assessment summary:

Strengths:

- Easy to understand and transparent method, as long as the inputs are clearly justified and/or based on a solid body of separate and available research.
- Does not require extensive data series.
- Can be easily tailored to users' needs and intended purpose of the forecast.

Weaknesses:

- Method is only as good as the external judgement or forecasts used.
- Might be resource intensive depending on the depth of research, especially if it involves stakeholder engagement.

Applicability:

- Can be applied in contexts of high data or resource constraints.
- More suitable in cases where reliable and well-known external sources are available to mitigate bias and enhance trust in outputs.

This method has broad applicability for different users because it can be tailored to the forecast's intended purpose, for example by using sector-specific inputs. Recent work led by the Green Jobs Delivery Group gathered evidence from each green sector,[39] relying on industry-led modelling of workforce planning based on current and future green projects. This information is then liaised with all actors across the supply chain. Local inputs, such as sectoral growth by region, can also provide local users with the region-specific information they need to inform their own analysis. For 'central planner' users, using macroeconomic forecasts with a degree of consensus behind them, such as Office for Budget Responsibility (OBR) economic growth projections, can help to align results for comparability with other forecasts, either produced by other bodies within the government (e.g. Bank of England, Treasury) or by external organisations (e.g., proprietary models), and with government policies.

The particular external forecast or judgement used is also important when considering accuracy and versatility. Even if these inputs form part of an existent body of research or available forecasts, it is best practice to assess their internal and external validity, and their applicability to purposes. In particular, it is important for developers to be aware of

[39] The 7 green sectors considered are: power, business and industry, homes and building, transport, natural resources, enabling decarbonisation, and climate adaptation.

any assumptions underpinning the external forecast or judgement and report on these in a way that is accessible to users when presenting their forecast results.

Users' trust in a forecast that relies on judgements and external trends will be limited by the extent to which it is possible to validate the inputs used. This may be a challenge in cases where the existing body of evidence is limited, which may be more common for some sectoral forecasts than for economy-wide analysis. In the case that additional primary evidence gathering is necessary, this can be resource intensive. For example, as part of the 'UK's Horizon Scanning' study, an extensive evidence review was conducted to identify global and local drivers of change for the next 15 to 20 years and assess how relevant these drivers were for the UK's labour market and the demand for skills. This review included more than 130 sources.

In terms of validity, most of the economy-wide studies reviewed relied on commonly used sources (e.g., ONS, U.S. Bureau of Labor Statistics, OECD, HM Treasury, IMF), to mitigate bias and improve trust in their outputs. For example, Working Futures (see Box 1) applies a set of assumptions regarding the investment in the energy and water industries (i.e., global coal, oil and gas prices based on information provided by the IMF). Others might build on existing evidence already produced for other purposes as in the case of the 'UK Skill Mismatch in 2030' produced by McKinsey which relies on previous research.

For segment-level studies, the appropriate external forecast or judgement will vary by sector. For some sectors, economic growth may be a good proxy for segment growth. However, this will not be relevant for many sectors, particularly smaller or newer sectors, those which are subject to rapid and unpredictable change, or are dependent on the Government direction of travel. A key example of this is sectors involved in the transition to Net Zero, such as wind power: many of these sectors are likely new, involve novel technologies that are changing rapidly and will be heavily dependent on Government direction of travel.

Judgements of external forecasts differ in their ability to account for technology or other trends. Using trends such as economic or demographic growth will not be able to factor in technological changes. In some cases, accounting for trends will require separate exercises, such as the approach used in the UK Skills Mismatch report (discussed in Box 2).

The data requirements are typically low, as forecasts tend to use only a few data points (e.g. annual economic growth for each year of the forecast) rather than large amounts of granular data.[40]

[40] We note that a high volume of data is often involved in producing the external forecast itself, for example OBR's data requirements to produce forecasts of economic growth and public finances. However this data would not be required by the skills forecast commissioner/developer/user who uses the published forecasts as part of understanding impacts on employment or skills.

Technical resource requirements are similarly low (e.g. no econometric knowledge is required), although time resource may be high depending on the depth of research used to form a judgement (for example, if this involves significant amounts of stakeholder engagement). A well-researched judgement allows for a more accurate or tailored input.

In summary, using judgements or external forecasts is a simple, easy to understand and transparent method, as long as the inputs are clearly justified and/or based on a solid body of separate and available research (i.e., existing planning and strategic documents, international evidence from similar countries or a well-established forecast).

Horizon scanning

Description of the method

Horizon scanning in the context of forecasting future skills refers to the systematic qualitative process of identifying, monitoring, and analysing emerging trends, technologies, and changes in the external environment that may impact the demand for specific skills in the future. It involves looking ahead to anticipate shifts in the labour market, industries, and technological landscape, with the goal of assessing scenarios and inform workforce planning, education, and training strategies.

The 'UK's Horizon Scanning' study, commissioned by DfE, was produced as a complement to Working Futures as it was recognised that even though quantitative assessments provide an important starting point to better understand the occupations required in the near future, they are also subject to a number of limitations including their inability to incorporate disruptive events.[41]

The study uses a software-based qualitative scenario development approach (see Box 3), where a structured methodology with prescribed steps is applied to 'scan the horizon' of the labour market in the UK over the next 15 to 20 years by identifying key drivers and emerging trends and defining labour market scenarios.

[41] Although there are other unprecedented events that horizon scanning could not have predicted as well, such as the Ukraine war and the cost of living crisis.

Box 3. Case study - UK's Horizon scanning

The objective of this study was to scan the horizon of the labour market over the next 15 to 20 years to identify the drivers and emerging trends. Five scenarios of what the labour market might look like in the future were defined: (1) digital greening, (2) living locally, (3) protectionist slowdown, (4) continued disparity, and (5) generating generalists.

A systematic framework developed by Gausemeier et al (1998) was used which involves a structured 6-step process:

1. Identification of factors – Use of a literature review to identify key factors which would affect the labour market in each area of the PESTLE (political, economic, sociological, technological, legal and environmental) framework. The review included 130 sources focused on six specific sectors (construction, wholesale and retail, higher education, transport and logistics, health and social care and energy). This was supported by broader labour market expertise and previous scenario studies of socio-economic, demographic, environmental and technological developments.
2. Cross-impact analysis – Determine factors that are interlinked, important and uncertain. Experts were asked to qualitatively score the relationship between factor pairings. These scores were used to reduce the longlist of factors to a final shortlist.
3. Future projections – Produce future projections for each factor based on desk research and discussion with experts e.g. for 'trade' (key factor), potential projections are: 'international trade with EU as main trading partner'; 'international trade (share with EU declines)'; 'reduced international trade'.
4. Consistency analysis – Ensure that pairs of projections could plausibly occur in the future. Projections can be refined and highly correlated factors can be combined.
5. Cluster analysis – Use the ScMI software to generate clusters using the scoring from the consistency analysis.
6. Scenario narratives – Build narratives around the projection for each scenario.

The process was completed with a scenario workshop to validate the scenarios developed.

Assessment of the method

Assessment summary:

Strengths:

- Incorporates the analysis of broader trends and disruptive events that cannot be captured easily by standard quantitative methods.
- Highly versatile and transparent method that can be used in different contexts at any level of disaggregation.
- Does not require extensive data series.

Weaknesses:

- Relies heavily on experts' judgments and opinions, accuracy depends on quality of qualitative evidence.
- Might need specialised software.

Application:

- More suitable for assessing long-term trends and for users who are more interested in directions of travel rather than point estimates.

Using a combination of quantitative and qualitative assessments can improve the quality of skills projections by ensuring that the limitations of one type of analysis are balanced by the strengths of the other. This ensures a comprehensive understanding of the future of the labour market and skill needs under different scenarios grounded on a solid economic foundation.

> Bringing this kind of more qualitative piece of work with a more heavy econometrics modelling for robust decision making is an interesting and potentially meaningful piece of work for policy makers to take more robust decisions. – *Developer*

> Scenario planning is more suitable the further out you are looking at, while more quantitative models are a bit better for shorter term stuff, because uncertainty is lower. – *Developer*

In terms of its relevance, horizon scanning is particularly useful for users who are more interested in directions of travel rather than point estimates. For example, central planners may be interested to see how the workforce is likely to develop under certain policies, helping them to plan accordingly. It can also be used and adapted for policy stress-testing which allows an assessment of how different policies would perform under each scenario, or for ‘back-casting’ to identify which factors are more influential in adverse scenarios.

> The further you look into the future, the more you should be thinking about a range of plausible futures and preparing a range of scenarios rather than attempting to aim at one definite answer of what will happen. – *Developer*

Whilst the UK’s Horizon Scanning produces UK-level results, this technique can also be applied to specific regions or sectors to provide a more granular view which would aid both policymaking and policy evaluation at these levels.

A potential drawback of this method is that it does not provide details on the likelihood of each scenario and so it is less useful for decision making at the micro-scale. Whilst it can help a central planner determine large scale policies, it is less helpful for users who have to take these large-scale policies as given, for example workforce planners, as they do not know which scenario we may end up in.

In general, the method performs well against accuracy and ease of use (specifically transparency) requirements and is an example of best practice in this area, because the documentation clearly explains the process that was followed and its limitations. The scenarios are well explained and detail is provided on the process for selecting and engaging with experts. It also performs well in producing a narrative which is easy for users to understand, drawing out the key implications for the economy and for specific sectors.

In terms of accuracy, the structured approach to scenario building follows a well-known prescribed process with specific steps design to generate robust results. In each step experts are involved to validate assumptions and results, and the process is iterative. This is a more structured framework than the more generic scenario modelling and is particularly relevant to analyse complex situations.

This structured approach was designed to mitigate some of the limitations of qualitative techniques, but it comes at the expense of relatively high data and resource inputs as it requires the review of multiple sources and qualitative inputs from interviews and workshops. In particular, the method can produce a long list of key factors that need to be prioritised and narrowed down as it can produce inconsistent results and make the scenario analysis intractable. Nevertheless, the method can be easily updated when new data or evidence becomes available.

However, as with any method rooted in qualitative techniques, the accuracy of the horizon scanning method depend on the number of interviews and workshops, and the specific experts and stakeholders consulted which might not be representative of all interest groups. This is because the method relies heavily on expert knowledge and judgements, as well as policymakers and scenario specialists. Therefore, there is a risk that not all relevant perspectives are captured or that some might be speculative. At a minimum, providing a framework for how the stakeholders were selected provides more confidence in the outputs produced.

Compared to other assessments, horizon scanning is a highly versatile method because scenarios and changes in future trends linked to developments in technology and policy form the foundation of the model. These methods can also be adapted as needed on a more targeted basis in response to emerging trends or events.

The resource requirement of producing horizon scanning scenarios and updating them (e.g., the burden of a developer replicating this method using different assumptions) would be reduced if there was more publicly available information, such as a repository with a list of factors and relationships between variables.

> You can have an ongoing horizon scanning function constantly looking for different signals of change on a daily, weekly or monthly basis, which then you can assess to identify new trends and factors that are more important now than before. - *Developer*

A potential limitation of this method is that it relies on a specialised software for scenario management (i.e., Scenario Management International) which enables the development of scenarios by analysing all mathematically possible pairs of factors and eliminates those ones that are deemed inconsistent under each scenario. Therefore, to implement this method a basic knowledge of this software is needed.

Foresighting

Description of the method

Foresighting is a systematic qualitative approach aimed at understanding, anticipating and planning for the future needs of the workforce.[42] It goes beyond traditional workforce planning by incorporating a forward-looking perspective. It typically involves analysing current and emerging trends, identifying potential challenges and opportunities and developing strategies to ensure that the workforce has the right skills to meet future demands.

A recent development in the UK skills forecasting landscape is the ‘Workforce Foresighting Hub’, funded and developed by Innovate UK which builds on the work from the Emerging Skills Project. This uses a ‘challenge-based’ approach, where a challenge is defined for a specific sector based on government goals (e.g., ‘widespread adoption of batteries as the power source of the future in the automotive manufacturing supply chain’, ‘industrial digitalisation in aerospace manufacturing and maintenance’). Their

[42] Cedefop (2016) Developing skills foresights, scenarios and forecasts. A guide to anticipating and matching skills and jobs. Volume 2.

main objective is to prepare the education and training system in the UK to meet the skills demand of the future.

> The aim of getting the right skills, at the right time, in the right place.... we need to start now, not when the skill is needed. – *Developer*

> We're looking to the future and then look back rather than start from where we are and see how they [skill needs] might develop because what actually happens is there's quite a lot of new occupations appear in the future that we wouldn't be able to identify unless we started there rather than today. - *Developer*

Expert views are gathered from stakeholders including technologists, employers, educators, centres of innovation and government. Proprietary AI[43] is used to combine these expert views to understand future challenges for businesses and their supply chains. This process is described in more detail in Box 4.

In this section, we focus on assessing the 'future trends' stage of foresighting (i.e., gathering views from experts on trends, drivers and challenges and combining into a single view). In Section 4: Building block 3 - Linking trends or employment outcomes to skills, we separately discuss using the foresighting approach to analyse future skills.

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[43] For the semantic analysis of the qualitative evidence produced by expert groups.

Box 4. Case study - Emerging Skills Workforce Foresighting Hub

Foresighting involves asking four questions:

1. ‘What are the workforce trends and drivers and what are the industry challenges related to the emerging technology area?’
2. ‘What capabilities are needed by organisations to successfully address these challenges in the future?’
3. ‘Which capabilities are priority? How should the future capabilities be aligned with current and new roles?’
4. ‘What Knowledge, Skills and Behaviours (KSBs) does the workforce need to enable organisational capability in the future?’

Three expert groups are engaged in this process: (1) specialist technologists, who identify technology priorities and future trends; (2) expert educators, who identify the educational priorities from these technology technologies; and (3) expert employers, who verify the outputs are fit-for-purpose across the industry. Experts are engaged via a ‘lead’ from each group, who can identify and influence members of the group.

To date, the foresighting method has been applied to eight areas: three related to industrial digitalisation (aerospace manufacturing and maintenance, simulation and modelling, and data analysis and machine learning); electrification; battery manufacturing; power electronics; motors and drivers; and vehicle systems and vehicle software.

As an example, the following challenges were identified for industrial digitalisation in aerospace (by specialist technologists from the Aerospace Technology Institute and the Advanced Manufacturing Research Centre):

1. Using digital twins for modelling product and manufacturing.
2. Deploying automated and agile manufacturing.
3. Increased use of integrated systems for collection, analysis and presentation of large datasets.
4. Integrating digital and physical systems to support rapid design, test, fail and improve cycles.

Assessment of the method

Assessment summary:

Strengths:

- Switches the conversation from megatrends affecting the whole economy to targeted challenges for specific sectors and their value chains.
- Can be applied to bespoke and/or detailed sectors that may not be captured in standard industry or occupational classifications (also potentially to local areas).
- Does not require extensive data series.
- Incorporates different perspectives and fosters collaboration.

Weaknesses:

- Does not produce quantitative estimates, but directions of travel.
- Relies heavily on experts' judgements, accuracy depends on quality of qualitative evidence.
- Focus on emerging technologies: might be less appropriate for established sectors.
- Resource intensive, requires analysing high volumes of qualitative data.
- AI techniques to synthesise expert views can be non-transparent, difficult to understand drivers of overall results.

Applicability:

- Well-suited for segment-level users that prioritise strategic and workforce planning in emerging sectors and need to identify future challenges.
- Suitability depends on available resources i.e. to engage experts and gather a sufficient range of views and employ AI techniques.

By using specific challenges tailored to the sector rather than 'megatrends' relating to the economy as a whole, foresighting can identify very specific directions of travel for individual sectors. Because the method incorporates insights from industry partners in a systematic way, it is designed for their specific purposes and needs.

Currently foresighting is less useful for regional or local stakeholders as it does not provide results at these levels, although theoretically the challenge approach could be applied at any geographical level. As with any national projection, regional and local actors can also combine the forecasts produced by the Workforce Foresighting Hub with other sources of information to understand the skills needed based on the relative importance of sectors and their supply chain in their jurisdictions.

A limitation of this method for a central planner – related to its versatility – is that it does not explicitly consider broader trends affecting the job market and the future demand of skills, apart from key developments in technology innovation. It also has a shorter time frame than some other methods, such as horizon scanning, considering around the next 18 months to five years depending on the sector and development cycle.

> Typically between 18 months and five years because there's a near horizon which is not determined by demand actually, but by how long it would take to change things to meet the demand. – *Developer*

As in the case of horizon scanning, the challenge approach implemented as part of the foresighting method relies upon the appropriate selection of expert groups at each stage of the process which impacts its accuracy. The use of three expert groups (employers, technologists[44] and educators) alongside AI techniques contributes to the accuracy of these forecasts by combining the best state of current knowledge in a structured way.

However, the use of AI techniques makes it difficult for users to understand what drives the results – the process involves collecting a significant amount of qualitative data and so stakeholders would unlikely be able to synthesise all this information to understand which expert views have driven the findings.

In terms of versality, the method explicitly accounts for technology by talking to key stakeholders who are specialists in the emerging technologies associated with the challenge. Experts are selected via the 'lead' in each group and the intention is to select experts with an explicit interest in future technology, not just current technology. This ensures that future technology can be incorporated into the method, improving its performance against our versatility criteria.

Similar to horizon scanning, foresighting's benefits in versatility and accuracy come at the cost of high data and resource requirements. Extensive qualitative engagement alongside a proprietary AI model is used. On the other hand, since the method does not rely on external data, there is no risk of it not being able to be reproduced or updated in the future.

Composite indicators

Description of the method

This method involves combining different indicators to summarise generally complex or multi-dimensional issues or phenomena. Composite indicators are usually based on the aggregation of sub-indicators – which can be based on current data or future (external)

[44] Only technologists are reached out to understand future trends.

projections – that have no common meaningful unit of measurement and there is no obvious way of weighting their relative importance. In the skills forecast landscape, it mainly allows judgements and comparisons to be made based on the rankings of occupations, although it can also be applied to skills.

The Canadian ESDC – 3 year's composite indicator (discussed in Box 5 below) uses forward looking measures, but other studies identified in our longlist typically also include only static measures. For example, the OECD's 'Skills for Jobs Indicator' builds a composite indicator to assess occupational imbalances (at the 2-digit ISCO level) uses various labour market indicators (i.e., median wage growth, employment growth, average weekly hours worked, change in employment rate, and change in under-qualification rate). The selection of indicators is grounded in economic theory as they represent quantitative signals of labour pressure.[45]

Another example is the approach applied by the Migration Advisory Committee (MAC), which ranks occupations by nine shortage indicators from multiple sources combined with qualitative evidence from stakeholders through an online questionnaire. The aim of this analysis is to identify where employers find it problematic to secure an adequate number of workers. Shortage indicators are also selected based on economic theory – related to common symptoms of shortage – and are related to wages, vacancies and employment.

[45] OECD (2017) Getting Skills Right: Skills for Jobs Indicators

Box 5. Case study - Canada Employment Outlook (ESDC): Composite indicator of recent and future labour market conditions

Canadian 3-year Employment Outlook (ESDC – 3 year) uses a composite indicator to assess whether the employment outlook for a given occupation (4-digit) within a specific providence or economic region, is ‘good, fair or limited’. The timeframe was chosen to avoid overlapping economic cycles and to complement the 10-year Canadian Occupational Projection System (COPS).

The ESDC – 3 year’s composite indicator is built from **three sub-indicators** which are calculated for more than 500 occupations based on the Canadian National Occupational Classification (NOC) by providence, territory and economic region – it is not calculated at the national level.

These three sub-indicators are:

1. Forecasted employment growth rates
2. Forecasted replacement needs rate
3. An index capturing the number of experienced unemployed workers at the beginning of the forecast period.

Each of these indicators (as well as a composite indicator of all three) is given a rank of 1 to 6 (where 1 is the jobs with the best employment outlook) by assessing the historical data over the last 10 years, and these ranks are summed together to give an overall rank, which is validated with experts and provincial and regional stakeholders, as well as alternative quantitative and qualitative data sources. The outcome of this exercise is a set of trend statements for each occupation which are then used, amongst other applications, to inform a job outlooks platform.

Assessment of the method

Assessment summary:

Strengths:

- Simple method to develop, can summarise multi-dimensional and complex phenomena.
- Typically has lower resource and data requirements and is easy for users to engage with.
- Can be adapted to differing degrees of complexity.

Weaknesses:

- Simplistic representation of a complex reality and should be used as a starting point for further analysis and interpretation.
- Depends heavily on the type of indicators used, and the aggregations and weighting techniques used to build the composite index.

Applicability:

- Method can be applied in contexts of high data or resource constraints, provided selection of indicators is grounded in economic theory.

This method is typically simple to develop and understand compared to other methods, such as machine learning, horizon scanning or foresighting. As a result, it usually has lower resource and data requirements and is easier for users to engage with. Moreover, using a composite indicator to assess complex phenomena like future skills needs is likely to improve validity as compared to using a single indicator. The method can be adapted to differing degrees of complexity, allowing developers to increase the accuracy of the method by capturing different factors. For example, the ESDC – 3 year's method is better able to capture forward looking trends compared to methods which only use static measures.

Composite indicator methods are typically less versatile, (i.e. it can be more challenging to take account of different possible future scenarios or trends). Whilst it is theoretically possible for composite indicators to include metrics to capture specific external factors, for example to measure technology changes, we did not find any examples of this being applied in the studies reviewed. Nevertheless, it is likely difficult to use a single metric to capture complex external factors in this way.

Another potential limitation of this method is that it might send simplistic or misleading policy messages if it is used in isolation without considerations of the context or combining them with other sources of evidence (e.g., it might ignore dimensions that are not measurable). The value of the composite index may depend heavily on data normalisation and weighted methods that are not necessarily easy to interpret.

Finally, this method requires a theorical framework to select a meaningful set of indicators and to combine and weight them in way that reflect the dimensions that underpin future trends in the labour market. Any inter-relationship between indicators should be considered to eliminate highly correlated indicators. However, it is also important for developers to balance the desire to capture additional factors with other considerations. Adding more metrics turns a fairly simple, transparent method into a confusing one. This method is inevitability simplistic and so there is little to be gained from adding endless metrics which will not be able to capture details.

Machine learning techniques

Description of the method

Machine learning techniques (e.g., predictive modelling, natural language processing, deep learning, anomaly detection, clustering and classification) can be applied to skills forecasting by leveraging large volumes of data (usually structured or unstructured textual data) to identify patterns and predict future trends. Some examples we have identified are:

- The PwC's 'Potential Impact of Artificial Intelligence on UK Employment and Demand for Skills' (hereby 'PwC Impact of AI') report (discussed in Box 6) uses a propriety machine learning-based model to incorporate experts' predictions about the automation probability of a selected group of 70 occupations collected as part of workshops. Experts were asked to label tasks within occupations as 'automatable' or 'not automatable' within each occupation. This information was then projected onto all occupations using a machine learning technique (a random forest classification model) that links occupations based on the similarity of their task composition. A similar approach was applied by Nesta and Pearson's 'The future of Skills: Employment in 2030' report[46] and by Nesta and Brookfield Institute's 'Employment in 2030' for the Canadian context.[47]
- Similarly, the 'Workforce Foresighting Hub' study discussed above incorporates expert views using machine learning models to process a high-volume of qualitative evidence produced by experts groups and identify trends.
- Headai uses natural language processing of external data (both qualitative and quantitative, such as investment data, vacancy data and government policy reports) to get a picture of how employment skills needs will develop overtime.

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[46] https://www.nesta.org.uk/report/the-future-of-skills-employment-in-2030/?gad_source=1&gclid=EAIaIQobChMIrKuO5IjOhAMVj5JQBh0XLQTMEAAYASAAEgISifD_BwE
[47] https://brookfieldinstitute.ca/employment-in-2030/

- Some nowcasting[48] methodologies use machine learning techniques, such as the Australian NERO – Nowcast of Employment by Region and Occupation and Bank of England's 'Using online job vacancies to understand the UK labour market from the bottom-up' study.

Box 6. Case study - The Impact of AI: job displacement analysis

PwC's Impact of AI report uses machine learning to understand the impact of AI on job displacement across industries (SIC2) and occupations (SOC4). A high-level overview of the process is:

1. An expert workshop was used to label 70 US SOC occupations as 'automatable' or not. This provided the initial set of data labels that the machine learning model could be 'trained on'.
2. A random forest classification model was used to estimate the probability of an individual in the PIAAC* survey being automated, with this model fitted on the 70 occupations labelled by experts in the workshop. The probability is based variables such as: educational job requirements, percent time reading books, percent of time planning activities of others and percent of time spent presenting.
3. The individual level probabilities were aggregated up to occupation and industry level, weighting individuals based on the UK labour force.
4. Estimates were then crosswalked to UK SOC and SIC codes, with SOC3 results further disaggregated to SOC4.

*The OECD Programme for the International Assessment of Adult Competencies (PIAAC) assesses skills proficiency and information about how adults use these skills, including at work. Respondents are classified on their 2-digit ISCO 08 occupations, so this step also requires mapping to US 4-digit SOC codes.

[48] Nowcasting refers to estimating the current state of the labour market, at either a higher level of granularity than available in published labour market statistics, or at a more-up-to-date frequency. As discussed in the Methodology section we did not shortlist nowcasting approaches as they fall outside of skills forecasting but are a useful application of machine learning in this area.

Assessment of the method

Assessment summary:

Strengths:

- Enhance precision and efficiency of skills forecasts by extracting meaningful insights from multiple sources of information which is normally not included in standard quantitative approaches.
- Flexible: can be applied to in a range of ways to suit a wide range of users and purposes.

Weaknesses:

- High resource requirement, need for specialised knowledge and 'black box' nature might disincentive its widespread application.
- Objectivity of results depends on assumptions underlying machine learning models.

Applicability:

- Useful for users looking to answer tailored research questions and get insights on trends that are difficult to quantify with traditional data sources.

Regarding its relevance to different users, machine learning techniques can typically be applied in different ways to suit a wide range of users and purposes. For example, Headai uses natural language processing to produce skills forecasts for a number of different users, such as universities and governments, asking different research questions (e.g., mapping current skills needs in technical secondary education, skills needs in the tech sectors, mapping current skills sets with 'dream jobs' and upskill opportunities, etc.).

In addition, the versatility of machine learning models means users are able to build in different scenarios, for example Headai's model is able to assess the impact for skills requirements under different investment scenarios (public and private).

The use of machine learning to incorporate expert views on future trends, or the impacts of policy or technology, into a consensus view that can then be used in a quantitative forecast can be seen as a more structured (potentially more objective) way to incorporate a range of stakeholder views and improve its accuracy. Although we caveat that the true 'objectivity' of the results will depend on the underlying assumptions of the machine learning model.

> We are able to compress really big data sets into [an] understandable format. – *Developer*

The main idea of this method is that experts' predictions are forward-looking and implicitly include a range of historical and contextual knowledge. This is particularly relevant in contexts where particular trends and future economic disruptions or structural shifts are important but difficult to quantify. The ability to explicitly capture trends in this way and adapt to user needs gives the method high potential relevance and versatility. However, the outputs of predictive models using expert judgements depend heavily on the representativeness of expert views; if these views accurately capture the reality; and how forward looking they are, making the selection of appropriate experts crucial.

A key limitation of machine learning models is the extensive data requirements, although this varies across different models. For example, Headai uses a large amount of data including current job adverts, government reports and investment data. On the other hand, some other machine learning models use simpler data and the data itself may drive limitations. Legal restrictions on webscraping[49] limits the data availability for some models and therefore can restrict how well these models can capture the real world. At the same time, restrictions reduce the likelihood that unreliable data and misinformation are inputted into ML models.

Additionally, these methods have high resource requirements and can be 'black box', i.e. the key drivers are not easily interpretable. Machine learning models require significant technical skills and as a result are often outsourced, making them expensive for commissioners. The factors driving the results are typically not known or understood by either users or commissioners, and users may be sceptical of results they cannot understand.

Issues with trust in the outputs of machine learning models are exacerbated by the threat of false positives or negatives. Given the amount of data that needs to be processed and forecasted, there is increased complexity for machine learning models to differentiate between pure randomness and meaningful outcomes. Therefore, results from these models need to be interpreted carefully and combined with insights from other sources.

The 'black box' nature of machine learning techniques is inevitable but one way to reduce this is by sourcing findings (the approach taken by Headai). Another is to present sensitivities to key assumptions, or alternative insight into what the most important assumptions are, for example PwC Impact of AI presents a sensitivity to vary the 'majority' or 'supermajority' rule used to produce a consensus from experts' views.

> There are so many caveats associated with having that number of assumptions in the modelling. – *Commissioner/User*

Another limitation of machine learning tools comes from how the results are perceived by users. Users sometimes assume that an answer provided by AI is 'the answer' and this makes it difficult for developers to caveat the results appropriately.

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[49] Process of extracting information or data from websites using automated tools.

> Now in the AI phase, people are expecting black and white truth. – *Developer*

Projection of past trends

Description of the method

Some studies take an extrapolative approach to considering future trends and assume that the variables of interest will follow the same trajectory observed in historical data, or that they will return to some long-run and stable trend.

As an example, the methodology applied in the ‘Engineering skills needs – now and into the future’ report is purely a trend projection. The aim of this report was to provide an overview of the scale of the engineering and technology workforce if current trends continue in the coming 3-5 years. The US Employment Projections Programme also uses a method relying on continuations of the trends seen in recent historical data. The pace of continuing trends into the future is also informed by insight from occupation and industry analysts.

> If nothing changes from the past, developments and correlations between variables, then that's where we're leading to…it's also not really the goal to have like a point forecast for 20 years from now or 15 years from now. It's more a tool for political discussion and political policy advice. – *Developer/User*

Assessment of the method

Assessment summary:

Strengths:

- Leverages historical data to identify patterns and emerging trends.
- Easy to implement and does not require extensive resources.

Weaknesses:

- Strong assumptions, future conditions will not necessarily follow historical trends.
- Overlooks potential disruptions or shifts in the labour market. Needs to be complemented with other sources and insights.

Applicability:

- Better at predicting short-term change than longer-term patterns.
- More appropriate to analyse mature and less dynamic sectors, or where reliable historical data is available covering a long period of time.

Past trends provide a historical reference point, identifying patterns, recurring cycles or trends that may continue in the future. This method can provide a baseline for forecasting, i.e. a starting point from which assumptions can be changed or additional evidence built in.

In terms of accuracy and versatility, projecting past trends might overlook external factors and unexpected shocks that can significantly impact future outcomes. This method might be more effective for short-term forecasts, but less accurate for long-term forecasts where unforeseen events, such as economic crises or technological breakthroughs may disrupt established trends. Related to this, projecting past trends may struggle to anticipate paradigm shifts or fundamental changes in the context.

Historical data is often readily available making this method more convenient and accessible, especially at the economy-wide level. It is also more appropriate to analyse mature sectors where the past is a good predictor of the future, or where reliable historical data is available covering a long period of time (e.g., demographic data). However, if data is not frequently updated, forecasts based on outdated variables may led to inaccurate outcomes.

Comparison across methods

When selecting the appropriate method to consider future trends, commissioners and developers should consider the trade-off between different assessment criteria. For example, a method scoring highly on accuracy by incorporating a wide array of data may also be costly in terms of data and resource requirements. It might be too costly, or there may not be enough data available, to use the most complex method, so a simpler one has to be used instead.

Machine learning techniques have the highest resource requirement, although the method can be tailored to the forecast’s intended purpose and produce more accurate results than may otherwise be possible. In particular, using vacancy data for employment forecasting provides real-time insights into the current demand for labour in specific industries or regions. This is useful when trying to identify emerging trends that are not appropriately captured by traditional sources. However, accessing detailed vacancy data typically requires purchasing a licence.

On the other end of the resource requirement spectrum, **composite indicators** and **external forecasts or judgements** are simpler to implement – but this can come at the cost of accuracy. In the case of composite indicators, challenges arise in the subjective selection and weighting of individual indicators, as the choice of components may introduce biases. Moreover, the potential oversimplification of complex dynamics can lead to a loss of nuance, potentially hiding variations within specific sectors or regions. When using these methods, developers can use the appropriate techniques (for example the right indicator or well-known and reliable external forecast) to improve accuracy, account for technology and tailor output to users’ needs.

Horizon scanning and **foresighting** are two novel techniques which use significant qualitative input alongside machine learning but are flexible and can be tailored to diverse use cases. Horizon scanning provides a high-level picture for the longer-term and can be used to test the effects of different scenarios, whilst workforce foresighting provides a granular picture of skills needed for a given sector.

Horizon scanning offers the advantage of a proactive and comprehensive method to forecasting employment needs by systematically identifying emerging trends and change drivers. However, horizon scanning's limitations include potential uncertainties in predicting the exact impact of emerging trends and the challenge of balancing the breadth of factors considered, as it may be challenging to prioritize and focus on the most influential elements affecting employment.

Workforce foresighting provides a strategic advantage by incorporating a forward-looking perspective into employment forecasting based on a ‘challenge’ and ‘supply chain’ approach. By analysing current available data from multiple sources, and engaging different groups of stakeholders to identifying trends, workforce foresighting facilitates a holistic understanding of the future skills required to overcome future economic challenges. Limitations include the potential loss of the big picture by focusing on specific technologies.

Effective implementation requires close collaboration with diverse stakeholders, which can be resource-intensive and may encounter challenges in aligning interests and priorities. In contrast, **simple projections of past trends** offer a straightforward and easy-to-understand method for forecasting based on historical data. This method is particularly useful when historical patterns exhibit stability and consistency. However, its drawbacks include the assumption that past trends will continue unchanged, which may lead to inaccurate predictions if external factors or disruptions occur.

Overall, simpler approaches might be more appropriate for the following cases:

- Short-term forecasts, where the emphasis is on analysing historical trends and it is expected that the economy will remain stable.
- Short-term forecasts where the immediate skills needs are the primary focus rather than projecting long-term terms. For example, short-term workforce development strategies, especially when designing training courses or programmes targeted at developing fundamental and transferable skills.
- Stable sectors, where past trends are expected to be a good indication of the future, compared to sectors that are more dynamic and subject to rapid changes. This is well-suited for sectors where the demand for skills is expected to remain consistent overtime.
- In situations where there are constraints in obtaining timely and reliable data on future trends, publicly available external forecasts that can be used at low cost might be supplemented with other evidence or with qualitative input to discuss how trends might affect the results (particularly useful where trends are highly uncertain).

In instances where forecasts omit explicit considerations related to future trends or adopt a straightforward method, like relying on past trends, the forecast report or accompanying documentation should openly address the limitations associated with not factoring in future trends, and it is essential to communicate these caveats with key users and/or commissioners.

Building block 2 - Linking trends to employment outcomes

A typical skills forecast will link the future trends (identified using the methods in the previous sub-section Building block 1 – Approaches to future trends) to implications for the labour market in terms of employment outcomes by industry or occupation.

For example, many developed countries are expecting the demographic trend of an ageing population – identifying and/or quantifying this trend is the output of building block 1. This demographic trend can be expected to lead to an increasing demand of healthcare professionals, or home healthcare aides – identifying and/or quantifying this impact is output of building block 2.

As another example, automation and AI technologies are advancing with increasing capabilities to perform routine and repetitive tasks. While these technologies can enhance efficiency in certain industries, it may lead to job displacement in others, while creating new job opportunities in fields such as robotics, data analysis and AI development. In the 'PwC Impact of AI' report, step 1 (building block 1) identified the pace/likelihood of automation of different tasks. Step 2 (building block 2) related the automation of tasks to net job displacement.

In the Section 'Building block 3 - Linking trends or employment outcomes to skills', we discuss how the employment or occupational forecasts produced by building block 2 can be then linked to skills information.

Forecasts of employment (by sectors, regions, occupations, etc.) are typically conducted using standard econometric techniques, such as time series, or macroeconomic models. Both types of models typically rely on past trends.

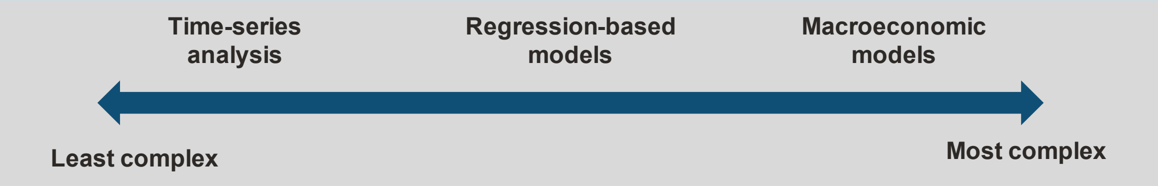
The following two tables present a summary of the strengths and limitations of each of these methods across our five assessment criteria. (For detail on the definition of each criterion, see Section: Assessment criteria).

Table 7 considers the 'relevance' criterion for each of the four representative user types that we identified during scoping. (For detail on the definition of each representative user type, see Section: Assessment criteria). Table 8 assesses each method across the other four assessment criteria.

In the sections following the Tables we describe each method and provide more detail to support our summary assessments.

Box 7: Standard econometric forecasting methods

The three main econometric methods used to link trends to employment are time-series analysis and projections, regression-based models and macroeconomic models. This delineation is a simplification and, in practice, methods lie on a spectrum from simple time series projections to macroeconomic models with methods often used in combination. We have divided the studies reviewed along this spectrum based on the available information.



Time-series analysis and projections: This method involves using historic data to estimate future employment, whether projecting forward past changes in employment or using a past relationship between employment and a trend outcome. Examples include 'Engineering skills – Now and in the future' and Australia's National Skills Commission. This is typically the least resource intensive method.

Regression-based models: Regressions are mathematical representations of economic relationships. Whilst time series models analyse the observed patterns of a time-ordered sequence of observations, regressions can include multiple, not necessarily time-ordered, variables. In addition, they differ from macroeconomic models because they do not include interdependent equations and supply-demand feedback effects. We typically find examples of regressions being combined with macroeconomic models, such as the UK Skills Mismatch report and the Working Futures model.

Macroeconomic models: These use a system of linked equations to represent interdependencies in the economy which can capture more complex dynamics. Some examples we have identified in the shortlist are the Working Futures model and CSN Industry Outlook.

Table 7: Building block 2 – Linking trends to employment outcomes - relevance assessment

	Central planner	Local user	IFATE	Workforce planning
Time series analysis and projections	Amber – More useful for short-term compared to long-term needs. Some helpful applications but may need to be used alongside more complex methods.	Amber – Simpler than other methods (regression, macro models) and so scope for using lower quality/quantity of data typically available at a local level.	Green – Limitations of the method are less likely to be an issue over short-term horizons. Simpler method may provide scope for using lower quality/quantity of data e.g. Burning Glass.	Amber – Can provide very granular outputs at a sector level where data availability might limit more complex options (e.g. Lightcast). More relevant for some industries than others (e.g. stable industries compared to novel/innovative industries).
Regression-based and econometric models	Green – Typically combined with macroeconomic models to construct centralised economy-wide forecasts. Scope to focus on specific issues via regression equations (e.g. McKinsey's Impact of AI report).	Amber – Typically combined with localised macroeconomic models to construct local-level forecasts, although lower quality data input limits usefulness compared to economy-wide models. Scope for forecasts with a local focus to include variables relevant for the area but limited by geographical classification of data.	Amber – The granular data needed for these regressions may not be available. However, lower data requirements than macroeconomic models so may be more suitable.	Amber – Scope for forecasts with a sector focus to include variables relevant for the area. More suitable for sectors well-defined by standard industry classifications.

	Central planner	Local user	IFATE	Workforce planning
Macroeconomic models, input/output and simulation models	Green – Typically used to construct centralised economy-wide forecasts. Helpful to understand the economy as a whole and its many components. Allows for scenario analysis and impact evaluation of policies.	Amber – Macroeconomic models typically have a local focus, although lower quality data input limits usefulness compared to economy-wide models. Limited by the geographical classification included in the data.	Red – Macroeconomic models typically not built for this short timescale. The granular data needed for these regressions may not be available.	Amber – Scope to focus on the specific sector, but typically not broken down to the level of granularity required. More suitable for sectors well-defined by standard industry classifications. Macroeconomic models unlikely to be built for small sectors.

Table 8: Building block 2 – Linking trends to employment outcomes – other criteria assessment

	Accuracy	Versatility	Data requirements	Resources and ease of use
Time series analysis and projections	Amber – Simplifies relationships between variables so may fail to capture important features. However, the simplicity increases transparency, making it easier to defend and justify.	Red – Difficult to account for potential disruptions or shifts in the economy. Scenarios cannot be built easily into this approach.	Amber – Typically constructed using publicly available data, but higher data requirements are needed to construct a more granular picture (e.g. Lightcast).	Green – Typically easier to understand the drivers of changes compared to more complex models. Building the model is typically less resource intensive compared to other models. Depends on the complexity of the time-series analysis.
Regression-based and econometric models	Amber – Simplifies relationships between variables, but able to account for additional factors beyond time series analysis. However, less likely to be 'black box' compared to a macroeconomic model.	Amber – Scenarios less easy build in compared to macroeconomic models. However, relevant variables can pick up shocks and changes in regression equations – and the variables can be easily updated over time.	Amber - Varies based on the complexity of the equations and data used. Regressions can typically use publicly available data, but proprietary data may be beneficial.	Amber – No interdependencies between equations so typically easier to understand what drives changes. High software and technical knowledge required to develop models, although less so than macroeconomic models.
Macroeconomic models, input/output and simulation models	Amber - Able to capture more relationships between variables (e.g. supply and demand dynamics). However, require a large number of assumptions and are typically 'black box' (often proprietary).	Green - These methods can be built to explicitly allow for different scenarios and can be used to capture more complex changes in the economy (such as technology) - although not all examples make full use of the scenario-based approach.	Amber - Typically built on the publicly available data of a given country. The better the data available, the better the result: the limitations with the UK's data are discussed elsewhere in this report.	Red - Very high resource requirement to develop, although once the model has been built once this resource requirement reduces slightly. Difficult to understand and interlinkages in the model mean it is not possible to attribute changes in results to any given change.

Time series analysis and projections

Description of the method

'Projections' are typically defined as those statistical methods which use the historical change in employment and project these forwards, without adjusting for future trend rates differing from the past. This can involve techniques such as moving averages or exponential smoothing. Time series analysis can also include estimating employment using the past relationship between employment and a trend outcome (e.g. output by industry or economy-wide growth).

Some examples we have identified from the shortlist are:

- 'Engineering skills needs – now and into the future' uses 3, 5 and 8-year time trends projections from a composite dataset based on eight official data sources and their proprietary data.
- Australia's National Skills Commission uses autoregressive integrated moving averages (ARIMA) and exponential smoothing with dampened trend (ESWDT).
- Headai use novel time series analysis of knowledge graphs[50] constructed using a combination of multiple methods (e.g., natural language processing) and sources, including job adverts. This time series analysis is used to link trends to both employment outcomes and skills.
- NHS workforce projections (REAL Centre/Health Foundation Projections) analysed the volume of NHS staff needed in future years by projecting the future health care activity needed to keep up with current demand pressures, based on demographic and morbidity past trends.

[50] A knowledge graph combines data from multiple sources and creates connections between them based on their semantic similarity.

Assessment of the method

Assessment summary:

Strengths:

- Enables use of standard historical data produced by national agencies.
- Easy to implement and does not require extensive computational resources.
- When combined with other novel data it can be tailored to various uses cases and needs.

Weaknesses:

- Relies on strong assumptions.
- Might overlook potential disruptions or shifts in the labour market, and structural breaks in the economy. Scenario analysis cannot be formally incorporated but can be included on an ad-hoc basis.

Applicability:

- Usefulness may be restricted to short-term policies. Performs better at predicting short-term change than longer-term patterns.
- More appropriate to apply in situations where a simple representation of the economy is suitable to capture the main dynamics of the labour market.

Time series methods typically rely on simple but strong assumptions (e.g., variables of interest will follow the same trajectory observed in historical data, or that they will return to some long-run and stable trend) or simple and stable relationships between variables. The accuracy of the results produced is limited to these (strong) assumptions.

Scenario analysis does not tend to fit easily into this method as normally it is assumed that future trend rates will maintain the same trajectory over time. However, scenarios can be introduced by exogenously adjusting the underlying parameters or assumptions used to calculate occupational demand (or supply). The quality of these scenarios depends on the quality of the evidence used to justify these adjustments. Due to these limitations, the versatility of this method is limited, and in some cases a different method is applied to assess scenarios.

As mentioned before, this method might overlook external factors and unexpected shocks that can significantly impact future outcomes. Therefore, this method might be more effective for short-term forecasts, but it might be less accurate for long-term forecasts where unforeseen events, such as economic crises or technological breakthroughs may disrupt established trends. Therefore, their policy usefulness and relevance may be restricted to short-term policies (e.g., temporary migration).

For example, the NHS Workforce Projections report analysed the future supply of general practitioners under ‘optimistic’ and ‘pessimistic’ scenarios by varying assumptions regarding their leaver rates and the expansion of the direct patient care staff. The Australia’s National Skills Commission outsources separate computational general equilibrium (CGE) models (a type of macroeconomic model) for scenario-based analysis.

On the other hand, the simplicity of these methods means they are typically easier to understand than other methods discussed in this building block. Users are able to understand the drivers of the model and, in interviews, one developer noted that these time series models can be easily defended and justified – a key advantage compared to more complex models. Some developers of projection-based methods also noted that they are not attempting to produce a forecast of what ‘will’ happen (which will always be affected by unforeseen shocks), but instead are clear that the results should be treated as a ‘what-if’ analysis if recent trends persist.

> When we talk to our customers about it, we explain that we provide it as a baseline – if local industry sales in the past is a good guide to the future, then this is what the future would look like. – *Developer*

> We’re not offering a crystal ball. We don’t say that that is the future. – *Developer*

Time series methods typically require less computational resources than more complex econometric and macroeconomic models. This means they are used more widely in situations where very limited time series information is available. It is also more appropriate to apply in situations where a simple representation of the economy is suitable to capture the main dynamics of the labour market rather than in more complex cases where inter-linkages between sectors is more relevant. Similarly, they are also more applicable for sectors which are more stable (e.g., construction) compared to those undergoing rapid change or more exposed to unpredictable shocks, for example sectors more vulnerable to technological changes (e.g., retail).

In addition, when there is a lack of long-term time series, they can be complemented with insights from experts or the analysis of novel data. In particular, using novel data can help overcome the limitations of time series projections based on traditional sources of data – which can also be restricted in terms of availability and granularity.

For example, the ‘Engineering skills needs’ forecast uses proprietary Lightcast data[51] to construct a granular picture of employment which is projected forward. The projections were developed to 2030 from a bottom-up level using 4 digit SIC codes, using 3, 5 and 8-year time trends. An advantage of Lightcast data – as with any vacancy data – is that it provides a rich source of data of labour demand (e.g. including detailed information on

[51] Lightcast (formerly Emsi Burning Glass) collect and analyse real-time data about the labour market (occupations, skills, career pathways) from multiple sources including job adverts and government data.

skills and job tasks) that typically is not collected through traditional surveys or databases (e.g., job titles, job descriptions, requirements, accurate posting dates).

However, vacancy data only provides a partial view of employment outcomes as it does not contain information on replacement demand and only covers those jobs advertised online. It is also inherently biased towards currently available jobs. This may not fully capture emerging skills or those required by industries that are not extensively represented in job postings. Nevertheless, in the case of the 'Engineering skills needs' forecasts, Lightcast data allowed for a bespoke definition of 'engineering roles', which diverged from traditional SIC/SOC code industry/occupational definitions.

Regression-based and econometric models

Description of the method

Econometric methods – such as multivariate or autoregressive models – sit between macroeconomic models and trend projections in terms of their complexity. Econometric models are mathematical representations of economic relationships, expressed in a set of equations, that are used to analyse and quantify the relationship among economic variables. The number of variables used in econometric models depend on how many relationships are captured in the model; this might be informed by the method taken to understand future trends.

Some examples we have identified from the shortlist include:

- Methods used to estimate relationships between employment and other relevant variables, including trend indicators such as GDP growth, inflation rates, business investments, or industry-specific indicators (e.g. automation rates). The process involves estimating the parameters of the model based on historical data, and once the model is validated, it can be used to make predictions about future values of employment. Two examples are:
    - ESDC's Canadian Occupational Projection System (COPS), which forecasts employment demand and supply over a 10-year period. The COPS model applies a simple econometric model of replacement demand as a proportion of required employment.
    - Working Futures, which projects historical patterns in total employment and occupational structure by industry using econometric methods.
    - Methods used to estimate relationships between trend indicators, such as the 'UK Skills Mismatch' report, discussed in Box 8.

Box 8. Case study - UK Skills Mismatch in 2030, estimation of number of new jobs

This report for the Industrial Strategy Council (also discussed in the previous Section 'Approaches to future trends') explores which 'qualifications, knowledge and workplace skills are likely to face greater or lesser mismatch by 2030 as a result of the changing nature of work'.

The report uses separate econometric equations to explore the relationship between economic growth and the 'key trends' identified in an earlier part of their report (as previously discussed). Regressions were run on a sample of 46 countries based on 2014 data. Some examples of the regressions run were:

- *Rising consumption:* Consumption per capita by category (e.g. accommodation, food services, automobiles etc.) regressed on GDP per capita.
- *Ageing population:* Two separate regressions of health care professionals per 1000 people regressed on: i) GDP per capita and ii) the share of the population over 65.
- *Infrastructure investment:* Infrastructure spend per capita regressed on GDP per capita.

The estimated coefficients from these equations were used in the macroeconomic model: they were combined with job multipliers from input-output tables to project the number of future new jobs in 2030.

Assessment of the method

Assessment summary:

Strengths:

- Rigorous statistical technique which provides insights into the causal relationships between various variables influencing future employment outcomes.

Weaknesses:

- Does not account for any sources of labour demand beyond the relationships included in the model, nor interlinkages between different parts of the economy, or supply and demand feedback effects.
- Scenario analysis cannot be formally incorporated but can be included on an ad-hoc basis. Requires large volumes of historical detailed data to obtain meaningful results, and high levels of technical expertise.

Applicability:

- More appropriate where the intended purpose of the analysis is to focus on specific relationships between employment and occupations, and a defined set of variables.
- More suitable for sectors that are well-defined by standard industry classifications.

Compared to time series analysis which focus specifically on analysing the observed patterns of a time-ordered sequence of observations, econometric methods allow for the inclusion of multiple variables, which may or may not have a time-series component. Variables do not only depend on their own past values but might also have some dependencies with other variables.

We distinguish between econometric methods and macroeconomic models (discussed in the next section) as regression methods normally do not include interdependent equations and supply-demand feedback effects[52]. This means that basic econometric methods do not consider potential shifts of employment across sectors or changes in the occupational composition of sectors.

In terms of their relevance, econometric methods are more appropriate in situations where the intended purpose of the analysis is to focus on specific relationships between employment and occupations and a defined set of variables. In contrast, macroeconomic

[52] For example, an increase in demand for one occupation will lead to an increase in wages, therefore increasing supply in the longer-term. This won't be captured in simple regression models but will be captured in macroeconomic models.

models are more relevant when a more comprehensive overview of the entire economy is required. In practice, models often use a combination of both regression-based methods and macroeconomic models to gain a comprehensive understanding of the economy and the labour market.

Since econometric methods typically sit between macroeconomic models and trend projections in their complexity, regression-based methods fall between these two methods in the transparency-complexity trade-off. They still required large volumes of historical detailed data to obtain meaningful results but relationships between variables are often simple and derived from economic theory. Similarly, these models are situated between macroeconomic and trend progressions in terms of their resource requirements. High technical and time resource is needed to implement econometric methods, although less so than for macroeconomic models.

However, as mentioned, econometric methods do not account for supply and demand dynamics or feedback effects, which can reduce the accuracy of the relationships between variables. For example, a particularly important feature which cannot be formally incorporated in econometric methods is the demand and supply implications after a change in wages. These interactions would typically be built into a macroeconomic model.

Additionally, the analysis of scenarios or changes in trends are not formally dealt with in econometric models, limiting their versatility. However, scenarios can be incorporated by examining how outcomes change after adjusting a set of assumptions or key variables. The simplest way to assess scenarios within an econometric model is to define which scenarios will be included in the analysis (which can be informed by previous building block), determine which (independent) variables are most likely to be impacted by these scenarios, adjust these variables to reflect the specific conditions of each scenario and simulate and compare results in each case. This can be done manually based on previously collected and reliable evidence, as in the case of time series analysis, or through a more systematic process. However, given that econometric models do not incorporate feedback effects or interlinkages between sectors, it might under or over-estimate the impact of these scenarios.

Box 9. Case study - Alternative scenarios in Skills Imperative 2035, part of Working Futures

Skills Imperative 2035 considers two different automation scenarios. These build from an intermediate scenario (the Automation scenario) which assumes no job creation from automation. The two scenarios make the same assumptions about job losses as the intermediate scenario but assume that total demand for labour is unaffected (so an equal number of jobs are created as are destroyed). The scenarios differ in their assumptions about job creation:

- *Technological opportunities scenario*: Jobs are created in the management of technologies, the transition to net zero and higher quality education and health and care services.
- *Human-centric scenario:* 'Soft' or non-cognitive skills become more valued, with more emphasis on jobs less susceptible to change.

How are scenarios built using econometric techniques?

Econometric methods are used in the baseline model to project occupations based on occupation shares from the Labour Force Survey. Building alternative scenarios requires making appropriate adjustments to occupational shares. Based on a review of evidence and trend analysis, manual adjustments to the shares were based on key factors such as occupations at risk of automation, labour market flexibility and trend analysis of Labour Force Survey data 2011-2021 and vacancy data 2019-2021.

Regression-based models can also be easily updated to bring in new variables in the future, whether through additional equations or replacing variables used in current equations. Regression models benefit from additional complexity whilst remaining less 'black box' than a macroeconomic model; it is easier for users to understand the drivers of the results compared to macroeconomic models.

When working with regression models, developers should clearly set out the equations estimated, and the variables used to improve the transparency and trust in the outputs. In addition, validating the accuracy of regression models requires taking the appropriate econometric steps. The appropriate variables should be included, both that are theoretically sound, i.e. grounded in economic theory, and empirically relevant to the economic relationships under study. Studies should deal with endogeneity and multicollinearity issues[53]. Reporting on these steps, as well as econometric tests or

[53] Endogeneity is the econometric term for two variables which affect each other. For example, wages affect the number of people employed whilst the number of people employed affects wages. Multicollinearity refers to variables which are included as independent variables but are highly correlated, which can affect the results of the regression. Any econometric model needs to consider these two issues.

sensitivities conducted and any caveats, is important to support technical users' trust in the model and its outputs.

The data requirements for regression-based methods can be defined by the developers, although depending on the model specification chosen, a minimum volume of data might be required to obtain meaningful results. Regressions can be based only on publicly available data, as in the 'UK Skills Mismatch' study, but proprietary data may be beneficial if available, although these are normally costly to obtain. More complex data, for example use of job advert data or other industry specific data, may be able to produce more insightful results that are more tailored to the intended purpose of the model.

Macroeconomic models

Description of the method

Macroeconomic structural models use a system of linked equations to represent interdependencies in the economy which enable them to capture more complex dynamics (not necessarily linear) when linking future trends to employment outcomes. Unlike time series analysis and econometric methods, macroeconomic models are more flexible as each equation included in the model can be defined and parameterised independently.

These methods are common for economy-wide forecasts and are typically seen as best practice for central economy-wide forecasts commissioned by the government, such as Working Futures, the EU's Cedefop, the ESDC's COPS model and the US Employment Projections programme, especially when combined with econometric methods. Among the shortlisted studies, we identified one example of a segment-level study using a macroeconomic model: the CSN Industry Outlook produced for the construction sector.

> Having firm baseline results based on hard quantitative evidence (a quantitative benchmark that combines macro modelling and econometric analysis) is best practice across the world – you can then complement this with other methods like big data, but to have accurate and reliable results depends on if you have the data right in the first place. – *Developer*

Some of the macroeconomic models used for skills forecasts that we have identified are:

- Working Futures uses a Regional Multisectoral Dynamic Model of the UK economy (MDM-E3) developed by Cambridge Econometrics. Each region is modelled separately with regional results being scaled to UK results.
- Germany's central government forecast (Project QuBE) uses the QINFORGE model which is described as an 'econometric prognosis and simulation'[54] model,

[54] Simulation models are bottom-up models with inter-industrial interactions.

that is ‘bottom up’ (based on detailed modelling of individual sectors) and has ‘full integration’ (simultaneous modelling of all sectors).

- The Sectoral and Regional Skills Assessments undertaken by Skills Development Scotland use Oxford Economics' Local Authority District Forecasting Model.
- CSN Industry Outlook uses separate macroeconomic models for each English Region and Scotland, Northern Ireland, and Wales, designed and managed by Experian. The models are interrelated and constrained to a UK aggregate. The models forecast demand and supply separately based on construction output and productivity.
- ESDC’s Canadian Occupational Projection System (COPS) is a set of models used to produce occupational outlooks based on a system of future trends in job openings (expansion demand and replacement demand) and job seekers (school leavers and new immigrants) by occupation over the medium term. It includes different modules to incorporate demographics, immigration, economic growth by sectors, etc.
- McKinsey’s ‘UK Skills Mismatch in 2030’ report uses the McKinsey Global Growth Model (GMM) projections, produced from a global macroeconomic model that tracks long-term economic trends and their interactions with growth drivers, including demographic factors, education, energy supply, urbanisation, physical capital, determinants of total factor productivity, amongst others.
- Finland uses the VATTAGE model for anticipating regional development in labour markets and the MITENNA model for anticipation of long-term demand for labour and educational needs.

Box 10. Case study - CSN Industry Outlook, using macroeconomic models for sectoral forecasts.

CSN forecast demand by occupation as well as upskilling and training needs for the construction industry. The model is developed by Experian and commissioned by the Construction Industry Training Board (CITB).

The macroeconomic model that underlies the analysis is tailored to understanding scenarios and looking at the impact on the construction industry. Qualitative input through expert workshops and a network of stakeholders is used as an input into future trends and to quality assure the scenarios. Stochastic modelling is used to consider the possible range of impacts. For example, one of the scenarios CSN analyse is the ‘climate change scenario’ which uses as input data the energy performance certificate (EPC) ratings of the housing stock and housebuilding to consider demand for retrofits and the associated occupational and skill demand.

Are macroeconomic models always appropriate for segment-level forecasts?

The construction industry is especially well-defined, for example in SIC and SOC codes as well as economic data (for example the ONS publishes a monthly output series for the construction sector). It is also a relatively large sector, with sufficient official data coverage including within government office regions, which may not be the case for other smaller industries. This makes the construction sector more suitable for use of a macroeconomic model than for other industries.

Assessment of the method

Assessment summary:

Strengths:

- Provides a comprehensive view of the labour market dynamics, incorporating multiple economic factors and relationships to inform employment projections.
- Allows for scenario analysis and impact evaluation of policies.

Weaknesses:

- Might overlook sector and local-specific nuances and changes in occupational composition.
- Data limitations might reduce their relevance among some local and sectoral users. Sensible to assumptions and parameters.
- Resource intensive and requires high technical expertise.
- 'Black box' nature.

Applicability:

- Macroeconomic models are more relevant when a more comprehensive overview of the entire economy is required.
- Suitable for long-term forecasting.
- Best practice formal national-level quantitative models often use a combination of both regression-based methods and macroeconomic models.
- More appropriate for sectors that fit well into the standard industrial classifications.

Similarly to econometric methods, macroeconomic models rely on historic and time-dependent relationships between variables to generate forecasts. However, macroeconomic models provide a holistic view of the economy which allows for a better understanding of the overall economy structure within which employment trends are embedded.

These models inherently integrate various economic sectors which are interlinked while also capturing the interdependencies between all main actors of the economy (i.e., households, businesses, government and the external sector). Therefore, they are particularly useful to understand how changes in employment in one sector may affect other sectors. They are suitable for forecasting employment patterns over extended periods of time, accounting for structural changes based on demographic shifts, technological changes and other future trends.

Of the methods used to link trends to employment, macroeconomic models require the highest resources and data requirements to develop. Whilst time series or regressions may only rely on a small number of sources of labour market information (LMI) data, macroeconomic models often use all LMI data as well as other time series such energy prices and industry output.

However, as the number of variables and equations increase, these models can become complex. For example, the Working Futures model includes 5,000 behavioural relationships, excluding accounting identities. This increased complexity comes at the expense of transparency and ease of understanding. According to interviews, macroeconomic models are often seen as ‘black box’ models by users and commissioners which are unlikely to fully understand the quirks of the model so cannot defend their results as easily. The interlinkages in the model mean it is not possible to attribute changes in results to any given variable. A way to mitigate this issue might be to use projections developed by the Government (e.g., OBR, Treasury, Bank of England) instead of proprietary models.

> The negative side to that is that they have some quirks that don't really look right and the fact we don't have control over the model or the information on the model, it's actually quite hard for us to defend them or explain them. – *Commissioner*

Usually, developing a macroeconomic model requires very substantial time, resources and technical expertise. A commissioner would typically use and trust a model that already exists and is well-known (e.g., Oxford Economics, Cambridge Econometrics, McKinsey’s) rather than commissioning a new one or relying on industry-led models. In some cases, there is a legacy issue, as commissioners prefer to use national models that have been used for decades due to their reputation. For example, a similar methodology has been used in UK since the early 1970’s with a few gradual refinements to incorporate novel data.

> With trade bodies - sometimes the data is really useful - but what bias are they bringing to it? and I'm always considering that. – *User*

> If it's government published, you know that it's had to have gone through a process to make sure it stands up. - *User*

Assessing accuracy of macroeconomic models is challenging as differences between forecast and outturn employment can depend on external factors (e.g., government strategy, reviews of underlying historical data, policy announcements) as much as modelling errors. Only a minority of studies (e.g., CSN Industry Outlook, US Employment Projection Programme, Working Futures) explicitly assess the performance of previous forecasts against outturn data. As accuracy is difficult to assess, users might rely on the reputation of the forecast (and underlying model).

> Challenging to assess how accurate a forecast is and to identify which part of the difference between the forecast and what actually happens is due to modelling errors as opposed to other things. – *Developer*

> I think we all need to recognise that we're doing projections and we're never going to be perfect or 100% accurate… No one can predict the future. No one would have been able to predict what happened in 2020 with the pandemic… It is [instead] recognising that and doing our best to gather all of the information that we can that we have available to us. – *Developer*

Accuracy is not only related to how close forecasts are to actual outcomes, but also to how well the relationship between variables is captured in the model. Most macroeconomic models conduct sensitivity analyses to test the robustness of their results, which increases users' trust in the outputs.

> I mean it helps you just understand the model and think about how useful it is for drawing any conclusions. And then it also helps you think a bit about the significance of those conclusions and how much weight you would put on them. - *Developer*

Macroeconomic models also allow for scenario analysis by simulating the potential effects of different economic scenarios on employment, whether this be technology developments, policy changes or Covid-19. For example, the macroeconomic model QINFORGE used in Germany is developed with scenarios in mind: a key use of the forecast is to test different policy implications within government.

> We are trying to see how different policies that are discussed or decided will influence the labour market…we have the basic forecast basically without any changes about future laws, for example, then we know there's is this law that will be coming that influences the labour market in certain ways…then we can make certain assumptions in the model to see how well this policy influence the labour market in the future. That's what we're mainly using the model for. - *Developer/User*

Even though the relationships and structure of the macroeconomic models might be not as transparent as in the case of econometric methods or time series analysis, these models are typically built on publicly available data from official sources of a given country. The better the data available, the more accurate and granular the results that can be produced. As these models are projected forward using historical information, if the data is not accurate, then any forecasting error will be compounded over time. Therefore, the uncertainty of any forecast increases as the horizon extends further into the future. However, this is true for any of the economic forecast techniques and developers interviewed are aware of these limitations.

> Any point projection of the future is almost inevitably incorrect, you need to recognise we are not making a precise prediction of what the future will look like...we don't have a crystal ball…the best we can do is to provide a quantitative benchmark based on past trends and our view of how these might evolve in the future. - *Developer*

Due to UK data limitations, results from the Working Futures model at high levels of granularity (e.g., detailed sector, gender, occupations, spatial area classifications) should be interpreted with caution (as is also true of other economy-wide forecasts). Detailed occupational information is sourced from the quarterly Labour Force Survey (LFS). The sample includes approximately 40,000 households and 100,000 individuals and is intended to be representative of the entire population of the UK. While the LFS is a valuable source of information for understanding the labour market, it has some limitations:

- **Sampling bias:** The LFS relies on a sample of households to collect data. While efforts are made to ensure the sample is representative, the size of the sample may not capture the full diversity of occupational patterns, particularly in smaller or specialised occupations. This can lead to limitations in the accuracy of forecasts for specific occupations.

- **Standard classifications**: The LFS uses standard occupational classifications (SOC), but these may not capture evolving or emerging job roles.

- **Reporting bias:** The method relies on individual self-reporting: individuals or key informants may not report occupations accurately due to lack of awareness of specific job titles or misuse of terminology to describe roles.

- **Data lags and seasonal variations:** The survey is conducted at regular intervals (quarters) which might introduce temporal lags in the availability of data. In fast-changing industries or occupations, this lag can be a limitation for timely and accurate forecasting. The survey's periodicity can also lead to challenges in accounting for seasonal variations in certain occupations.

- **Missing data:** The survey provides information on broad occupational categories but may lack granularity for detailed occupational analysis. As the sample is representative at the national level, some SOC codes might be missing.

Most studies we reviewed are very clear on the caveats about their modelling method and limitations of data sources, which is in line with best practice. Due to these limitations, the UK would benefit from an information system that gathers information regularly on occupations, skills, qualifications directly from businesses rather than households.

> What anyone can do is very much dependent on the data that you can build these models with…a forecast should be part of a process and be updated regularly as new information becomes available. - *Developer*

Macroeconomic models are typically able to produce outputs which suit a wide range of users, and are commonly used for economy-wide forecasts, particularly those commissioned by central government. From the nine shortlisted economy-wide methods, four of these use macroeconomic models and all of these are commissioned by central governments (or the EU). At the more disaggregated levels, these models are intended to be used as a foundation for reflection and debate, rather than as a top-down workforce planning exercise.

The outputs of these models can be used by regional or local authorities as they typically produce forecasts broken down by sector or regional/local level. For example, Working Futures includes forecasts for 87 sectors (SIC2007 2-digit) at the UK level (75 at the highest level of disaggregation), and 46 sectors at the regional level. Results for Local Enterprise Partnerships (LEP), Local Skills Improvement Plans (LSIP) areas and Mayoral Combined Authorities (MCA) are also published although these are only disaggregated for 22 groups of industries.

Box 11. Case study – The Working Futures model, MDM-E3 regional models

Regional forecasts

Working Futures is built on MDM-E3, which models each region separately and scales to UK-wide results. At the regional level, forecasts are produced for 46 industries (at the UK level the forecast is for 87 industries). The model relies on the best use of regional data, noting that regional data availability is limited compared to national data availability. It uses incomplete and partial data and only where the data is judged to be robust enough does it incorporate this data into econometric analysis.

To deal with issues with the regional data, the model uses all possible sources to cross-check the data, uses UK totals to control the regional data as much as possible and incorporates the views of regional experts.

Local forecasts

Even more granular forecasts are produced at the level of Local Enterprise Partnerships (England) and Economic Areas (Wales), using Cambridge Econometrics' Multi-Local Area Forecasting Model. This is produced for 46 industries and aggregated to the 22 sectors published in Working Futures.

These local forecasts are intended to be a starting point for future analysis and come with even more caveats than the regional and national forecasts, not least the fact the results are more sensitive because of larger spatial disaggregation. Their purpose is to provide a "*quantitative benchmark for local areas… based on the same macroeconomic scenario and assumptions as used for the national projections*".

These forecasts do not include local knowledge or insight and instead assume that employment in the local area will continue to maintain the same relationship with the regional level. The key drivers of results are the same as drivers at a national level, not accounting for any 'local surprises' such as major inward local investment or closures.

The availability of disaggregated results is an important starting point for local and sectoral stakeholders to get some insights about the direction of travel of the labour market. This allows them to assess what this mean for employment in their jurisdictions or sectors. However, in the UK, data limitations might reduce the relevance of macroeconomic models for some of these users:

- Local users are limited by the geographical classification included in the data. For example, the West Midlands Combined Authority does not align with the 'West

Midlands' region as defined by data sources. As the 'West Midlands' region includes other areas, results are not able to capture local challenges.

- Sector-level forecasts are not typically broken down to the level of granularity required by workforce planners. Some sectors can overcome this challenge by using their own macroeconomic models, like in the CSN Industry Outlook report. But macroeconomic models are not suitable for all sectors because of data availability. Other sectors build their own bottom-up forecasting models like in the case of the Green Jobs Delivery Group or combine outputs from macroeconomic models with qualitative data and other inputs – as discussed in the 'Qualitative inputs' subsection.

> The Unit for Future Skills and DfE have put some additional funding to get local forecasts out…that's been really useful for testing with qualitative data from employers, and actually lots of that resonates with what we are already seeing in the labour market, where the direction of travel is what employers are saying. – *User*

Other methods of linking to employment

Description of the method

The three methods discussed capture the large majority of the shortlisted studies we reviewed. Some studies apply alternative methods (e.g., PwC 'Impact of AI' discussed in Box 12).

Others do not use an explicit quantitative link between future trends and employment, but instead link to skills directly (e.g. Workforce Foresighting Hub, Green Jobs Taskforce), as discussed in Building block 3 - Linking trends or employment outcomes to skills.

As discussed in Section 5, not using an explicit link between future trends and employment is, under certain conditions, justified, especially in cases where sectors do not align neatly with standard industrial classifications (e.g., green, gig economy, creative industries) or when occupations fail to adequately capture the tasks performed within a sector.

Box 12. Case study - The Impact of AI: Estimating job creation and displacement

An alternative approach to link trends to employment is taken by the PwC in their ‘Impact of AI’ report.

Instead of forecasting *levels* of employment, the study focusses of the impact of AI on employment (i.e. *changes* in occupational employment). The key overarching assumption is that total job creation is equal to total job displacement, i.e. that the total net effect on employment is zero (this assumption is tested through a number of sensitivities). Net effects on jobs are calculated by industry, occupation, region, socio-economic and demographic groups.

When is this method useful?

In cases where the effect of employment is very uncertain, a net change in jobs approach is helpful to understand the distribution of the effects – across occupations, industries and regions. The method can be set up to allow for the level of granularity most useful for the user, depending on the data available, and it could be useful to assess the impact of policies. For example, a central planner involved in levelling up may use this method to understand how a particular trend or large-scale government intervention might affect different areas of the economy.

Limitations of this method

As with levels of employment, changes in employment as a result of policy or technological change are inherently uncertain and some users suggested in our interviews that this may lead them to place less trust in the ‘point estimates’ produced from a forecast like this, particularly over the longer time horizons, although the direction of effects and relative magnitudes in the results are still relevant. In addition, users discussed the drawback of the large number of assumptions required (in particular, strong assumptions such as zero net displacement, although these were tested with sensitivities).

For disruptive technology impacts, insights drawn from net employment changes can also be limited by the assumption of a continued occupational structure, i.e. missing the impacts of the creation of new types of jobs and industries not currently captured in SIC/SOC codes. On the other hand, this assumption may currently be unavoidable in most contexts without a large increase in the resource requirements of the work and the number of underlying assumptions.

Comparison across methods

There is no silver-bullet method. In practice the methods applied to link trends and employment outcomes can lie on a spectrum from simple to more complex methods. The choice between these methods depends on data availability, research objectives, the level of detail required, and the trade-off between model complexity, transparency and accuracy.

Time series analysis offers advantages in capturing historical patterns, identifying trends, and revealing seasonality in employment data. This method is particularly effective for short-term forecasting, providing insights into the immediate trajectory of employment based on past trends. However, its limitations include a narrow focus on historical data, overlooking broader economic dynamics, and assumptions of stationarity that may not hold in the presence of structural shifts.

Econometric methods allow stakeholders to identify causal relationships between employment and other economic variables. The flexibility in model specification allows for the incorporation of various variables, making it well-suited for the analysis of more detailed time-series data. Nevertheless, econometric methods are sensitive to data quality and assumptions.

Finally, **macroeconomic models** provide a comprehensive overview, capturing interdependencies between economic sectors. These models are suitable for long-term forecasting and analysing trends, but also face challenges in aggregating diverse economic agents, relying on theoretical assumptions, and struggling to capture the full dynamic complexity of the economy, especially in rapidly changing environments.

In practice, formal national-level quantitative models often use a combination of different methods such as econometric methods and macroeconomic models, to link future trends to employment outcomes to gain a comprehensive understanding of the economy and the labour market. This is because relying only on macro-level relationships only can lead to generalisations that might not be accurate.

However, in some instances having an explicit link between trends and employment outcomes is not necessary, as discussed in Section 5: Combining building blocks.

An additional step – Disaggregating results

The outputs produced from top-down models, such as macroeconomic models, sometimes require an additional step to disaggregate the results, for example from national employment/occupations forecasts to regional or sectoral forecasts, or from a higher digit SOC or SIC code, to lower digit levels. Introducing this step typically means the more granular data is less accurate because it requires making additional assumptions. Segment-level users often find top-down approaches less valuable for workforce planning due to their potential oversight of sector-specific details (see Reconciliation methods section).

Nevertheless, disaggregating results provides an additional level of granularity which makes the forecasts more relevant for a wider audience, in particular local and sectoral users. These results can be then enhanced by incorporating more qualitative and industry-specific components. Some examples we have identified are:

- Working Futures uses a macroeconomic model to forecast changes in industry employment for 87 sectors at 2-digit SIC2007. These are then linked to occupational econometric models which produce projections of occupational employment shares for the 26 2-digit sub-major SOC2020 groups within each industry based on extrapolations of past trends using information from the Labour Force Survey. This produces a SIC-SOC matrix with historical shares of occupations by industry employment which are then applied to the industry forecasts from the macroeconomic model to obtain occupational employment levels. The approach assumes that the occupation composition within a given 2-digit SIC remains constant over time.
- The Impact of AI report disaggregates from 3-digit to 4-digit SOC using the 2019 ONS automation probability study. Whilst this introduces greater uncertainty, it increases granularity without assuming that there are no differences in 4-digit SOC estimates within a given 3-digit SOC and so therefore improves the likely validity of the estimates. The developers suggest this is worthwhile despite the uncertainty it provides as the figures are not meant to provide specific results and instead provide insight into the likely distribution of impacts.
- The Canadian 3-year Employment Outlooks rely on maximum entropy[55] to estimate missing values when disaggregating data to more granular level. The process is used to create yearly matrices which can convert for the annual employment growth by industry into growth by occupation.

Segment-level forecasts are designed to incorporate sector specific effects and so we have not identified any examples of disaggregation at the industry/occupational level in these forecasts. Using disaggregation in these studies would be a particular limitation because users of these forecasts require more granularity and expect sector-specific insight to drive results.

Building block 3 - Linking trends or employment outcomes to skills

In this section we describe how the studies reviewed produce outputs in terms of skills. This building block has two stages: (1) definition of skills taxonomy (or skills proxy), and (2) mapping skills (or skills proxy) to trends or employment outcomes.

[55] Maximum Entropy allows probability distributions to be set up with only partial knowledge.

The first step involves deciding how a ‘skill’ should be defined. The second involves linking the outputs of building blocks 1 or 2 (i.e. future trends, or future employment outcomes) to what this means for skills.

Stage 1: Choosing a skills taxonomy

In general terms, a skills taxonomy is a systematic and structured classification system that organises a diverse range of skills and competencies into a hierarchical framework, and links them to specific job roles or occupations. ‘Skills’ could be defined in a variety of different ways, for example this could be in relation to tasks, knowledge, behaviours, qualifications, or education.

A detailed assessment of skills taxonomies[56] is outside the scope of this report, as this analysis sits alongside the report *A Skills Classification for the UK* (DfE, 2023).[57] Our focus is instead on the forecast element of the methods considered, however this sub-section outlines first the ongoing work to produce a UK-specific skills taxonomy, and then some of the common taxonomies or methods used in the studies reviewed.

Ongoing work: UK-specific skills taxonomy

Relatively few of the shortlisted forecasts directly forecast skills, or in some cases the link to skills was made only qualitatively (see example under sub-Section ‘Linking to skills without a specific taxonomy’).

In the UK, this is largely due to the lack of a common language of skills and lack of a crosswalk between occupations, qualifications and skills. Part of the problem is the lack of regular data collection on skills. Systematising information on the skills required in each occupation can be highly complex as this can change over time and because existing classifications may not accurately capture nascent sectors and occupations.

> We seem to have lost a standardised way to say when we're looking at the labour market and skills issues, we're gonna look at these things and this is how they interact with each other…why aren't we doing it in a coherent way like there's no connectivity between you know, skill taxonomy. - *User*

> There's a tricky balance to strike between the taxonomy not becoming like a dinosaur, like it actually being relevant to the current labour market, but at the same time not changing all the time because the process is expensive but also needs to be consistent. - *Commissioner*

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57 Elias, P., Dickerson, A. & Bachelor, N. (2023) A skills classification for the UK.

Given the lack of skills information, studies have applied different workarounds. For example, the Skills Imperative 2035 programme maps US SOC with UK SOC to use the US O*NET taxonomies at an aggregate level.[58] This has its own challenges (e.g. mapping may require simplifying assumptions, US taxonomies might not be updated frequently or might not reflect reality of UK economy, etc.).

One of the challenges, as described by a commissioner and developer is that *"skills means different things for different people"* so providing a clear taxonomy that defines skills and is used widely would enable comparisons and reconciliations of different types of data. To address this issue, DfE has commissioned plans for development of a UK Standard Skills Classification (SSC), which will provide a common language to describe skills and associated knowledge required to carry out job-related tasks. It is a technical tool which will enable jobs to be linked to courses/qualifications via skills. The work is divided in two phases: (1) stakeholder engagement and development of conceptual framework on how this classification should look like to meet a wide range of user's needs (completed), and (2) implementation of plan and development of the skills classification (in progress). [59]

For a comprehensive national skills forecast that can be effectively used by a range of stakeholders, with clear and detailed information on the kinds of skills that are likely to be required for occupations of the future, a UK-specific taxonomy would be beneficial.

Without a UK-specific taxonomy, forecasts take different approaches based on the purpose of the skills forecast and the intended users, as discussed in the following sections.

O*NET

The most adopted skills taxonomy is O*NET, a fully comprehensive taxonomy of the skills that exist in jobs in the USA. It links skills to occupations and has a variety of other data categories including abilities, knowledge required, and sample job titles. On average, 721 of the 923 occupations are updated every year[60], meaning that any system that relies on O*NET also must update annually or risk using an out-dated version. The O*NET online database is built through an extensive data collection process from multiple sources. This includes expert views and a survey of employers' views on changes in future skills, which is an advantage over other economy-wide forecasts that do not always include inputs from employers or other stakeholder engagement. The US Employment Projections programme will soon extend its analysis to link to O*NET.

The Skills Imperative 2035 work (Working Paper 3) uses O*NET as a framework for four main areas – Abilities, Knowledge, Skills and Work Activities – in the absence of a UK-

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[58] Dickerson, A., Rossi, G, et al (2023) The Skills Imperative 2035: An analysis of the demand for skills in the labour market in 2035

[59] More detail can be found in DfE (2023) A skills classification for the UK. Plans for development and maintenance

[60] O*NET overview

specific taxonomy. This enables a complex ranking of each of the four main areas, and an analysis of which skills will be more or less important by 2035 at the aggregate level. This granularity in terms of skills needs, rather than broad occupations, or qualification levels, reflects the demands from regional and sectoral organisations, to enable them to use the information for their respective regions or sectors.

Qualification levels

Information about qualifications levels required in the future is included in most skills forecasts. This relatively broad analysis typically identifies the extent to which higher level skills will become more important. These levels are of most use when combined with a clearer understanding of the skills needed for different occupations, and then at which level.

A challenge with this analysis is that any single occupation is performed by people with a diversity of qualifications, linked with age (i.e., older workers might rely less on formal qualifications than on years of experience) and other factors. Using qualification levels does not generate detailed data on education and training requirements to inform training policies but given data limitations it is a starting point to identify trends and guide the discussion on skills gaps.

An analysis of the highest qualification held *'making the most of the limited data available'* from LFS is included in the Working Futures model, using England's Regulated Qualification Framework (RQFs) and the respective levels in other nations. Projections are published for nine qualification categories for each 26 sub-major occupational groups by region, LEP, LSIP and MCA, and by region and main industry sector for nine major occupational groups.[61]

There is also an International Standard Classification of Education (ISCED)[62] which gives comparable levels, established by UNESCO in the 1960s and regularly reviewed. The levels are broadly comparable to English levels, with a Level 6 being a full undergraduate degree, a Level 2 being lower secondary education and a Level 3 being higher secondary education. There is no division between academic and vocational qualifications, and particularly for the UK, where we have limited Level 4 and 5 qualifications[63], there is limited granularity.

ISCED has been used together with occupational groups and sectors to project labour supply and demand in Project QuBe in Germany. This project is mainly concerned with labour market flows rather than skills, so only combining levels of qualification with occupations is appropriate. Forecasting skills also requires levels of qualification, but alongside skills and occupation (i.e. rather than qualifications alone).

[61] DfE (2023) Labour market and skills projections: 2020 - 2035
[62] Eurostat. International Standard Classification of Education (ISCED)
[63] Although the Government is keen to increase the numbers of individuals with these levels of qualification, known in England as Higher Technical Qualifications.

The proposed SSC plans to adopt skills levels as 'an underlying conceptual principle' (ref: A Skills Classification for the UK, p39) of its structure. These will be based on ISCED qualification levels. This approach will ensure that both skills and qualification levels are available.

Data-driven skills taxonomies

A common data-driven taxonomy approach is to use online vacancy data to understand the changing skills within job roles and changing job roles. Lightcast, for example, have created a taxonomy of skills clusters based on vacancy and job advertisement data, which is about four times as granular as UK SOC. This methodology has been used in reports for Nesta, the OECD's 'Skills for Job indicators', and Engineering UK.

The common thread in these projects is a desire to understand a fast-moving industry or economy and to pick up on recent changes to be able to propose or make adjustments in training or advice. Interviewees spoke of clear discussions, influencing assumptions and parameters, and satisfaction with the outcomes. They were all aware of the limitations of this analysis, but with the challenges of existing data and uncertainty around a UK-wide skills forecast, they were open to new methodologies that could reflect more recent changes.

This kind of analysis works best in industries where most, if not all, jobs are openly advertised online and well described in advertisements. The web-scraping techniques can recognise patterns and provide a useful picture of changing demand very quickly. However, job posting data is noisy and it can be easy to overinterpret a trend, so the level of granularity should be moderated with the level of accuracy. The Lightcast skills taxonomy and cluster model was considered useful by commissioners and users, but it is also proprietary data and so not available beyond what commissioners are prepared to publish.

Interviewees felt this was a useful addition to UK-wide skills forecasts and enabled them to have the most up-to-date data on skills demanded by employers. This being said, it was clear that it was seen an addition to publicly available skills forecasts, and not a replacement. There are substantial limiting factors for this kind of analysis to work across all sectors, most obviously the differing hiring practices in different industries. However, for the sectors where it is possible, it provides useful additional data.

A way to overcome the limitations of vacancy data is to combine it with other publicly available sources which are more forward-looking (e.g., investment, government strategies, R&D, news, training courses, procurement offers). This approach is implemented by Headai which analyses this data using machine learning techniques. Their approach identifies meaningful words and words pairs and the meaning behind them to identify skills and group them into clusters.

Other method-specific approaches

Other proprietary taxonomies include the McKinsey Global Institute classification of qualifications, knowledge and tasks (applied in the 'UK Skills Mismatch' report).

The approach used by the Workforce Foresighting Hub (discussed in more detail in Stage 2: Mapping skills to trends or employment outcomes) defines skills in terms of the capabilities and competencies needed to address the challenges identified for particular sectors. The competency statements produced by the Workforce Foresighting Hub can be mapped to existing IFATE qualification standards – as they use the same classification of knowledge and skills.[64]

Linking to skills without a specific taxonomy

Skills that are discussed by stakeholders and experts without specific reference to a taxonomy can be helpful at a high level. They can provide a general direction of travel through the use of broad skills descriptors. For example, in the 'UK's Horizon Scanning' report, it was projected that the wholesale and retail trade sector would experience a "higher demand for workers with programming skills" under the 'Digital Greening Economy' scenario.

Broad skills descriptors can be loosely mapped to a skills taxonomy.[65] However, they are not comparable across different reports or analysis, for example developers might disagree about the exact definition of a 'programming' skill.

Stage 2: Mapping skills to trends or employment outcomes

Once the taxonomy or 'definition' of a skill has been chosen, stage 2 is to link the output of building blocks 1 or 2 (i.e. future trends, or future employment outcomes) to what this means for skills.

Currently, the most common way this is done is to use the output of building block 2 (employment outcomes, usually at an occupational level) and then directly map the occupations to skills, using the chosen skills taxonomy. Less commonly, skills can be forecasted directly without producing an employment forecast.

The **mapping of occupations to skills can be static** (e.g. using a taxonomy such as O*NET or qualification levels without additional analysis). While this method is widely used and the output easily interpreted, the principal drawback of static mapping is that these classifications do not take account of how skills might change within occupations in the future. For example, one interviewee gave the example of the now near-universal requirement for Microsoft Office skills in most desk-based jobs, which would not have been a requirement for these jobs in the past. Looking forward, certain tasks might

[64] Behaviours are not currently including in this mapping.
[65] As described in the new UK skills classification which is in developed (see DfE (2023) A skills classification for the UK. Plans for development and maintenance)

become automated, or replaced by generative AI, which will change the skills required to perform a given occupation. Static skills mappings cannot account for these changes.

Mappings to employment can also be dynamic, accounting for how skills within occupations might change in the future. This typically requires higher volumes of data and machine learning techniques (e.g Headai).

Another option is to 'skip' building block 2 and **forecast skills directly** without the intermediate step of forecasting employment outcomes. An example is using a survey to ask employers how skills needs will change in the future. Another example is the method used by the Workforce Foresighting Hub. This allows the changing nature of skills within occupations to be considered. However, this may not be suited to all use cases, as some users require employment outcomes as an output of the forecast, alongside skills.

In the next sections we discuss each of these possible approaches. We note that this discussion covers a minority of the forecasts reviewed, as only a minority link to skills using a clear structure. This is partly due to the lack of an effective UK skills taxonomy as discussed in Section 'Stage 1: Choosing a skills taxonomy'.

Static mapping to employment

Assessment summary:

Strengths:

- Provides a structured framework allowing for an understanding of core and specialised skills.
- Fosters alignment and collaboration as all stakeholders use same skills language.

Weaknesses:

- Mapping between occupations and skills can be complex and resource intensive.
- Static taxonomy might overlook rapid changes in job market, in particular, if the taxonomy is not updated frequently.
- Limited ability to identify new and emerging skills. Subjective nature of skills assessment.
- O*NET or other international taxonomies might not reflect the reality of UK economy.
- Cannot account for changing composition of skills within occupations.

Applicability

- Appropriate for central planners and users interested in strategic workforce planning or the design of tailored education and training programs.
- Appropriate for shorter term forecasts.
- Less appropriate for considering trends that are disruptive to the nature of work and how occupations are performed (such as AI and automation).

As covered in the previous section, a static mapping approach takes a chosen skills taxonomy and maps to the output of building block 2 (employment outcomes by occupation), without using additional analysis steps. This is a less resource intensive approach but may have limitations for accuracy, particularly for analysing emerging sectors, disruptive trends, or labour market outcomes further into the future.

Defining skills in relation to occupations is key to this approach. The National Occupational Standards (NOS), as noted in Section 1, are a key part of the existing skills infrastructure in the UK. The standard skills classification (DfE, 2023) proposes constructing occupations by applying a ‘bottom-up’ approach, combining granular skills with level of qualification and occupations. Providing all three elements in this way would meet the needs of not just users of economy-wide forecasts, but also of regional and sectoral organisations.

Occupational classifications are currently a key part of the Working Futures model forecasts. As part of the Skills Imperative 2035 research programme, a complementary analysis was conducted to combine the occupational-level employment forecasts with projections of the skills that will be required in the future (at a national level). This was performed by combining the O*NET skills taxonomy with the employment projections produced by the MDM-E3 macroeconomic model and the econometric occupational models.

Occupation in the form of job roles was typically part of Sector Skills Assessments by Sector Skills Councils, and are still particularly important for sectoral bodies, as described by interviewees from Engineering UK and ScreenSkills. Canadian COPS projections provide a clear view on job roles and likely changes at a local level, providing effective labour market information. These projections do not include skills and do not themselves consider the likely changes to job roles, but they are designed to enable others to use the projections for more in-depth analysis around skills and qualifications.

NHS projections, partly due to the occupational specificity of health roles, are based on occupations. The REAL Centre produced a comprehensive skills forecast only for nurses in the first instance, because they are a clearly defined group in the SOC, as well as having specific training requirements.

> Only in this case, because of the fairly well-defined training pathway, system dynamics seems like a good approach because you can model roughly how long it takes for a nurse to come through the system, education and training. You can make the tweaks there where required, so if you want to change training types or types of degrees and so on, and you can also model stocks and flows quite effectively. – *Commissioner/User*

Whilst it is still helpful for these kinds of forecasts to cover the skills within the occupation to understand how the occupation, and qualifications/training required for the occupation, will likely change, they are fundamentally tied to an occupation. Providing the skills requirements, the qualification level, and the occupation, in skills forecasts means they can be more effectively considered by a range of users.

‘Static’ mappings can differ in how well they predict future skills mixes depending on how frequently the taxonomy is updated to reflect the changing requirements in the skills to perform a given occupation. Updating taxonomies can require significant resources.

As an example, the Working Futures macroeconomic model which produces an employment forecast by occupation (building block 2) also uses historical trends in the distribution of qualifications across occupations to project forward qualification demand in the future (building block 3). The underlying taxonomy is updated with each new forecast as the qualification projection takes into account the up-to-date data inputs on the relationships between occupations and qualifications. However, producing this forecast can be complex and data intensive, including multiple relationships and combinations between sectors, occupations and skills. This can also make it challenging to interpret outputs.

The 'UK Skills Mismatch' study uses a static taxonomy, with an augmented approach to account for automation impacts. The McKinsey Global Institute (MGI) skills taxonomy assigns the 2000 activities associated with all 800 occupations in the O*NET databases into one of 25 'workplace skills' required to perform the activity. The impact of automation is assessed by identifying which activities which will be automatable by 2030. Automation is assumed to result in proportionate aggregate job loss.[66]

Although this approach allows some consideration of the changing future skills mix, it does not provide a complete picture of changing skills within occupations because it does not account for new tasks or the growing importance of tasks within occupations and the skills associated with these. This approach may not be appropriate for considering the impacts on occupational skills mixes of other labour market trends, such as an ageing population or AI, or skills required in emerging industries.

[66] *"We make an assumption that each hour of work that could be automated results in proportional job loss, for example if 10 percent of current work activity hours in an occupation will be automated, then 10 percent jo jobs in that occupation will be displaced"* [McKinsey (2017) Jobs lost, jobs gained]

Dynamic mapping to employment: Machine learning techniques

Assessment summary:

Strengths:

- Allows analysis of changing mix of future skills within occupations.
- Scalable and efficient way to analyse large datasets.
- Can be continuously updated.

Weaknesses:

- Typically focused on jobs advertised online.
- Relies heavily on how training data is labelled, so can include researcher bias. Limited transparency due to ‘black box’ nature.
- Might not capture the context-specific nuances of certain occupations or skills.

Applicability:

- Well-suited to analyse large amounts of unstructured data.
- Appropriate for users interested in skills that are not captured properly by static taxonomies, or to analyse rapidly evolving industries.

Machine learning techniques can be used to identify and establish connections between specific job roles and the skills associated with them.

Typically, this involves the analysis of large volumes of data to identify patterns in past and current vacancy data. If the sources include forward-looking information, machine learning techniques can also be implemented to predict future skills (e.g. Headai).

When appropriately applied and validated, machine learning techniques offer a powerful tool to automate the linkage between occupations and skills: this can be less time-consuming than traditional methods of mapping, allowing for more frequent updating and use of the most up-to-date information which enhances precision; as well as potentially avoiding manual errors.

Job adverts are typically the data source used with machine learning techniques, for example Engineering UK or Headai. Another application of machine learning techniques is the Workforce Foresighting Hub. Expert Educators determine the knowledge, skills and behaviours (KSBs) needed to support the development of technologies (based on the ‘organisational capabilities’ determined by Expert Employers). Machine learning is used to synthesise these expert views to produce a list of KSBs for each role.

Direct forecasting of skills: Employer surveys

Assessment summary:

Strengths:

- Provides insights of those directly involved in the recruitment process, including industry-specific real-world skills demands.
- Fosters collaboration.

Weaknesses:

- Resource intensive, which might disincentive widespread use and frequency.
- Employer perceptions might be subjective and results are subject to reporting and sample bias.
- Relies on a well-designed questionnaire.

Applicability:

- Well-suited for sectoral or regional analysis when scope is narrow.

This involves gathering information directly from employers to understand the skills required for specific jobs within their organisations going forward. This method relies on employers' first-hand knowledge of the skills needed in the workplace, providing valuable insights into the current and future skill demands associated with various occupations.

Some of the studies reviewed conducted their own surveys to collect data on skills needs, for example the Food and Drink Association and The Quarterly ScreenSkills Barometer which is informed by a short online survey and a rolling panel of industry experts, providing regular updates on skills gaps.

Unless produced by the government on a large scale (such as the US employer survey which informs the O*NET classification), specifically commissioned forecasts are typically only feasible at a small segment or local level, where the pool of potential respondents is smaller. An alternative is to use published data like the National Employer skills survey[67], as used by CSN Construction Outlook. Core indicators are available at the 2 digit SIC code or Mayoral Combined Authority level, with more limited data at the SOC level. However, it only provides figures such as vacancy numbers and skills gap numbers, rather than providing granular information on the skills required.

[67] Employer skills survey: 2022 (gov.uk)

Box 13. Case study - Food & Drink Association: Future Workforce and Skills Survey

This report by the Food & Drink Association identifies the key challenges facing the workforce today and sets out the policy recommendations based on these challenges. Rather than looking at future skills, the report predominately focuses on the current state of skills in the workforce.

The findings are based on a survey of 170 businesses across the sector and supplemented by interviews. The qualitative approach is used to identify the skills required by the sector, and it provides a view of skills needs at different breakdowns (such as ‘generic’ vs ‘business specific’ skills, and a breakdown across tasks such as ‘management and directorship’ and ‘engineering and technology’ skills). It also provides employers’ views on the qualifications required across skill levels.

In addition, the survey is able to provide a picture of current training of the workforce. This includes formal qualifications like apprenticeships, as well as informal support to meet employee’s development needs which is unlikely to be picked up by other data sources. This information helps to provide an understanding of how employees are attempting to fill the skills gaps and what the workforce may look like going forward.

Direct forecasting of skills: Foresighting

Assessment summary:

Strengths:

- Can be targeted at the capabilities, knowledge, skills and behaviours required in specific sectors (which might not be captured in a whole-economy-level skills taxonomy)
- Does not require extensive data series.
- Ability to map skills requirements to IFATE's qualification standards.
- Ability to analyse changing skills composition within occupations looking forward.
- Incorporates different perspectives and fosters collaboration.

Weaknesses:

- Does not produce quantitative estimates, but directions of travel.
- Relies heavily on experts' judgements, accuracy depends on quality of qualitative evidence.
- Focus on emerging technologies: might be less appropriate for established sectors.
- Resource intensive. Requires analysing high volumes of qualitative data.
- AI techniques to synthesise expert views can be non-transparent, difficult to understand drivers of overall results.

Applicability:

- Well-suited for segment-level users that prioritise strategy and workforce planning in emerging sectors and need to identify future skills that are specific to their sector and can be mapped to qualifications and training requirements.
- Well-suited to analysing occupations that are likely to change rapidly over the short-medium term, e.g. in nascent sectors or where jobs are likely to change a lot as result of new technologies.
- Suitability depends on available resources i.e. to engage experts, gather a sufficient range of views, and employ AI techniques.

Foresighting uses qualitative information provided by sector experts, along with AI techniques, to understand the skills required to meet future challenges for businesses and their supply chains, map these skills to the current educational offer and highlight where new standards, qualifications and upskilling courses are needed. For a detailed description of the method, see Box 4 in Section: Building block 1 – Approaches to future trends, above.

In this section we discuss the strengths and limitations of using this method specifically to forecast future skills needs.

Foresighting produces lists of capabilities required across occupational profiles and the supply chain, and skill gaps analysis for a specific sector. This is helpful for most user types as it switches the analysis of skills needs from megatrends to specific challenges tailored to the sector. For example, it is helpful for a range of government departments to understand the skills needed to meet the key goals in their areas (e.g., Net Zero related goals).

Foresighting uses a common skills language (based on 'competencies') across 'challenges', allowing comparisons of skills across different sectors. This is particularly useful for users working cross-sector such as central planners or industry bodies covering multiple sub-sectors. Moreover, competencies can be compared to IFATE's qualification standards, allowing an understanding of the current gaps in qualifications. Additionally, employers can understand the future skills needed in line with technology innovation and train their workforce accordingly.

A key advantage to this approach is that by directly forecasting skills needs, foresighting can capture changes in how skills within occupations could change in the future. This could capture for example an increased need for programming skills in the future, to perform an occupation that already exists. This is particularly for important for job roles that are changing rapidly over time, e.g. because of wider technology trends (such as automation and AI) or because of emerging or rapidly changing sectors.

However, there are weaknesses to foresighting for this purpose that will make it better suited to some contexts than others, as discussed previously in Section: Building block 1 – Approaches to future trends and detailed in the assessment summary box.

Qualitative inputs

Summary

Qualitative inputs could be used at any stage of the skills forecasting process, to inform and enhance any building block. They add insights that quantitative data cannot, such as providing employer views or better understanding emerging trends.

When choosing what type of method to use and at which stage, there is a trade-off between relevance and resource requirements, including time, budget and expertise, as qualitative methods tend to be resource intensive. It is important to strike the right balance between scalability and depth. Table 9 provides an indication of what qualitative input might be useful for different purposes.

In this section we review qualitative techniques of data capture and techniques to incorporate expert insight into forecasts. Qualitative techniques can be used to provide depth, context and nuances that quantitative data alone might not capture. They can be used to better understand the skills landscape; collect evidence on emerging trends and context-specific skills; engage with diverse stakeholders; and validate and interpret assumptions, methods and results.

Qualitative methods can be used before, during, and after quantitative skills forecasting methods, to provide a clearer understanding of the data, likely scenarios, and to indicate amendments to the quantitative assumptions and analysis. They are particularly useful to triangulate data and ensure the output 'feels' right.

Segment-level studies currently rely more heavily on qualitative inputs from industry representatives and experts, compared to economy-wide studies. Typically, organisations aiming to get a detailed view of future skills requirements in specific sectors or local areas will combine quantitative published data and analysis with qualitative data to achieve a more tailored perspective. This kind of triangulation is generally viewed as best practice and uses several different types of qualitative method.

> I don't think a generic set of projections are really going to address them (future skills). I think you need to really have in depth analysis. – *User*

> Models can only get you so far and you really do have to have that intel that sits behind it, that can really challenge the outputs. – *Commissioner/Developer*

> I would trust [a method] more because I know that they've got the industry knowledge and the expertise and they would have engaged widely. – *Commissioner/User*

In Table 9 we list the common techniques used to capture qualitative input and list the reviewed studies that used each of these techniques.

Table 9: Qualitative methods across reviewed studies

Qualitative method	Studies using this method
Surveys	• UK Commission for Employment and Skills (UKCES) insights • Skills Forecast Service and Quarterly Screen Skills Barometer • Preparing for a changing workforce: A food and drink supply chain approach to skills
Expert groups	• The Potential Impact of Artificial Intelligence on UK Employment and the Demand for Skills • CSN Industry Outlook - 2023-2027 • Workforce Foresighting Hub - Emerging skills project • Green Jobs Taskforce: Report to Government, Industry and the Skills sector • Preparing for a changing workforce: A food and drink supply chain approach to skills • *(not shortlisted as a case study but included in interviews):* Specific regional forecasts, for example LSIPs and West Midlands Combined Authority
Interviews	• Labour market and skills demand horizon scanning and future scenarios • Green Jobs Taskforce: Report to Government, Industry and the Skills sector • Preparing for a changing workforce: A food and drink supply chain approach to skills
Expert advice and Delphi panels	• Working Futures • US Employment Projections Programme • Cedefop • Germany QuBe • Australia’s National Skills Commission • Canada’s 3-year employment outlooks • Skills Forecast Service and Quarterly Screen Skills Barometer • UK Skills Mismatch in 2030

In Table 10, we set out the applicability of qualitative methods. This table summarises our discussion below, showing where one qualitative method is more suitable than another. It shows what these qualitative methods are able to achieve relative to quantitative methods.

Table 10: Applicability of qualitative methods

Qualitative method	Examples of uses
Surveys	• Collect data where no official sources are available, such as specific sectors or local areas. • Collect employer views, particularly useful to understand changing skills within occupations.
Expert groups	• Develop scenarios and understand the impact of future changes, such as technology. • Tailor broader outputs to specific groups, such as specific sectors or local areas.
Interviews	• Similar to expert groups but can be used where expert groups are not possible (e.g. for logistical reasons) or where more specific or confidential insight is needed.
Expert advice and Delphi panels	• Test and get feedback on outputs. • Reach a consensus from a combination of inputs.

Surveys

Surveys are used in a variety of ways, capturing insights from employers, employees and other stakeholders to understand current and future skills needs. For example, ScreenSkills use surveys to understand both the current workforce, through an annual census, and to understand future demand by asking both current workers in the industry, and employers:

> Most of our research was kind of done via surveys. It is quite difficult to forecast skills within the screen industries. – *Commissioner/User*

Sectors like the screen industries, which are not well-served by SIC and SOC, and that have high levels of self-employment, use surveys to ask individuals and employers directly about changes in work and potential future changes. However, there are challenges in ensuring representativeness when the sector is ill-defined in existing data:

> We don't know the size of the workforce, so it's very hard to estimate what is kind of a good statistical rate of response. So given that we don't know, it becomes quite difficult to validate in that kind of way if

> you know there's estimates of the … workforce as being between 80,000 and 200,000, so it becomes very difficult to say if this is statistically significant. – *Commissioner/User*

Box 14. Case study - ScreenSkills: High-end television in the UK 2021/22 workforce research

This report aimed to understand workforce challenges, including skills gaps and shortages and their drivers, and perceptions of future skills issues. It involved 40 qualitative interviews with a sample of those working in the industry and 56 survey responses including open and closed questions.

The report found that there were severe skills-related issues due to the impact of Covid-19 on television production, alongside high levels of demand for production work. Although this led to an increase in pay, there were urgent needs to provide training to ensure there are the requisite number of staff at different grades.

The sharp decreases and then increases in demand had not been predicted in any skills forecasts, which had suggested a modest increase over the next 5-10 years in the arts and entertainment industries. The qualitative interviews in this research project by ScreenSkills were particularly valuable in helping to develop an understanding of the likely future skills needs.

The outputs of the report were used to inform the direction and spending of the skills fund on training and supporting the industry. The report goes to the High-end Television Council and related Working Groups who make decisions about the spending of the skills fund. The skills fund for High-end Television is administered by ScreenSkills who have a remit to provide data and information as well as commissioning the education and training as directed by the Council and groups.

Recent Local Skills Improvement Plans, developed by the Chambers of Commerce, also use surveys, usually of employers to ask them about future skills needs and how their workforce might change over time. Although these methods have downsides, particularly in terms of self-selection bias, they can often be an effective way of capturing the current situation from a large group of individuals or employers who are otherwise not well-served by official data sources.

Many surveys have seen falls in participation over time, as online surveys and feedback have become more prevalent for a range of purposes. As such, preventing bias and ensuring representativeness of surveys has become more difficult, particularly for surveys of individuals.

Surveys allow for standardised data collection, ensuring consistency in responses and facilitating quantitative analysis. However, to enhance the effectiveness of skill forecasting through surveys, it is crucial to design well-structured questionnaires, ensure representative sampling, and encourage honest and comprehensive responses through effective recruitment processes.

Expert groups – workshops, focus groups, panel etc.

Involving expert groups as a way of better understanding the potential changes to skills can be used at different points in a skills forecast. Workshops bring together stakeholders for collaborative discussions, fostering the exchange of ideas and the exploration of diverse perspectives, while focus groups are often smaller and more homogenous so there is a higher risk of skewed results.

As explained above, the Workforce Foresighting Hub uses three expert groups – employers, technologies/solutionists, and educators – and aims *"to ask the right group the right questions"*. These expert groups test any data collected by the Hub, so that expert input is incorporated at each stage of the process. As groups, they come with different perspectives and can challenge each other to work towards a common view.

A similar process happens in the West Midlands Combined Authority, where six expert panels in specific growth sectors identified by the Mayor assess national data (including the Working Futures forecasts) and highlight challenges they are facing. These groups stay in post for some time, allowing individuals to build relationships and be sufficiently confident to raise concerns. Refreshing the groups regularly is important however, to avoid group think.

> As well as a place based approach we take quite strong focus on sectors and clusters and engage with sectoral organisations, but also individual employers, because we need not only to meet demand but to stimulate demand. – *Commissioner/User*

By bringing together a range of types of information and gathering expert input, the data is brought to life and tailored for the specific sector or local area, making it possible to use skills forecasts appropriately to support any changes needed. However, the outputs of these techniques depend on the specific experts and stakeholders participating in workshops and focus groups which might not be representative of all interest groups.

Interviews

Interviews can be a useful option when bringing together expert groups is not possible, or when specific expertise is sought. The Horizon Scanning report focuses on six sectors, and after an evidence review uses expert interviews to help develop scenarios and define assumptions, which are then tested in a workshop. This is a similar approach to the

Workforce Foresighting Hub discussed above, although using interviews before moving to expert groups.

> You need people who understand the nature of those sectors, and
> the pros and cons of analysis collection.
> You've got to have people who understand the industry.
> *– Commissioner/Developer*

An interview methodology, in terms of developing skills forecasts, builds on existing data then uses the qualitative input to either confirm or amend particular forecasts, and in the case of the Horizon Scanning report, to extend the horizon and develop specific likely scenarios to test. They could also be used to help develop the scenarios, and then use a quantitative modelling method to test these scenarios.

As in the case of workshops and focus groups, interviews are particularly effective in capturing qualitative data, uncovering subtle nuances, and obtaining detailed contextual information that surveys may overlook. However, these methods can be resource-intensive, requiring time, expertise, and coordination. They may also be subject to facilitator bias, and the small sample sizes may limit the generalisability of findings.

Expert advice and Delphi process

Expert advice, where individuals are specifically selected to provide feedback on findings, has also been used effectively in skills forecasting. This method is used in the Canadian COPS model where regional economists contact experts to validate the outlook for local labour markets.

The ScreenSkills report also includes advice from experts, using the Delphi process. The Delphi process is normally used in qualitative studies and involves iterative rounds of surveys or questionnaires to a panel of experts. In the case of ScreenSkills, it combines advice from specific experts through systematic engagement with an initial position paper, followed by individual telephone interviews and a questionnaire sent by email. The objective of Delphi panels is to reach a consensus position amongst the experts, so could be conducted through focus groups or other qualitative methods. The ScreenSkills analysis also aimed to create a shift in thinking from the current situation to what could be the case in future.

Reconciliation methods

As part of our review, we examined how different forecasts can be reconciled to deliver a consistent view of skills needs across different segments of the economy. We examined how segment-level forecasts use information from forecasts produced at the economy-wide level, and vice versa, and the challenges involved.

We found that, for regional or sectoral bodies, reconciliation typically involves considering an economy-wide forecast in the first instance, typically the Working Futures forecast in the UK, and then using this data to triangulate with other methods to focus specifically on the relevant sector or region.

While it is technically possible to develop forecasts that attempt to reconcile a series of individual sector or regional forecasts up to an economy-wide forecast, it is very challenging to do so whilst avoiding duplication or overlap of labour demand. Perhaps unsurprisingly, the review did not identify any examples of this kind of reconciliation. One commissioner indicated that it is important for stakeholders to consider how their own forecasts fit in the broader UK picture to avoid undue fragmentation of the skills forecasts landscape:

> You could end up in a bit of a land grab where these sector bodies are thinking, well, that relates to my sector. So I'll include that in my projection and the other sectors are doing the same and you're duplicating and then if you added up all the projections across all the sector bodies, your economy would be 125% of what it actually is. So it's important to you know, provide that sort of top down constrained picture. But it wasn't that we were saying you can't use your own forecast, you just have to use the two - a local forecast from your sector and a national top-down forecast. – *Commissioner*

Having an economy-wide forecast as a common starting point, from which segment-level forecasters can build, makes segment forecasts more easily comparable with other segment level forecasts which are consistent with the same assumed economy-wide trends, for example national GDP growth and demographic trends. This principle of maintaining consistency is also applied by the economy-wide forecasts, to ensure the forecast is internally consistent and externally in line with official sources. In the Working Futures research all employment data by occupations have been constrained to match the headline figures and overall patterns published by ONS in the UK and regional labour market statistics bulletin or similar publications.

That said, there were several motivations for segment-level forecasters to build on the outputs of Working Futures. These included:

- to build in information on **specific segment-level factors**, in particular qualitative inputs; and
- to forecast at the level of **sectoral or regional definitions** not included in Working Futures output.

In the following sub-headings, we discuss each of these motivations in more detail and the challenges typically faced when producing segment-level forecasts.

Specific segment-level information and trends

In all cases reviewed for this report, those producing segment-level forecasts included expert feedback on specific segment-level factors. This typically involves bringing in *additional* information on the unique characteristics of specific sectors or regions (rather than making *different* economy-wide assumptions to those made in Working Futures). For example, in the construction sector, forecasting includes bringing in knowledge about ongoing or upcoming infrastructure projects and their workforce requirements in specific areas. This process ensures that workforce planning, education, and training initiatives are well-informed and tailored to specific needs. A further example of the ScreenSkills forecast is given in Box 15.

> You've got to always have the quantitative and the qualitative which brings in the intelligence of the people….that's where you need really strong collaboration across industry across sectors, across skills, bodies. – *Commissioner/Developer*

We found that there was no common framework for how to build in this additional information on segment-level drivers. Guidance for segment-level forecasters alongside more coordination and information sharing could improve the quality of the evidence produced. The need for additional work by sectoral bodies may also be reduced by building in sectoral-level qualitative input to the economy-wide forecast: this is a current gap in Working Futures as we discuss further in Section 6: Findings and recommendations.

Box 15. Case study – ScreenSkills: High-end television in the UK 2021/22 workforce research

Data from the Working Futures forecast showed that during the Covid-19 pandemic the entertainment industry had experienced a decline, with a baseline projection that the workforce would be back to pre-pandemic levels by 2025.

In contrast, the ScreenSkills 2021/22 survey of the high-end TV workforce in the UK highlighted significantly increased demand and serious skills shortages in a range of TV-related occupations, taking the workforce more than back to the size before the pandemic by 2022. The pandemic created additional demand for TV programming that estimates from Working Futures were not able to foresee. The growth in the industry post-pandemic suggests that the skills shortages are acute, although recent industrial disputes in the USA later caused a slowdown.

ScreenSkills had an awareness of these issues from discussions and feedback from employers before the survey was launched and was able to tailor questions aimed at trying to reconcile this scenario with the predictions from Working Futures.

This reflects a challenge in using a longer-term forecast to predict short-term demand for skills. Over time, the forecast for the film industry has begun to move to something more like the Working Futures forecast, but in the short-term had significant variation as described. Ways to address this challenge could include more information for users and guidance on short-term trends. Sectors and regions may find that their own qualitative and expert advice is more accurate in the short-term, while the economy-wide forecast is more useful in the long-term.

Specific sector-level definitions

In some cases, sectors are defined differently by the relevant sectoral body compared to the definitions used in economy-wide forecasts.

Engineering UK, for example, use a wider definition of ‘engineering’ than that used by Working Futures, or in SIC/SOC codes – the Engineering UK definition includes around 20% of jobs in the UK under engineering roles. This bespoke definition was developed based on the job roles listed in Lightcast data on online job advertisements. Bespoke sectoral definitions may also be used in emerging or fast-growing sectors, where new roles are appearing which are less well-aligned to existing classifications, and for occupations which are required in many different industries (e.g. programming).

> Historically different job names have grown up for similar jobs and the challenge is now when we're looking at workforce planning, aligning job names to SOC codes. – *Developer/User*

Another consideration for the Engineering UK work was the description of certain roles in a neutral way. Many skilled roles requiring Level 2 or Level 3 qualifications are described as 'low skilled' according to ISCED and in other reports. Employers are aware there is demand but the framing of the roles as 'low skilled' makes it difficult to argue for additional training.

> Lots of jobs in demand not considered highly skilled in terminology. For example we really need welders which isn't classed as skilled but clearly is. – *Commissioner/User*

This is particularly a challenge where an economy-wide forecast may suggest that there are sufficient skills in the labour market, but employers know they are unable to meet the skills demand in their own industries.

> There were some specific skills like forklift or tipper driving where everyone was wanting to go and build houses instead. So if you're a forklift driver or tipper driver, you were working for house building companies. You wouldn't go and they couldn't get them to work in [a different] sector. So It was really eye opening because we were just going from that kind of macro level of skills and data to actual professions or actual jobs and tasks that needed doing, it was a much more interesting way of thinking about skills. – *Developer*

Specific analysis on key areas, determined in discussion with sectoral representatives, adds value to a general economy-wide forecast. It can be particularly useful to focus on shortage occupations or smaller roles that might not otherwise be available in the broader forecast.

Specific regional definitions

Regional bodies require outputs at a geographic level which is typically more granular than the level of government office regions (output of Working Futures), e.g. this could be at the level of local enterprise partnerships (LEP), mayoral combined authorities (MCA), or, at the most detailed level, lower layer super output areas (LSOA).

Making a simplifying assumption that labour demand and skills drivers are the same in these more detailed geographic areas as at government office region level is not always appropriate. Some sectors have labour demand which can be very locally concentrated, and this is an important consideration for workforce planners and designers of training. In large and diverse areas, local economic conditions and workforce dynamics can vary, requiring a more detailed understanding of sub-regional trends.

One way to examine these trends is to use expert panels, appointed to interpret national forecasts and identify local challenges and opportunities, as is used by the West Midlands Combined Authority. This qualitative approach is often taken because quantitative data is not available at a sufficiently granular level. As described by one interviewee:

> A really in-depth engagement with employers has been one of the key ways in which we've sort of added value to that data and to test what that means… for example say you get a big report saying in the manufacturing sector you need this, and we think how about the manufacturing businesses in this region who do this part of the supply chain [will react]. And I think it's only by having those more detailed conversations with employers that we've been able to really nuance what the need is for the [our region] as opposed to what the national need is. – *Commissioner/User*

A challenge for regional forecasting is that sectoral or regional data may be less readily available or of lower quality compared to national-level data, which can limit accuracy. As described by one interviewee:

> It feels to me having spent quite a lot of my career and looking at national issues, then moving into local issues that combined authorities are not adequately resourced with the sort of data that central government has that would enable it to do its job well by collecting data sources and access to them. And I think that's a challenge. And in this particular region, one of the challenges we have is [that our] Combined Authority (CA) is not the same as the region. It is [a collection of] local authorities and one of the challenges that to some extent is starting to be addressed now is that data is therefore often not available for the CA. It comes out to the region and places like [specific local area] which are in the region but not in the CA, often distort some of the particular challenges that we have. And so having [the CA] level data in a way that is timely and accessible would be really good. It is really important for us and I know some of that work is starting to be done. But I think there's still much, much further to go on that. – *Commissioner/User*

Potential extensions of an economy-wide forecast could provide some or all of these definitions used by sectoral and regional bodies as individual reports. These would need to be reviewed on a case-by-case basis to ensure they align with government priorities, but for example, providing data for mayoral combined authorities in addition to government office regions could be an effective way of supporting users of skills forecasts. This would have the added benefit of ensuring that all users are working from the same data, rather than producing their own with slightly different assumptions or definitions.

Section 5: Combining building blocks

Our assessment in Section 4 focussed on individual building blocks of a skills forecast which answer specific questions – for example, how does time series analysis compare to macroeconomic models in linking future trends to employment? Or how can qualitative inputs be used to enhance skills forecasts? However, developers also need to consider how to effectively combine these building blocks in a way that is efficient and aligns with their needs and intended purpose of the forecast. In this section, we provide guidance across three key questions:

- Are all building blocks equally relevant?
- Is there a 'correct' ordering of the building blocks?
- How should methods across building blocks be combined?

Are all building blocks equally relevant?

Using all building blocks is typically advantageous, but not strictly necessary

Using all three building blocks is generally advantageous. Each building block has a particular purpose and using all three ensures a well-rounded understanding of the skills landscape by systematically identifying emerging trends, and linking them to employment, occupations and skills outcomes. Developers and commissioners should consider each of the three building blocks and begin with an assumption that all three are important.

Moreover, the link to skills, either from future trends or employment outcomes, is a crucial part of any *skills* forecast. As mentioned in Section 4, only a few of the shortlisted forecasts include a structured approach to forecasting skills, and many only incorporate occupations or qualifications (as a proxy of skills).

The necessity of including each step, and the level of detail and resources allocated to each, depends on the specific goals of the forecasting effort, the availability and quality of data, resource constraints and the level of detail required for decision-making. In particular, there are some circumstances in which it may be valid to exclude some of these building blocks:

- When the **focus of the forecast** does not require one of the building blocks. For example, if the goal is to understand the broad trends affecting the labour market and their impact on skills, then a link to employment outcomes might not be necessary (e.g, UK Horizon Scanning). A link to employment outcomes is also less relevant where the goal is to understand the impact on skills within jobs of sub-sector specific technology changes (e.g., Workforce Foresighting Hub). This is particularly the case for sectors where occupations are not that clearly defined and skills are less specialised (i.e., could be transferable across various occupations or even sectors). Other forecasts might be more interested in projecting occupations rather than skills (e.g., Canada's 3-year Employment Outlooks).

- It is also important to consider the **other priorities of potential users**. Different users may have specific interests or concerns related to future skills requirements. In some instances, a high-level overview may be sufficient for strategic planning, while if detailed insights about specific occupations, industries or regions are required, a more interconnected analysis may be necessary.
    - Many users are interested in understanding the skills demand for different jobs which makes it important to link to employment.
    - Those designing sector specific qualifications (such as apprenticeships) will have some interest in understanding general changes in skills in the economy as a whole (e.g., rising demand for AI skills), but they are also concerned about the changes in skills across jobs so that apprenticeship standards can be updated accordingly (which requires more granular projections).
    - Users interested in workforce planning will require an understanding of what skills are required for different jobs: whilst it is useful to know changing skills requirements for the sector as a whole, a breakdown by different roles within the sector will be important to aid recruitment and training of workers for the appropriate roles.
- When there are **limited resources** (time and budget). Integrating multiple layers of information requires significant resources for data collection, analysis and validation. In some cases, resource constraints may limit the depth of analysis and a more targeted approach might be more feasible. The time horizon of the forecast can also impact the relevance of certain building blocks. Short-term forecasts may place less emphasis on future trends compared to long-term forecasts, especially in stable economies or mature sectors less vulnerable to shocks.
- When **availability and quality of data** are limited. If reliable data on labour market trends, employment outcomes, and the associated skills are accessible, combining this information can offer a more detailed and accurate forecast. However, in situations where data are limited or of questionable quality, a more focused and simple approach may be necessary. This is well-suited for cases where insights of the direction of travel are more relevant than specific point estimates.
- When the relevant **crosswalks** between building blocks are not fit for purpose. For example, when crosswalks between occupations and skills have not been developed, are not that straightforward or boundaries set out by standard classifications and taxonomies might be too restrictive to capture a complete picture of emerging trends. Given the lack of a standardised skills language in the UK linking future trends to skills directly might be appropriate, without being bound by the limitations imposed by occupational or industrial classifications. Use of

building block two, linking trends to employment, assumes a pre-established and constant relationship between occupations and skills. This is not necessarily realistic (e.g., disruptive technologies like automation can change the skills composition within an occupation) and so the building block may not necessarily be appropriate.

In these cases, a mix-and-match approach (i.e., choosing the building blocks in line with context) might be more appropriate, compared to an approach which always combines all the building blocks.

In Box 16 and Box 17, we contrast two of the shortlisted studies which take different approaches in terms of the combination of building blocks. Foresighting (Box 15) skips the 'Linking trends to employment outcomes' block whilst the Engineering Skills UK (Box 16) uses all the building blocks. These examples highlight when it might be appropriate to skip building blocks depending on the purpose of the forecast.

Box 16. Case study – Skipping building block 2 (occupational employment forecast)

Workforce Foresighting Hub

Foresighting is an approach which goes directly from trends to skills, skipping the second building block (linking to employment). Once the trends are determined based on expert input from with expert technologists, these are linked to the organisational capabilities required (using input from industry experts), which are in turn linked to Knowledge, Skills and Behaviours framework (KSBs) (using input from expert educators). Once the KSBs are determined, gap analysis of current IFATE qualification standards is undertaken.

Why was this approach chosen?

Foresighting begins with the identification of the challenges imposed by future technologies in a set of sectors and their supply chain. Skills are the centre of the analysis due to the realisation that having the right skills in place is important to be able to exploit technology being developed in the future. By skipping the link to employment, the approach does not rely on static links between employment and skills and is able to account for the impacts of changing technology on skills demand. within occupations.

Box 17. Case study - Using all 3 building blocks

Engineering Skills – Now and in the future

This study uses all three building blocks: (1) future trends are based on a projection of past trends; (2) a forecast of job counts for industry, occupation and local area is produced using Lightcast in-house data; (3) future skills are forecasted using Lightcast's skills clusters taxonomy (for more detail see Section 4).

Why was this approach chosen?

Lightcast's in-house projection model can be applied across different sectors. Combining these building blocks in this way has many advantages:

- Uses Engineering UK's own definition of the engineering sector that is wider that the one used in Working Futures, making the results more relevant to the sector.
- Uses more tailored language about the changing nature of jobs, rather than simple high/low skilled job definitions.
- Provides precise estimates of job counts for industry, occupation and local area, with an in-house occupation taxonomy that is four times more granular than UK SOC.

Each building block is crucial for this approach, and these advantages rely on the inclusion of all building blocks. In particular, the granular skills forecast first requires a granular employment forecast that the taxonomy can be applied to.

Compared to many other approaches which only forecast employment or qualifications, or include skills only as an afterthought, this all-in-one approach is skills-focussed. It provides a good example of how all the building blocks can be combined to produce a forecast with a reliable link to skills.

On the other hand, the approach is only applicable where the past is a good predictor of the future. It is only relevant for industries which are well captured via online job adverts, for example agriculture jobs are typically not posted online. combining all three building blocks in this way may not be suitable for other industries or use cases.

Is there a 'correct' ordering of the building blocks?

An ideal forecast considers the building blocks sequentially

The ideal sequence involves starting with identification and analysis of future trends, followed by linking these trends to employment or occupation projections and then associating these with future skills requirements (or a proxy of skills such as qualifications). Including all these building blocks in a sequential way is a structured and comprehensive approach that has become the standard for developing national forecasts in developed countries. In particular, all of the nationally commissioned quantitative skills forecasts shortlisted[68] use all the building blocks sequentially.

Beginning with an analysis of future trends establishes a contextual understanding of the overarching drivers influencing the economy and the job market which could affect future skills needs. This is relevant as it establishes the foundation for the subsequent steps in the analysis. Linking these trends to employment outcomes adds specificity, translating broad trends into implications for specific job roles and industries. Finally, linking occupations to skills completes the connection, identifying the specific skill sets that will be in demand. This order ensures that the outcomes of the skills forecasts aligns with the evolving economic landscape and supports effective strategic and workforce planning.

The key limitation of this sequencing, as it is currently used, is that forecasts using all three building blocks also typically use a static mapping to employment which can miss some key details about future skills, as discussed in Section 4. This is not an inevitable outcome of using all 3 blocks sequentially but is how forecasts up to now are most commonly constructed. More novel methods that aim to dynamically forecast skills may get around this problem by skipping the employment forecast step (see Section: 'Are all building blocks equally relevant?'), or instead use the standard sequencing but with an iterative approach. We discuss this in more detail below.

Starting with a general understanding of future trends is always important

Doing this provides a forward-looking perspective that helps anticipate changes in the labour market, ensuring an approach that is proactive rather than reactive. This allows all stakeholders in the skills landscape, including policymakers, educators and employers, to prepare for emerging opportunities and challenges. It also helps establish a contextual framework to guide the analysis by providing insights on the macroeconomic, technological and demographic factors that might influence future skills needs.

Additionally, beginning with future trends enables the identification of emerging industries, occupations, and skills which might not be captured by standard classifications or previous research. It also provides evidence to back up assumptions and information on potential scenarios to be assessed. This allows developers to make an informed decision of the appropriate methods to be applied in later stages of the analysis.

Using an iterative approach to ensure skills at the centre of the forecast

A lineal sequential order assumes a direct and straightforward crosswalk between occupations and skills, meaning any predicted increase or decline in skills requirements depends on occupational projections. However, as mentioned in Section 4, this mapping

[68] Excluding Canada's 3 year Employment Outlook forecast, which does not including the 'Link to skills' building block.

is not straightforward and it might overlook skill requirements within specific job roles that are not likely to change in volume but rather in tasks/skills mix. For example, if forecasts suggest that employment among engineers will increase, this approach will imply that all their associated skills will increase; this is not necessarily realistic. Some skills might be impacted differently by economic trends and therefore the skills composition might also change.

Another limitation of the sequential approach is that is it may place a high importance on long-term trends at the expense of short-term immediate needs. Linking trends to employment, and then to skills, requires a static taxonomy which might not capture short-term changes such as immediate skills gaps or emerging challenges in rapidly changing industries. Skills requirements can evolve rapidly due to technological developments, changes in business models and industry processes, or even behaviours and attitudes towards remote working. In addition, tying the assessment of skills to a static and rigid occupation classification might not accurately reflect the dynamic nature of the labour market.

Therefore, developers and commissioners need to consider the extent to which capturing changes in skill composition within occupations or sectors may be relevant for potential users. This is particularly true for economy-wide forecasts which tend to rely on existing industry, occupation and skill taxonomies and might not capture the dynamic nature of certain jobs.

An additional issue with the typical sequential approach is that skills can become an ‘afterthought’, especially if the focus is disproportionally centred around occupations. In these cases, there is a risk of neglecting the granularity of skills needed within different job roles. This is particularly important for skills that are transferable across a wide range of occupations which might also have different growth potential. For example, forecasts would be better at picking up the increase in demand for more data scientist roles rather than the demand for data science skills for economists. Without a dedicated focus on skills, the forecast may overlook critical skills gaps which can hinder initiatives aimed at addressing specific skill mismatches.

Addressing the risks that are inherent in a sequential approach requires a balanced and iterative approach that puts the assessment of skills at the centre of the forecast, incorporating ongoing feedback loops, real-time data updates, and the flexibility to adjust the forecast based on evolving conditions in the labour market. Making the forecast process iterative is also essential for adapting to the dynamic and unpredictable nature of the workforce landscape.

For example, as explained in Section 4, Headai has built a dynamic machine learning model fed by large volumes of textual data acquired from the open web (e.g., scientific articles, reports, curriculums, course descriptions, job vacancies and job descriptions) which is always updating. The key benefit of this approach is that it does not rely on a static skills taxonomy and so is able to account for changing skill demands within occupations.

How should methods across building blocks be combined?

There is a large number of ways that methods from each building blocks can be combined. There is no one single best approach and the suitability of each method depends on the specific goals of the forecasting effort and its intended use.

Commissioners and developers can typically choose any methods from each building block to produce their forecast. For example, most of the central economy-wide forecasts combine external judgements with macroeconomic models, but there is no reason they could not combine other techniques such as machine learning with these macroeconomic models. These macroeconomic models are typically followed by a static skills taxonomy, but it would also be possible to use dynamic skills taxonomies instead.

Some general principles based on our assessment in Section 4 can be considered when combining building blocks:

- **Relevance:** Tailor methods to the intended purpose and user's needs. Different sectors or local areas might require different analytical approaches based on their unique characteristics. Short-term and long-term forecasts might also require the application of different methods depending on their underlying assumptions. As an example, the assumption that past trends will continue in the future is more realistic for short-term compared to long-term forecasts.

- **Methodological rigor:** Choose methods that are grounded in sound statistical and economic principles or data-driven approaches. Rigorous methods enhance credibility of the forecast and trust in outputs. This includes taking reasonable steps to analyse the performance of the methods used.

- **Versatility:** Recognise the dynamic nature of the labour market and choose methods that offer flexibility and adaptability. Methods should be capable of accommodating emerging trends, and various scenarios.

- **Data quality and availability:** Ensure that the chosen methods align with the quality and availability of data. Consider the accessibility and limitations of data for each phase and choose a method that can effectively leverage available information.

- **Incorporating qualitative insights:** Balance quantitative methods with qualitative insights in a systematic way across all stages of the forecast process. Qualitative information from interviews, focus groups, or expert opinions can provide nuanced perspectives that quantitative methods may not capture.

- **Stakeholder engagement:** Stakeholder engagement ensures that the forecast reflects a comprehensive understanding of the labour market. This should be based on a framework[69] to guide the selection of diverse stakeholders in order to capture different perspectives, including experts, employers, educators and policymakers.

- **Sensitivity and cross-validation:** Test the reliability of the forecast against alternative methodologies and scenarios to understand potential variations and uncertainties. This might include quantitative sensitivity tests to understand the role of certain assumptions or testing outputs with experts.

- **Iterative process to incorporate continuous feedback:** Establish an iterative process to receive and incorporate feedback. This ensures that the forecast remains responsive to evolving conditions (e.g., new data, emerging trends).

- **Documentation and transparency:** Document the chosen methods and their rationale. Clearly communicate the assumptions, parameters, limitations and uncertainties associated with each building block. This builds trusts and facilitates informed decision-making.

- **Reconciliation:** If possible, sectoral and regional skills forecasts are most useful from a policy viewpoint if they reconcile economy-wide forecasts with their own estimations. This helps alignment with national priorities and fosters collaboration.

Box 18 and Box 19 provide two examples based on the shortlisted studies we reviewed. One example shows a typical combination of methods, whilst the other presents a novel approach.

[69] This framework can include but is not limited to data collection methods and toolkits, research protocols, sample design, questionnaires/topic guides, ethics, data protection and codes of conduct, etc.

Box 18. Case study - Best practice for government-commissioned economy-wide forecasts

Working Futures uses the following methods:

- **Approaches to future trends:** Combination of (1) external data from sources such as ONS to define certain parameters such as economic growth rates, (2) existing evidence to inform assumptions such as automation rates; and (3) expert judgement.
- **Linking trends to employment outcomes:** A macroeconomic model developed by Cambridge Econometrics, complemented with simple econometric methods to project forward historical patterns in occupational and qualification structure of employment within industries.
- **Linking to skills:** The macroeconomic model also produces qualification outcomes (an approximation of skills). Separately, additional work conducted to map UK SOC with US SOC based on O*NET data.

What works well?

This forecast can produce detailed, granular outputs for the entire economy at both a sector and regional level. Users identify that results from Working Futures can be incorporated with other insights, both quantitative and qualitative.

The outputs produce a breakdown at different levels: industries, occupations and qualifications, with an additional link to skills. The mapping based on O*NET data is a particularly helpful addition as it provides more granular skills information compared to what was previously produced.

This approach also allows for scenarios to be developed, as discussed in section 4, and these are useful for users in understanding different impacts of automation.

What are the limitations?

The key limitation of this approach, as discussed elsewhere, is that it does not account for changing skills needs for a given occupation. In addition, mapping UK SOC to skills via US SOC required significant resource requirements.

As with all macroeconomic models, Working Futures is seen as very ‘black box’ – although it is noted that the developers were continuously chosen because of their transparency compared to other developers.

Box 19. Case study - Novel approach: Combining time series analysis with machine learning

Headai uses the following methods (see Section 4 for more detail):

- **Approaches to future trends:** Machine learning techniques applied to job adverts and other data sources (e.g., investment data, research, policy etc.) to produce 'knowledge graphs' of the job market in the future.
- **Linking trends to employment outcomes and skills:** Knowledge graphs can be compared overtime, in a form of time series analysis.

What works well?

This is an example of time series analysis which does not simply project past trends but incorporates insights from future trends. Time series analysis is particularly useful in this case because it can take the knowledge graphs produced from the understanding of trends and compare these knowledge graphs overtime. It would likely not be possible to incorporate these knowledge graphs in a similar way in other methods such as macroeconomic models.

Another benefit of this approach is that it can look directly at skills, rather than forecasting skills via employment, overcoming the problem of static taxonomies as discussed in sub-section *Building block 3 - Linking trends or employment outcomes to skills*. The technique can be tailored for the intended purpose, with different focus on skills and employment as required by the user.

What are the limitations?

This method has a very high resource requirement. It would require a high fixed cost to build up the method so will be difficult for others to replicate. Using job adverts to define skills means that not all occupations will be well captured – for example agricultural jobs are typically not advertised in conventional ways. Developers at Headai emphasise the need to compare outputs from their other forecasts. For example, with reference to comparing different results from AI models:

> When they all are in same direction, this is good. … But if they all give you a different answer … the topic might be too complex to model or other data sets were complex. … Using different systems is really good, using not only generative AI, also old school statistics, because now if old school statistics [forecasts] a different story than AI predicts. And the question is why? – *Developer*

Section 6: Findings and recommendations

In this section we discuss our overall conclusions from the assessment in Section 4: Assessment of approaches to skills forecasting and Section 5: Combining building blocks.

We include our key recommendations for the next steps to improve cohesion across the skills forecasting landscape and to consider the role of the central economy-wide forecast.

Finding 1: Users have different needs so there is a role for a range of forecasts

Users have different needs, requiring different methods and different granularity of outputs. We identified four representative types of users: (1) central planners; (2) local/regional planners; (3) workforce planners and those engaged in labour market information (LMI); and (4) those designing qualifications and standards. No one method will suit all users and each of these users will face specific challenges and requirements:

Users	Requirements and challenges
Central planners	Use forecasts for a wide range of purposes. Long-term, economy-wide skills and employment forecasts are typically useful, alongside other forecasts with more specific focuses.
Local users	Benefit from forecasts with a local focus. A particular difficulty faced by local users is that outputs are often not available at the level of geographical granularity needed nor are assumptions defined with a local view that considers the specific local challenges.
Workforce planners	Benefit from segment-level forecasts with tailored methods. For example, sectors differ in their data availability. We discuss this in more detail below.
Technical qualification design	Requires more granular forecasts than produced centrally. Typically look at the short to medium term (3 to 5 years) but require a link from occupations to skills.

Segment-level forecasts complement economy-wide forecasts by bringing in a level of sector detail that is not possible to include at the economy-wide level. These can be reconciled with economy-wide forecasts as discussed above.

> I think you need to really have in depth analysis …. You need to look at more data sources, look at more information and really dig deep. … When we're doing a generic set, we can't do that for [all sectors]. - *Developer*

Specific industries face their own challenges, so require tailored methodologies. For example, some industries (e.g. agriculture, creative industries) do not generally advertise through conventional online job adverts but rather through social media and word of mouth – meaning that using, for example, Lightcast data is not possible. Moreover, some industries can be hard to define (e.g. the digital sector), making published data broken down by SOC or SIC less meaningful. Others are easier to define and have specific output series, such as construction. One challenge identified by the screen industry is seasonality, which makes it important for the forecast to consider representative periods over the year. In addition, 'generic' forecasting methods might not have the capability to include important sector specific information, for example the construction sector needs to account for the particular workforce requirements of large ongoing and upcoming infrastructure projects.

Even within a user group, **different users have different preferences** for trade-offs between our assessment criteria. For some users, a complex model will be a strength as they will value the additional internal validity provided by modelling relationships between different variables. In contrast, other users might prefer a simple model that is easy to follow, justify and communicate.

Each method has strengths and weaknesses. Users should balance these strengths and weaknesses against their needs and resources, as set out in Section 4. This involves being **very clear what question they are trying to answer** and what evidence is required to answer these questions. For example, users should be clear about the horizon of the forecast: IFATE typically requires short-term forecasts (3-5 years), whilst a central planner looking at GCSE reform would need to consider a longer period as they are equipping students with skills for careers which may begin further in the future. Users should also be clear about whether they are interested in a sense of magnitude and direction of travel, or whether they need detailed point estimates. Since there is no perfect forecast, commissioners/developers should challenge themselves as to whether the level of detail being sought is justifiable given uncertainties and data available.

> It's got to be done for a purpose and people have got to understand that it will have limitations. Never going to give people exactly what they want. – *Developer*

As a result, **many users will value different methods for different purposes, and benefit from bringing the results together.** For example, central planners described combining industry reports to pull out key trends with the use of Lightcast data for more quantitative figures and to look specifically at skills. Similarly, local users and sector bodies typically triangulate insights from skills forecasts with other sources and use them to test qualitative evidence, e.g. collected from local employers.

Finding 2: Reducing fragmentation would be beneficial

Recommendation 1: Create a central repository for skills forecasts and related documentation and information, including signposting to relevant methodologies and datasets.

Recommendation 2: Provide synthesis and associated commentary summarising the latest skills forecasts and highlighting key gaps in the evidence base.

Although multiple forecasts are needed for different purposes, greater coordination and information exchange between stakeholders (central government, regions/sectors, educational institutions; skills councils/bodies) would be beneficial. Currently, there does not appear to be an understanding of 'best practice' across the landscape, and forecasts typically 'start from scratch' each time a new method is commissioned.

This fragmentation creates **difficulty in comparing and reconciling methods** and in keeping track of new forecasts produced and developments in the forecasting landscape. In addition, 'starting from scratch' each time **increases the resource requirement for producing new forecasts** and **reduces the quality of forecasts produced.** Providing a focal point for stakeholders can foster collaboration and allow for a more efficient allocation of resources, ultimately improving the evidence available in future skills.

As a starting point, a central repository of skills forecasts and key datasets, and commentary around how to navigate the current evidence base, would be beneficial.

Finding 3: Some general best practice principles apply to all forecasts

Recommendation 3: Develop best practice guidance for how skills forecasts should be commissioned, developed and/or used. This could include guidance on: engagement with experts and incorporating this into a forecast; assessing accuracy; and the framing of results and how to use and interpret outputs.

Because the evidence base on skills forecast is large and fragmented, users would benefit from centrally provided guidance. One potential form for such guidance is a decision tree. One way to implement this could be to create an expert panel – similar to the Evaluation and Trial Advice Panel (ETAP)[70] – to provide tailored advice to commissioners, developers and users.

Guidance could include, but is not limited to:

[70] The Evaluation and Trial Advice Panel (gov.uk)

- How best to identify and engage with stakeholders and experts.
- How to assess and improve the performance of difference methods.
- How developers can frame outputs and results, and how these should be interpreted by users.
- How to tailor the sophistication of the selected method appropriately, especially given user's needs and data limitations.

Below we outline some of the best practice principles identified from our assessment, primarily from interviews, as a starting point for developing guidance.

Identifying and engaging experts

At the segment-level, qualitative expert engagement is typically used to capture industry specific features. This could be understanding future industry trends (as discussed in the first building block in Section 4) or to link trends to employment or to skills (as in the case of foresighting). At the economy-wide level, in many cases, experts are only engaged in a meaningful way to sense-check outputs once they are produced. It is likely beneficial to **incorporate more expert engagement earlier on in the process**, for example when developing central government economy-wide forecasts.

Because **expert engagement can be resource-intensive**, developers should consider the trade-off with relevance and accuracy. Forecasts which engage with more experts are likely more able to capture an accurate picture of skills needed in the future. It is important to strike the right balance between scalability and depth. This being said, qualitative engagement can sometimes be under-valued and there may be instances where resources used for quantitative work could be more meaningfully diverted to expert engagement.

Identification of appropriate experts is also important. Studies which provide details on the process for selecting experts and list the experts used are more transparent. They allow users and commissioners to be aware of potential biases or expert areas that are under-represented (whether this be sectors, regions, specific technologies etc.).

Assessing the performance of a forecast

Only **a minority of studies apply a formal methodology** to assess performance or use sensitives to assess robustness. As an example, the CSN Industry model tests the accuracy of the output by comparing to actual data in the previous year. However, they note that this is not a fundamental measure of how 'good' the model is: forecasts will never pick up future shocks, and so will always be off to some degree. Nonetheless, assessing accuracy – through sensitivity and consistency checks – is important to consider changes that are needed to improve the forecast going forward.

Given that accuracy is difficult to assess, **users instead rely on the reputation of the commissioner and/or developer.** For example, there is a feeling that industry-produced reports may contain bias and so government users may be more likely to trust forecasts produced by government or arms-length bodies. Users identified that there is more trust that these have gone through a rigorous quality assurance process.

In the absence of assessing accuracy, the **use of sensitivities** to test the impact of key assumptions is common practice. For example, the PwC 'Impact of AI' report produces a sensitivity for job displacement which uses the 'supermajority' instead of 'majority' rule when collating expert input on the likelihood of automation. Commissioners noted that sensitivities were important in trusting the output of the forecast they commissioned. Forecasts sometimes publish the results of some key sensitivities, but some commissioners discussed sensitivities which had been used for internal, model development purposes.

> I got into quite a lot of sensitivity around this just to see how sensitive the results were, which I think is useful … for two reasons. One, it I mean it helps you just understand the model and think about how useful it is for drawing any conclusions. And then it also helps you think a bit about the significance of those conclusions and how much weight you would put on them. – *Commissioner/User*

In addition, **sense checking of outputs** is common. Cedefop's sense-checking includes both qualitative expert engagement and more systematic, quantitative checks. The developers have built an algorithm to check whether the changes projected by the forecast are plausible. In addition, national experts are used to check the results, first at the sectoral employment stage and then again once these projections are translated into occupational projections and replacement demand. Input from national experts is used to finetune results and adjust the model as necessary. In Finding 3, we discussed the benefits of reducing fragmentation: reduced fragmentation allows developers to more easily sense check their outputs with other forecasts and provide more opportunities for 'sense checking' support from other bodies.

Framing of results and outputs

While developers are aware of the limitations of forecasts**, users/commissioners are not always aware of these limitations**.

> Any point projection of the future is almost inevitably incorrect; you need to recognise we are not making a precise prediction of what the future will look like...we don't have a crystal ball. – *Developer*

Documentation should be clear about the limitations, the intended purpose of the forecast and how the results can or should be interpreted. This includes being clear that a forecast is not a prediction and setting out the assumptions and methodology used, whether in a technical annex or when engaging with commissioners.

> I would be willing to use [results] that I knew was quite 'wrong' [in the sense of not accounting for certain trends, shocks etc] if I could explain the caveats associated with it - and make sure that it wasn't taken as gospel. – *Commissioner/User*

> You get different data sources and they tell you different things and we don't hide from that with our customers, we don't try to tell them that actually everything is nice and simple. – *Developer*

Being clear on caveats is particularly important when published material includes more than just a report on findings. For example, sometimes granular forecast results are published in an Excel output but in interviews developers noted that these outputs can be misinterpreted. Commissioners sometimes benefit from having a model that they can ‘play’ with, for example by adjusting the parameters; this makes it particularly important to communicate the caveats and methodology to commissioners.

Moreover, commissioners and developers should think about **how their forecasts can be communicated with the public more broadly** – beyond just the typical users:

> You're trying to make it relevant or real to the people that are out there. – *Commissioner*

> The results of the macro analysis often are just not tangible to people… Without some other dialogue, people just don't connect to it… it's great that you're telling me that there are more net jobs gained than lost, but what about my job? – *Commissioner/User*

Tailoring complexity to purpose

More complexity is not always better: there is a **trade-off between the complexity and accuracy of a study and its ease of use and relevance**. A less rigorous, simpler model might meet the same intended purpose and might be more friendly for a wider audience. It is particularly difficult to understand what drives results when studies include multiple interactions and parameters. Commissioners typically want to be able to understand the model in order to have confidence in what they are publishing and to be able to defend their model.

One developer noted that the messages which commissioners and users take away from a forecast are often the results that are already known: these results can often be shown using a less complicated model (although these must be justified by evidence to avoid spurious results).

In cases of high uncertainty (e.g., when assessing scenarios/disruptive events or impact of AI) or data limitations (e.g., limited granularity), **users might be more interested in the order of magnitude/direction of travel rather than precise forecasts**. This information can still be very valuable for commissioners and users. This links to Finding 1: users need to be aware about the level of granularity they need and choose methods appropriately, particularly given that a more 'complex' model may rely on more significant assumptions and so come with larger caveats.

> I don't think I would necessarily trust actual numbers of jobs and people - but [instead I would want] some understanding of how skills are going to change, where the increase is going to be and where the decreases are going to be. – *Commissioner/User*

> You're getting a lot more usable intelligence if you can actually say these jobs are changing in some way and there's something new and different about them. – *Developer*

Finding 4: There are some notable gaps common to a large number of forecasts

Across all the case studies, we found some common gaps in the evidence base on future skills, discussed below.

Difficulties linking from trends or employment to skills

Forecasts typically encounter **difficulties linking from macroeconomic trends or employment to skills** i.e. producing a skills forecast, rather than forecasts at an employment level.

The **UK currently lacks a skills taxonomy** which can be used as a central reference point. Some studies have applied different workarounds given the lack of a skills taxonomy (e.g., mapping US SOC with UK SOC to use US taxonomies) but this has its own challenges (e.g., mapping is not that straightforward, taxonomies might not be updated frequently, taxonomies might not reflect reality of UK economy, etc.), as we discuss in more detail in Building block 3 - Linking trends or employment outcomes to skills.

To address this issue, DfE has commissioned plans for the development of a common classification of skills linked to occupations and qualification/training for the UK.

Changes in skills composition within occupations

Most forecasts produce outputs at Standard Occupational Classification (SOC) level, but **few forecasts currently attempt to understand how the specific skills within**

occupations may change (e.g. will the changing nature of work mean that more digital skills are required in the future in a given occupation?).

An understanding of within-occupation skill changes is crucial to understanding the impact of key labour market trends such as automation and AI. Understanding these impacts is particularly important for segment-level forecasts in industries likely to experience technological change in the more immediate future or those which look at a longer-time horizon. Additionally, high-level economy-wide approaches might struggle to account for these heterogeneous impacts across industries unless changes in the tasks/skills mix within occupations is explicitly accounted for in the analysis.

Current forecasts which consider the impact of automation, such as the PwC 'Impact of AI' report or the alternative scenarios presented in the Skills Imperative 2035 work, typically only consider how current occupations are likely to be automated and not how automation may affect the skills required by each occupation. One exception is the 'UK Skills Mismatch' which considers the impact on skills within occupations as activities become automatable based on the McKinsey Global Institute (MGI) skills taxonomy and O*NET. However, it is not able to account for new tasks or the growing importance of tasks within occupations and the skills associated with these. This approach may not be appropriate for considering the impacts on occupational skills mixes of other labour market trends, such as an ageing population or AI, or skills required in emerging industries.

As discussed in Building block 3 - Linking trends or employment outcomes to skills, **forecasting changing skills compositions is challenging and requires moving beyond the more traditional approach of a static skills taxonomy**.

A lack of granularity

Forecasts can lack sufficient granularity to support all user needs. **Some users will need more granular information than is available from outputs at the SOC level**, for example those designing industry standards need forecasts at a detailed qualification level.

Data limitations are a particular constraint. The more granular forecasts we reviewed tended to rely on non-public data, often related to online job ads (e.g. Lightcast or LinkedIn). Other forecasts used qualitative data to fill the gaps, whether through expert engagement or surveys of the sector.

How to fill these common gaps

Data improvements

Additional data collection could help to fill some of these common gaps. The UK would benefit from an information system that gathers information regularly on occupations, skills, and qualifications from employers (as in the US), rather than households (e.g., LFS). The UK currently lacks:

- A robust time series on occupational employment patterns or qualification levels;
- Skills information that is regularly collected;
- A common language of skills and crosswalk with occupations and qualifications.

Detailed data on the link between occupations, tasks and skills, would make it easier to link employment forecasts to skills. Repeated collection as a time series would provide an understanding of how skills within occupations have changed over time, which would be a useful starting point for a more dynamic taxonomy to capture changing skills compositions over time. Time-series analysis could be used to project past trends into the future; qualitative inputs may be used as a complement to understand how future trends might differ from those in the past.

Alternative approaches to forecasts are likely needed

Dynamic skills taxonomies and foresighting are examples of newer approaches to skills forecasting which tackle the question of changing future skills compositions. However, it is not clear if these methods could feasibly be applied at an economy-wide level, because they require a detailed understanding of the impacts of technology at a very granular sub-sector level. This highlights the importance of reconciliation of segment-level and economy-wide forecasts to combine multiple approaches to forecasts.

More work is needed to consider how novel approaches and the use of alternative datasets such as vacancy data can be combined with the more traditional methods of skills forecasting to fill these evidence gaps.

Finding 5: Working Futures currently fills a key role in the landscape

There is a key role for a central economy-wide forecast. A single, respected foundational forecast at national level provides a focus for expert input and debate and enables cohesion across government. If consensus is built around this central forecast, it can act as a ‘starting point’ that others can use and build on (e.g. sectoral bodies; regions; LSIPs).

At the moment this role is filled by Working Futures. This forecast has a degree of trust and consensus around it as a central reference point, has users at the economy-wide and segment level. It is being developed as part of the Skills Imperative 2035 programme, for example to build in a more detailed skills taxonomy.

The methodology is in line with best practice globally. Other central economy-wide forecasts, such as Germany or the USA, follow a similar approach to Working Futures, combining macroeconomic models and econometrics with external data, existing evidence and expert input. We have not identified any methods, whether innovative or standard, being used elsewhere that are obvious candidates to replacing the current approach.

Developments are being made to address some of the limitations. The forecast has historically only produced a skills forecast at the level of qualifications. However, the most recent programme of work using the framework, Skills Imperative 2035, is in the process of developing the forecast to build in a more detailed skills taxonomy.

Finding 6: There are potential developments to be made to the Working Futures model

Recommendation 4: Develop Working Futures to address the current gaps. This could involve developing add-ons to the current approach (e.g. stakeholder engagement and scenarios). This could also involve investigating the potential to use new methods and inputs at certain steps of the overall approach (e.g. using vacancy data and data from employers; and/or using new methods alongside the core model, for example dynamic skills taxonomies). This would build further on Working Futures' existing position as a trusted central forecast.

Recommendation 5: If Working Futures cannot feasibly be adapted to close key gaps, then an alternative new forecast method could be considered. User needs may be better met by a forecast method that can deliver on some of the evidence gaps we have highlighted in our Findings. These benefits should be weighed against the time and resource costs, and the risk that having multiple economy-wide forecasts could reduce cohesion.

Recommendation 6: Develop a process for knowledge sharing and diffusion of information on the central forecast, for both segment-level and economy-wide users. Combined with recommendations 1-3, this will build consensus and encourage best practice use.

There are potential developments to be made to Working Futures. Some of these gaps could be developed as builds to the current model. First, additional **scenario analysis** could be built in, using principles employed by other economy-wide forecasts that would make the forecast more versatile. Whilst the Skills Imperative 2035 forecast made some developments in this area, including two scenarios, more development could be done to place scenario building at the centre of the forecast. For example, this could involve building in the UK Horizon Scanning approach (which supplements Working Futures by qualitatively assessing a range of scenarios) as an exercise which is frequently updated to take into account changing future trends. Moreover, additional **stakeholder engagement** could also be built in, for example based on the US approach where industry experts are consulted to validate and support assumptions made about industry-level trends. As discussed above, qualitative input from sectoral and regional experts may lessen the need for segment-level and local forecasts, although other benefits of these specific forecasts will remain.

Other gaps in Working Futures are common limitations across the UK evidence base as described in Finding 5. It is possible that these gaps could be addressed within the current approach, for example by drawing on additional datasets, or using new methods at certain stages alongside the core macroeconomic model (e.g. a dynamic skills taxonomy). However, the feasibility of doing this is relatively untested, and emerging methods that address some of these gaps have on the whole not yet been applied at the economy-wide level. We recommend that these developments to the approach be explored, alongside those described in the previous paragraph (Recommendation 4).

To the extent that Working Futures cannot meet these needs, an alternative central forecast could be explored which uses alternative methods. If this alternative forecast can fill some of the gaps we find across the UK evidence base, it might better meet user needs and be better equipped to answer current and future policy questions. The potential benefits should be weighed against the time and resource costs of development, and the risk that having multiple economy-wide forecasts could reduce cohesion (Recommendation 5).

Increasing knowledge sharing and diffusion around the central forecast will build consensus and encourage best practice use, by both segment-level and economy-wide users (Recommendation 6).

Section 7: Conclusions

This report adds to the evidence base on UK skills forecasting by providing a detailed assessment of the benefits and limitations of current methods used in the UK and internationally (at both the economy-wide and segment-level). We find that no single method will suit all users and provide an assessment of methods for different user types. This assessment can be used to support the provision of best practice advice for users and commissioners when determining which forecast is most suitable for them.

Despite the wide range of methods used, we identified key limitations across the landscape: a lack of granularity; a difficulty linking from trends or employment to skills; and an even greater challenge forecasting changing skills needs with occupations.

A key finding of this research is that there is a high degree of fragmentation in the UK skills landscape. Whilst a range of different forecasts are needed to suit the needs of multiple user types, we have provided recommendations for improving cohesion across forecast in the UK skills forecasting landscape in the future.

We have also found that a central government forecast is beneficial for users. Working Futures currently fills this role and follows current international best practice. We have highlighted the potential areas of improvement to better meet users' needs, and areas for research on how new methods and data collection might help fill some of the remaining evidence gaps.

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