A Systematic Review of the Relationship Between Skills and Productivity

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Abstract

Objectives: We conducted a systematic review of the literature to identify and synthesise evidence on the relationship between skills and productivity in the public sector. Our first objective was to identify whether there is a relationship between the skills of government and public sector workers and public sector productivity and, if so, the nature and magnitude of the relationship. Our second objective was to identify the contexts and conditions that influence the skills-productivity relationship in the public sector. This work was commissioned by Government Skills, which is part of the UK Cabinet Office and funded by the HM Treasury Labour Markets Evaluation and Pilots Fund.

Methods: We augmented the Population-Context-Conditions framework to develop a set of criteria to determine the inclusion of studies in our synthesis. We included English language evidence with quantitative results published since 2014 that examines the relationship between skills and productivity at a macro level (e.g., organisation or firm, region, sector, country). Studies examining this relationship solely at the individual level were excluded. We included research examining the private and the public sectors. We searched a range of academic bibliographic databases (e.g., Web of Science, Scopus) and grey literature repositories, while also issuing a call for evidence and conducting citation searches. Risk of bias within the included studies was assessed using the Mixed Methods Appraisal Tool (MMAT). We used a combination of quantitative synthesis, through vote counting, and narrative synthesis. Overall, we screened the titles and abstracts of 2,949 papers retrieved from databases. Subsequently, 145 were read and screened in their entirety. In addition, we screened a total of 369 records from grey literature sources.

Results: This review includes 36 papers and 41 independent results within these. The literature was almost entirely of a quantitative descriptive nature, with no Randomised Control Trials. There is very strong evidence of a positive association between skills and productivity. In particular:

- 33 of 38 (87%) estimates found a positive association between skills and productivity.
- Results from a vote-counting exercise strongly rejected the null hypothesis that these results were purely by chance.
- It is challenging to convincingly establish the causality of the skills-productivity relationship.
- Limited evidence suggests that the relationship may take time to materialise and might be stronger in high-skilled sectors.

We identified several pieces of evidence that demonstrate that the relationship between skills and productivity is context-dependent, and it depends in part on factors over which organisations have some control. Factors that evidence suggests can affect the strength of the skills-productivity relationship include the degree to which skills and utilised in people’s jobs, the degree of innovation in the workplace, and

management practices—all of which are things that are, in principle, within the power of workplaces to influence. However, no single contextual factor was studied by more than three papers.

Discussion: There are important limitations of the existing evidence base. The causality of the skills-productivity relationship at the level of large units of analysis remains a key uncertainty. The nature of the evidence is very heterogeneous, especially methodologically. This makes comparison across studies difficult and inhibits meaningful synthesis of the magnitudes of the skills-productivity association. Quantitative evidence on the role of contextual factors in the skills-productivity relationship is also scarce and would be an appropriate priority for future research.

Introduction

Review rationale

The UK's public sector employs almost six million workers, including more than half a million in the civil service (Office for National Statistics 2024). The productivity of this sector and its implications for the UK economy have been the focus of much analysis in the past decade (e.g., Warner and Zaranko 2024).

A number of studies within and outside the government have identified the skills of the workforce as an important driver of productivity (Becker 1994; Conlon et al. 2023; Gambin, Green, and Hogarth 2009; OECD 2016). The public sector, in the UK and elsewhere, has invested significant resources in developing skills (DFE 2024; NHS England 2024; Government People Group 2024), and public sector skills priorities have been discussed and developed within the context of attempting to enhance productivity, provide value for public money, and ensure the long-term sustainability of the public finances (HM Treasury 2024).

For the civil service to make effective decisions about how and how much to develop the skills of its workforce, it needs to understand the overall strength of evidence for a relationship between skills and productivity, and the contexts and conditions under which any such link is the strongest. The role of contexts and conditions is important for at least two reasons. First, the academic literature that directly studies the links between public sector skills and public sector productivity is especially sparse (Ark 2022). One challenge, therefore, is to gauge the relevance of existing evidence, often from outside of the public sector, in the contexts and conditions found in different parts of the public sector. Second, understanding the influence of wider systemic factors on the skills-productivity relationship offers the possibility of identifying factors that are themselves subject to intervention and which can strengthen the impact of skills on productivity—complementing efforts to strengthen skills themselves.

The empirical literature on the relationship between skills and productivity is very diverse. This means that, without a synthesis of the evidence, it is difficult to identify what is known about the links between skills and productivity and can therefore be used to inform policy and practice. Conversely, it is difficult to ascertain which policy-relevant questions remain unanswered and, hence, should be prioritised in future research and evaluation efforts.

The diversity of the literature spans a number of key dimensions. The units of analysis—the levels at which skills and productivity are measured—vary from individuals to firms and organisations, to whole nations. The ways in which skills and productivity concepts are operationalised are also highly heterogeneous—especially for skills, reflecting in part their multidimensional nature. For example, many studies focus on skills that relate to specific domains or tasks, such as digital skills (Douch et al. 2020), while many others focus on much broader measures of or proxies for skill level, such as the level of educational attainment (Conlon et al. 2023). Finally, empirical studies on the skills-productivity link are conducted across a wide range of contexts:

different countries, different sectors, different sizes of organisations, and so on. Without a framework for understanding how those contexts shape the skills-productivity relationship, it is particularly difficult to know what can be inferred from the evidence.

Against this background, Government Skills commissioned a systematic review to understand the extent to which workforce skills can be a driver of public sector productivity and the systemic conditions that this relationship depends on. This forms part of a wider programme of work that attempts to build a robust evidence base to inform policy efforts to deliver a skilled civil service.

Objectives

The primary purpose of this review is to develop a clearer understanding of the relationship between skills and productivity in the public sector and what this relationship depends on. It also seeks to build a clearer picture of what is not understood about this relationship.

To achieve this, the following research questions were addressed:

- **RQ1:** Is there a relationship between the skills of government and public sector workers and public sector productivity, and what is the nature and magnitude of this relationship?
- **RQ2:** Which systemic conditions and contexts influence the nature of the relationship between public sector skills and productivity?
    - **RQ2a:** Which types of skills levers can bring about systemic change towards higher productivity, and through which mechanisms do they have their effect?

Methodology

Overall approach

We conducted a systematic review (SR) of evidence on the relationship between skills and productivity. An SR is well-suited to provide an unbiased and reliable assessment of the available evidence by using transparent, well-defined, and replicable procedures. By synthesising insights from a fully comprehensive set of literature that satisfies specified criteria, it also delivers a clear view of where gaps are in the evidence base, helping to provide foundations for future research.

We conducted a mixed methods review, looking to synthesise both quantitative results and qualitative findings accompanied by quantitative results. This decision was made in light of the primacy of understanding the role of contexts and conditions in the objectives of the review, for which qualitative insight is well-placed to contribute. However, we did not find any qualitative results in the included studies, so our actual synthesis was entirely based on quantitative literature.

Our protocol resolved to use meta-analysis to synthesise the magnitudes of quantitative estimates of skills-productivity relationships, where the comparability of studies and the measures rendered this feasible. Where these conditions were not satisfied, our protocol outlined that we would use narrative synthesis, according to SWiM guidelines (Campbell et al. 2020). Narrative synthesis is the route we ultimately took upon examination of the highly heterogeneous literature. We supplemented this with vote counting: a quantitative synthesis technique that is an alternative to meta-analysis, focused on the strength of evidence around the existence and direction of an association, but not its magnitude.

Conceptual framework

Initial work conducted via searches of the literature and interviews with experts highlighted that defining and operationalising the concepts of skills and productivity would be a key challenge. This is due to substantial heterogeneity in how these concepts can be (and are) defined, measured, and described. The heterogeneity proved to be particularly wide in the case of skills.

Below, we describe how we define skills and productivity to capture the range of constructs relevant to the public sector. This directly informs our search strategy (described below).

We then turn to the other element of the conceptual framework we used to inform the design of our review: the framework for defining the features of the complex system within which a skills-productivity relationship operates. This framework informed our selection of the data we sought to extract from the included papers in our review and the structure around which we sought to synthesise the literature’s findings.

Defining skills

Through our scoping work, which combined scoping interviews with experts with exploratory searches of the empirical literature, we identified the following four categories of skills as being within the scope of the review:

1. **Skills related to the foundations of public administration**, working in government, and leading and managing, as identified by the Government Campus (2024). These provide the organising structure for learning and development interventions within the UK Civil Service.
2. **Skills from existing skills taxonomies and capability frameworks within the UK government**. These include core skills, skills for leading and managing, and skills for policy, project delivery, and operational delivery.
3. **Future skills**, informed by recent evidence, including a systematic review of the evidence on future skills (Kotsiou et al. 2022) and work by Government Skills that built on this, focused on government and public sector contexts.
4. "**General Skills**" found in the literature but not captured by the three sets of skills above. These include skills aggregated together in common ways (e.g., "foundational skills" and "technical skills")[1] and concepts such as "regional skills" or "sectoral skills," which combine a **macro unit of analysis** with reference to a non-specific skill—something we found to be common in practice in the empirical literature.

These sets of skills were combined into an integrated list and our search strategy aimed to generate keywords that would capture them.

We made some key exclusions to the skills concepts that were within scope:

- Individual-level skills (and productivity) are not within the scope of this review and are addressed in a sister project commissioned by Government Skills that focuses on the components of effective professional learning design.
- We attempt to exclude skills that are personality attributes (e.g., courage, persistence), which cannot be altered through intervention, although we recognise that the boundary between immutable attributes and malleable skills is fuzzy and contestable.
- We excluded skills that are distinct to specialist occupations (such as robotics, nanotechnology), to focus on skills relevant to most public sector workers.

[1] We also include relevant skill groups used by the US Department of Labour's Occupational Information Network (O*NET). This classification is a commonly used tool for analysing skills in literature in labour economics, and includes basic skills (e.g., active learning skills, writing skills), as well as cross-functional skills (e.g., complex problem-solving skills, technical skills).

Defining productivity

Productivity is also a concept that can be defined and measured in various ways. However, the task of creating a tractable and relevant set of productivity concepts was somewhat less complex than for skills, in part because Aldridge et al. (2016) have created a framework to understand productivity in public services[2]. That framework delineates between:

- How cheaply inputs are purchased (which we call “budget efficiency”).
- How well inputs translate into outputs (which we call “organisational productivity”).
- How outputs affect outcomes (which we call “effectiveness”)[3].

We considered each of these concepts as within scope. In practice, the literature we reviewed was mostly focused on organisational productivity. Common measures of this include labour productivity (measures of output per worker), total factor productivity (TFP, sometimes called “multi-factor productivity”), and “efficiency” measures used in operational research. The latter two measures differ from labour productivity in that they account for all inputs to production (not just labour), and they assess how an aggregated measure of those inputs compares to the level of output.

The system within which the skills-productivity relationship operates

A key objective of our review, encapsulated in Research Question 2, is to understand which factors influence the relationship between skills and productivity. To approach this question, we used a complex systems lens (Petticrew et al. 2019). This recognises that, given the complex linkages and interactions between different parts of a system, a joined-up view of all relevant features of that system is needed to properly understand it (Cheese 2023). We drew on two frameworks to facilitate our understanding of the system. To understand the contexts and conditions, we considered the “CATWOE” framework (Chowdhury 2021; Óskarsdóttir and Oddsson 2017), looking for the Customer, Actor, Transformation, Worldview, Owner, and Environmental constraints within which the skills-productivity relationship is formed. We also used Gillian Stamp’s “Tripod of Work” framework to understand practices that can influence the relationship between skills and productivity (Stamp 2009). We describe these frameworks in more detail in Appendix J.

[2] Aldridge and co-authors refer to this as “Efficiency,” but we interpret it as productivity.

[3] “Outputs” refer to the measurable results achieved by processing the inputs, while “outcomes” refer to the ultimate impacts brought about by those outputs.

Eligibility criteria

The eligibility criteria used in this review are based on the Population-Concept-Context (PCC) framework, along with additional restrictions (described below). We followed this approach as we expected the studies to be predominantly non-intervention-based, without control groups or randomisation, and the PCC framework is well-suited to that context[4].

Population: The review focused on studies examining in-work adults. Studies that include both in-work adults and other adults were to be included only if subgroup analysis for the in-work adults was available.

Concept: Studies that examined both skills and productivity, such that at least one of these constructs is measured at the macro (region, sector, wider economy) or meso-levels[5] (team, organisation, department) were included. The ways in which each of the skills and productivity has to be operationalised in order for a study to be eligible for our review were described in detail in the preceding section. Literature that studies the process of training or gaining skills (including training interventions) but does not measure the relationship between any resultant skills and productivity was also out of scope for this project, since we were interested in the relationship between existing stocks of skills and productivity.

Context: The review included studies examining the civil, public, and private sector workforce. Although the public sector is the ultimate focus of our research questions, the literature on skills and productivity specifically within the public sector is very sparse, and we adopt a more expansive scope to incorporate insights found in other contexts that could be applicable to the public sector.

In addition to the criteria outlined by the PCC framework, we added criteria as described below.

Geographical focus: Studies focusing on OECD countries were included. These countries are likely to have comparable levels of development and systems to the UK and to offer transferable insights. We also included larger regional units that include OECD member countries, such as “Europe.” A list of the current OECD member countries can be found in Appendix C. Studies from all other countries or without a country or region specified in the abstract were excluded. For multi-country papers, we included the results that were relevant to an OECD country.

Methodology: Studies with quantitative results were included in the systematic review. We also allowed for the inclusion of publications with qualitative findings, if they include quantitative analysis as well. All other methodologies were excluded.

Outcomes: Included studies had to contain outcome measures relating to productivity (see previous section for how we conceptualise productivity).

[4] As compared to the more commonly used Population-Intervention-Control-Outcome (PICO) criteria.

[5] For ease of exposition, elsewhere in this report we use “macro” to refer to both macro and meso-levels of analysis, as opposed from analysis focused on individuals.

Types of publication: Academic literature (i.e., peer-reviewed studies in journals) and grey literature (i.e., working papers, book chapters, dissertations, PhD theses, government-commissioned research, and reports) were included.

Date of publication: The publication date threshold was studies published from 2014 onwards. This was to ensure relevance of evidence to the modern workplace, especially in light of rapid developments in the use of IT and digital capital.

Time period of analysis: We included only studies for which the most recent year of data used in the analysis was from 1990 or later. This criterion was again chosen to help ensure applicability of findings to the modern services-dominated economy, with its extensive use of IT and digital technology and mass higher education.

Language of publication: Publications in English were included to ensure the evidence is accessible and relevant to the intended audience. All other languages were excluded.

Information sources

Our review sought to retrieve evidence from both academic literature and grey literature, such as publications from think tanks and research institutes. Grey literature was defined as within scope because skills and productivity are the subject of research outside of academia, and because it is a mitigation strategy against any publication bias that might arise if we focus only on academic papers. Hence, we used the following databases to search for evidence:

Academic bibliographic databases: Education Resources Information Center (ERIC), IDEAS/RePEc, Scopus, and Web of Science.

Grey literature repositories: gov.uk (filtered for 'Research and statistics' and 'Policy Papers and Consultations' only), OECD iLibrary (filtered for Journals and Articles only), ProQuest (filtered for 'Government & Official Publications,' 'Reports,' 'Scholarly Journals,' 'Working Papers,' and 'Dissertations and Theses' only), World Bank Open Knowledge Repository, Campbell Collaboration, Cedefop (Publications only), and Google Scholar, limited to first 200 results only based on Haddaway et al. (2015). Our searches on Google Scholar were conducted within a private window to avoid potential distortions due to personalised results.

Additional ways of adding relevant studies: In addition to the public databases, we are collecting research and studies from the following sources:

Call for evidence: We put out a public call for evidence that was circulated to selected stakeholders in the UK civil service and experts in the field of public sector skills and productivity. This includes publications collected through our stakeholder engagement. This was done to identify relevant published and unpublished studies that can address any publication bias in the review.

Relevant organisations: We also searched websites and databases of organisations that publish research on the topic of skills and/or productivity. The organisations were selected based on inputs received during scoping interviews with key stakeholders. The organisations included are Institute of Labour Economics at the University of Bonn

(IZA), the Warwick Institute for Employment Research, The Productivity Institute, and SKOPE at the University of Oxford.

Forward and backward citation search: We used a selective approach to forward and backward citation searching of studies that remain in the review, following assessment of study quality (explained below). This was done using the online tool Citation Chaser with documentation of the source.

Search strategy

Table 3 (in Appendix B) presents a list of keywords used to identify sources of evidence relevant to our research questions. During the scoping phase, we tested different combinations of keywords to arrive at a list that aligned with the ways in which our skills and productivity concepts are represented in the literature[6].

For the concepts of skills and productivity, we use selected synonyms that are used to refer to them. For skills, included synonyms are capability, competence, human capital, accreditation, and qualification. For productivity, included synonyms are efficiency and output.

These keywords were combined into search strings using Boolean operators (AND/OR/NOT) and other database-specific search operators. To construct the strings, we used the Boolean operators in a pragmatic manner to ensure wide coverage of relevant studies. Based on the specific requirements of database search engines, we also ran supplementary searches to fill in any gaps. We recorded all search strings and filters used across the different databases, as well as the total numbers for outcomes from our searches, in a Research Activity Sheet. A summary of this sheet is presented in Appendix B.

Selection process

Our selection process followed the steps recommended by the Cochrane Handbook, reported following the PRISMA 2020 statement (Page et al. 2021). We recorded the list of the retrieved references in the specialist software package Zotero. Zotero is a free, open-source reference management tool that stores citation information (e.g., author, title, and publication fields) and offers options to organise, tag, and search records. This has been used to store the collection of records identified by the searches. Any records sourced from other sources were added to Zotero if public citations were not available.

Zotero was also used to deduplicate the list of records to ensure there is no repetition. The records identified and the number of records removed due to deduplication were documented in the PRISMA flowchart (reported in Figure 1). We used Zotero to deduplicate the included studies and moved to the title and abstract screening.

[6] A log of all of our pilot searches is available on request.

Title and abstract screening

Our team reviewed the titles and abstracts of the 2,949 records using the online platform Rayyan. Rayyan is a free-to-use software to support systematic reviews, allowing the process of screening to be expedited through the use of a visual, colour-coded interface that highlights keywords associated with the inclusion and exclusion pathways[7]. It also documents the screening decisions of multiple reviewers for reconciliation and allows for the assessment of the inter-rater reliability score.

The first 10% of records (295) were double-screened by two reviewers. We found five conflicts, with an inter-rater reliability (IRR) score of 98%. The team discussed and identified the reasons for the discrepancies and resolved these to ensure a consistent understanding and application of the inclusion/exclusion criteria. Since the IRR score was above the threshold level of 90% stated in the protocol, we continued with single screening of the remaining records. Any “edge” cases that could not be clearly included or excluded based on the title and abstract were included for full-text screening.

Throughout the process, reviewers held end-of-day discussions to verify the findings and also ensure ongoing consistency in the application of the inclusion and exclusion pathways.

Full-text screening

Following the title and abstract screening, a total of 145 papers were included for full-text review. These were exported to Excel, and the records were retrieved where available. Any lack of retrievable records was also documented. For each of the records, we reviewed the full texts of the papers and applied the inclusion/exclusion criteria[8]. “Edge” cases were reviewed with additional inputs from the project Advisory Board.

Citation searching

Following the finalisation of the full-text screening, we carried out a citation searching exercise. The primary motivation behind this exercise is to guard against the possibility that our search strategy has systematic gaps and fails to pick up certain kinds of literature. Based on the principles noted in a recent paper on search techniques (Hirt et al. 2024), we constructed a seed group of papers to use for the citation searching exercise. We use the "unit of analysis" as the categorising variable for this purpose, as it was one of the key dimensions of heterogeneity that was sensitive to the keywords used in the search strategy. Our search had returned relatively few papers that focus on country-level and region-level skills and productivity. In case this reflected an unintended deficiency in the operationalisation of the search strategy, we used included studies with “country” and “region” units of analysis, as our seed group and used Citation Chaser to carry out a forward and backward citation search for these

[7] While Rayyan provides Artificial Intelligence (AI) capabilities for systematic reviews, in our review, we used it only for manual screening.

[8] In line with PRISMA reporting guidelines, we note one paper that appeared to meet the inclusion criteria (in particular, it included measures of skills and productivity, and included productivity as an outcome) but was ultimately not included because it did not actually address either research question (since it did not directly examine the link between skills and productivity within its structural equation model). This paper was Lopes et al (2019).

papers. The included papers were then subject to a title and abstract and full-text screening, with the same inclusion and exclusion criteria as the other papers. At the end of this process, we identified 36 papers for inclusion in the review.

Data collection process

Data from the included papers was extracted into a Research Extraction Sheet (RES). We first piloted data extraction for the five included papers, selected to span a range of methodologies, to ensure that the fields in the RES were clear to interpret and that they captured the information intended across a diverse evidence base. The review team discussed each field of the RES to ensure that they had a shared understanding. The whole RES is large, but we present key elements of it in Appendices G-I.

Discrepancy resolution procedure

After the pilot phase, we randomly selected four papers (10% of the sample) for independent double extraction of data. The following procedure was used to address discrepancies in data extraction process for the sample:

- Any discrepancies were to be discussed in agreement meetings.
- If reviewers did not reach a consensus, a third reviewer would be consulted for a final decision.
- Full agreement on all assigned codes in this sample must be achieved before proceeding with further single extraction.

If concerns about the interpretation were to persist after this phase, the team would assess whether additional double extraction or further refinements to the tool are necessary to resolve these issues. Following triangulation of findings from this sample, two reviewers separately extracted study characteristics and numerical outcome data from the included papers.

For selected papers where key information was missing, we emailed the authors to seek details. We reached out to the authors of three papers and received one informative response.

Dependent effect sizes

Dependent effect sizes were addressed in cases where results were obtained from the same (or an overlapping) sample of observations, meaning that the estimates are not statistically independent from one another. Failing to address this dependency can lead to inflated Type I error rates (i.e., an inflated probability of wrongly rejecting a true null hypothesis) because standard statistical tests are derived from the assumption of independence. We outlined this issue and our approach to handling it using a reductionist approach (López-López et al. 2018) in the protocol for the case of meta-analysis. A reductionist approach narrows down the set of results included within quantitative synthesis so that all included results are statistically independent from one another. As we explain in the “Synthesis” section, the quantitative synthesis technique we actually use in this review is vote counting rather than meta-analysis. However, the same statistical issue applies: to be valid, the sign test implemented within a vote counting procedure requires statistical independence between estimates (Bushman and Wang 2009).

In quantitative descriptive literature, it is common to present results from multiple models with different sets of control variables. In such cases, we select the result from the model specification with the most control variables. To extract a single effect estimate from each set of remaining non-independent estimates, we use the following rules, applied in sequence from first to last:

1. We select the result associated with the largest population (e.g., “all firms” instead of subsets like “small” or “large” firms).
2. We select results based on measures of specific skills or performance on tests over proxy skills measures like "years of education.” The rationale is to privilege skills that are more direct measures of things that are subject to intervention among the existing workforce.
3. We select the result that is obtained from the most recently collected data.
4. For results that focus on specific skill types, we use the following hierarchy: ICT skills, managerial skills, social skills, and other skills[9].
5. For papers with results that study both shorter- and longer-term effects of skills on productivity, we choose the result over the longer time horizon.
6. For non-independent results across multiple levels of skill or education, we select the result relating to the highest level (e.g., tertiary education instead of primary or secondary education level). This is because the public sector is, on average, relatively highly educated (Cribb, Disney. and Sibieta 2014).
7. If the papers present results using multiple assumptions about the production function, we select the one that assumes constant returns to scale.

Finally, a single paper (Madzik and Sieber 2024) presents results using two measures of “perceived” productivity within the firm, based on two different sets of variables. The first consists of organisational growth, competitiveness, financial performance, and innovation, while the second primarily consists of better awareness, automation, decision-making speed, and business process improvement. We select the latter on the basis that we judge its components to be more relevant to the public sector context than, for example, “organisational growth” and “competitiveness”.

We recognise that most decision rules could be contested. Given the nature of the literature, some judgement is unavoidable in deciding what makes a result more or less relevant for our review. The critical issue is that the selection procedures do not inadvertently introduce bias into our conclusions. We therefore conduct a sensitivity check and report a comparison of the effect directions for the results selected by the above rules with those not selected. They are very similar.

In combination, these rules deliver a set of independent results that can be used to perform valid statistical synthesis (vote counting). To align with the statistical

[9] This was applicable only for results that focused on specific skill types.

synthesis, graphical and tabular descriptions of results also draw only on those independent results. Other results can still deliver valuable insight for our research questions, so they are within scope of our narrative syntheses. We explicitly acknowledge any instance where two or more non-independent effect estimates are discussed within the same narrative synthesis.

Data items

The list of data items collected is provided in Appendix D and the outcome measures present in the studies are in Appendix I.

Study risk of bias assessment

To assess the quality of individual papers, we used the Mixed Methods Appraisal Tool (MMAT), which provides a framework for evaluating study design, data collection, measurement analysis, and reporting (Hong et al. 2022). The tool specifies criteria for qualitative, quantitative (RCTs, quasi-experimental designs, and descriptive analyses), and mixed methods study designs. This makes it well-suited to the diverse methodologies that are within the scope of our review.

For quantitative descriptive papers (those that utilise neither an RCT nor a quasi-experimental design), the MMAT assesses the following:

- Is the sampling/data collection strategy relevant to address the research question?
- Is the sample representative of the target population?
- Are the measurements appropriate?
- Is the risk of non-response bias low?
- Is the statistical analysis appropriate to answer the research question?

For quasi-experimental evidence, the MMAT assesses the following:

- Are the participants representative of the target population?
- Are measurements appropriate regarding both the outcome and intervention (or exposure)?
- Are there complete outcome data?
- Are confounders accounted for in the design and analysis?
- During the study period, was the intervention administered (or exposure occurred) as intended?

None of our included papers were based on an RCT or contained qualitative results, so the MMAT scales for those categories were not used in practice.

The MMAT quality appraisal was carried out in Excel, with the responses for each of the tool’s questions recorded for each paper. For each question, the response can be either “Yes,” “No,” or “Can’t tell”/“N/A.” For each study, the MMAT tool was completed by one reviewer, following which a second reviewer verified the scoring.

As explained in the “Results” section, we excluded two papers based on our assessment of methodological limitations. For the included papers, assessment against the criteria provided by MMAT was used as part of an evaluation of confidence in the cumulative evidence. Had there been many failures against MMAT criteria among the included papers, we would also have looked for evidence of a systematic relationship between study results and the MMAT quality assessment. However, among the included papers, there were very few failures against any criteria.

For quantitative descriptive literature, assessments using the MMAT tool should not be taken as a direct indication of whether estimated relationships are causal. For example, appropriate measurement of outcomes and low risk of non-response bias would be two necessary conditions for robustly identifying causal effects, but in the absence of random variation in skills, they are not sufficient. To be assured of causality, one would also need to be assured that all plausible confounding variables are adequately controlled for (either explicitly or implicitly, e.g., through the inclusion of fixed effects). This is typically a highly subjective judgement over which much reasonable debate can be (and often is) had. We do not attempt to give our own adjudication on causality on a paper-by-paper basis, as our view is that the high degree of subjectivity would render this of little value. However, as a complement to the MMAT quality assessment, we document the range of methods used in the literature (each of which uses different approaches and assumptions to try to identify causal effects) and how results differ according to those methods.

Effect measures

Our protocol set out a plan to use meta-analysis to synthesise the magnitudes of quantitative estimates of skills-productivity relationships, as long as the papers and the measures they used were sufficiently comparable. We judged that this condition was not satisfied, due to the wide methodological heterogeneity of included studies, as well as their wide range of skills and (to a lesser extent) productivity measures (explained more fully in “Synthesis methods”). Hence, rather than using standardised effect sizes, we conducted quantitative synthesis via the vote-counting method, which aggregates the effect directions of the primary results from each paper. We combined vote counting with narrative synthesis, in which we refer to results as reported in the papers directly, presenting them along with the context in which they are reported.

Missing data

Some papers do not consistently report items such as standard errors, the number of observations, and p-values. An advantage of the quantitative synthesis technique that we employ (vote counting) is that it requires none of that information—it requires effect directions—so the risk of bias from missing data items is minimised.

However, to support our synthesis, we do provide descriptive analyses that make use of other information (see “Synthesis methods”).

Synthesis

Eligibility for synthesis

Of the included papers that remained after exclusions on the basis of quality, those that provided results on the overall link between skills and productivity were marked for synthesis for RQ1 (31 papers). Those containing results on how the relationship between skills and productivity varies with other factors were marked for synthesis for RQ2 (eight papers).

In the vote-counting exercise that we conduct as part of RQ1, not all results within all papers are eligible since they are not independent. Our approach to dependent effect sizes is discussed in detail in the "Dependent effect sizes" section. Further information on the vote-counting exercise is presented in the "Synthesis Methods" section.

The papers that contribute to RQ2 are largely a subset of those that contribute to RQ1. However, we use three papers for RQ2 that we do not use for RQ1. These are papers that study the association between measures of skills mismatch and productivity. They do not directly estimate the association between skills themselves and productivity, so we do not use them for RQ1. However, we consider them of direct relevance to RQ2, which focuses on contextual factors for the skills-productivity relationship. This is because the very essence of skills mismatch is that it captures the extent to which skills are being applied to tasks for which they can be utilised. If skills mismatch affects productivity, it is therefore reasonable to conclude that this is because it weakens the extent to which skills translate into productivity.

Preparing for synthesis

Some of the fields in our Research Extraction Sheet (see Appendix D) were developed in vivo based on the nature of the included studies, while a number were defined in advance to structure our description of study characteristics and/or our syntheses addressing the research questions. These were:

Methodology: The included studies deploy an array of methods that, in particular, rely on different techniques and assumptions for identifying and interpreting associations as causal. To examine whether key conclusions of our synthesis were sensitive to the method employed, we categorised methodologies as follows:

- **Quasi-experimental:** Methods typically classified as quasi-experimental, including instrumental variables and difference-in-differences. (Ex post, this category was equivalent to "instrumental variables," since only one included paper was in this category.)
- **Regressions with time variation:** Methods for panel or longitudinal analysis, which account for unobserved or observed confounding variables if they are time-invariant, through fixed or random effects models.
- **Cross-section regressions with controls:** The most common form of method used, this includes papers that employ ordinary least squares (OLS) regressions along with controls for potentially confounding variables.

- **Correlations:** Methods based on the unconditional correlation between skills and productivity. This includes ordinary least square regressions without controls.
- **Other methods:** These include structural equation modelling (SEM), growth accounting exercises, stochastic frontier analysis (SFA), and data envelopment analysis (DEA).

Geography: We distinguished between studies using data from the UK, USA, EU (excluding Eastern Europe), Eastern Europe, multi-country studies, and others.

Unit of analysis: Different studies measure skills and productivity at the level of different units. We recorded whether these measurements were taken at the level of the firm, sector, region, country, or another level.

Types of skills: A list of skill types was developed during scoping and delineated in our protocol (and presented in Appendix A). In practice, only three types of skills were featured in the included studies: Core, Digital and STEM, and Managerial.

Productivity measures: As discussed in "Conceptual framework," most of the relevant empirical literature considers forms of "organisational productivity," which assesses outputs relative to inputs. We identified this during the scoping phase. Within this, we defined three common measures of productivity. Labour productivity measures output relative to labour inputs, total factor productivity (TFP) measures outputs relative to all inputs (rather than just labour inputs), typically by comparing the ratio between actual output and the amount of output that would be predicted based on the inputs, and efficiency measures common in operational research based on a comparison of outputs to the sum of inputs (and are hence conceptually similar to TFP).

Tabulation and graphical methods

We use the following tabulation and graphical methods to support the synthesis:

1. Tables reporting bibliographic information, data on population and concepts, and the measures and results used for each of the individual studies in Appendices G, H, and I, respectively.
2. A table presenting the results of the vote-counting exercise, which was the quantitative synthesis method used.
3. An **albatross plot** presenting the p-values of the included results against the sample sizes of studies (Harrison et al. 2017). We use it to examine evidence for publication or reporting bias. The plot was made in Stata (Harrison 2017).
4. **Effect direction plots** to show the frequency of positive and negative results, with their statistical significance. These were made in R using the ggplot package.

Synthesis methods

As per our protocol, we examined the included papers to assess whether it would be appropriate and feasible to carry out a meta-analysis. However, we judged that the wide heterogeneity in the studies precluded a meaningful comparison of effect magnitudes, and hence meta-analysis.

The primary barrier to meta-analysis was the wide methodological heterogeneity in included studies. Different methods rely on different assumptions to interpret associations as causal. These apply even when comparing papers that, at a high level, use a similar approach. For example, papers that rely on cross-sectional regressions with controls may nevertheless control for very different sets of variables. This means that they can fall a long way short of measuring the same quantity, even if the measures of skills and productivity are identical. In addition to this, the skills and productivity measures themselves vary substantially, as discussed.

For this reason, we utilise vote counting as a quantitative synthesis technique that does not rely on the aggregation of effect magnitudes. This is used as part of our synthesis for RQ1. Vote counting involves tallying the number of studies showing positive and negative results. In line with Cochrane handbook guidance (McKenzie and Brennan 2024), these are recorded without considering the significance levels or statistical precision at the level of any individual study. Instead, the aggregate proportion of positive (or negative) results is computed and then a formal statistical test is conducted, where the null hypothesis is that the true associations in these studies are evenly balanced around zero (equivalently, that 50% are positive).

For both RQ1 and RQ2, we described and synthesised study findings narratively following the SWiM reporting guidelines (Campbell et al. 2020). To structure this narrative synthesis, we drew on a combination of:

(i) Groupings of results that were defined a priori. We used these for RQ1, in the case of methodology. Descriptive effect direction plots were used to document results split by these categories, to support the narrative synthesis.

(ii) Groupings that were defined inductively based on the data extracted from the studies. For RQ1, this included a brief narrative synthesis of findings about the difference between short- and long-run associations between skills and productivity, and about whether the relationship is different in contexts where the baseline level of skills is already high. For RQ2, all of the narrative synthesis was structured according to this inductive approach, based on the very limited set of contexts and conditions explored empirically in the literature. This is contrary to the intention in the protocol to structure the synthesis around the framework outlined in “Conceptual framework,” because the evidence available did not provide enough content to flesh out this framework. We do, however, use those frameworks to help organise our discussion of evidence gaps, and how future research might take our understanding further.

Addressing risk of publication bias

This risk deals with missing or unpublished studies. For instance, publication bias can occur if studies with statistically non-significant results are not submitted or accepted for publication, while selective non-reporting bias can arise if certain statistically non-significant results are omitted from published reports.

We address these risks through two methods. First, to account for publication bias, we included grey literature in our search and collected literature through a call for evidence that was circulated, inviting relevant papers that might not be published, to a wide audience. However, none of the evidence gathered this way satisfied our inclusion criteria. We cannot be sure whether this is because such studies do not exist, or because our call did not identify them.

A funnel plot was not possible, as the heterogeneity in the studies did not allow for the calculation of a standardised metric. We use albatross plots (that plot p-values against sample sizes), allowing for a visual check of whether p-values cluster at just below standard significance thresholds, which would be evidence of publication bias. We do not find any such evidence. The albatross plot does not, however, provide a direct estimate of publication bias, and it does not allow for formal statistical tests.

Confidence in cumulative evidence

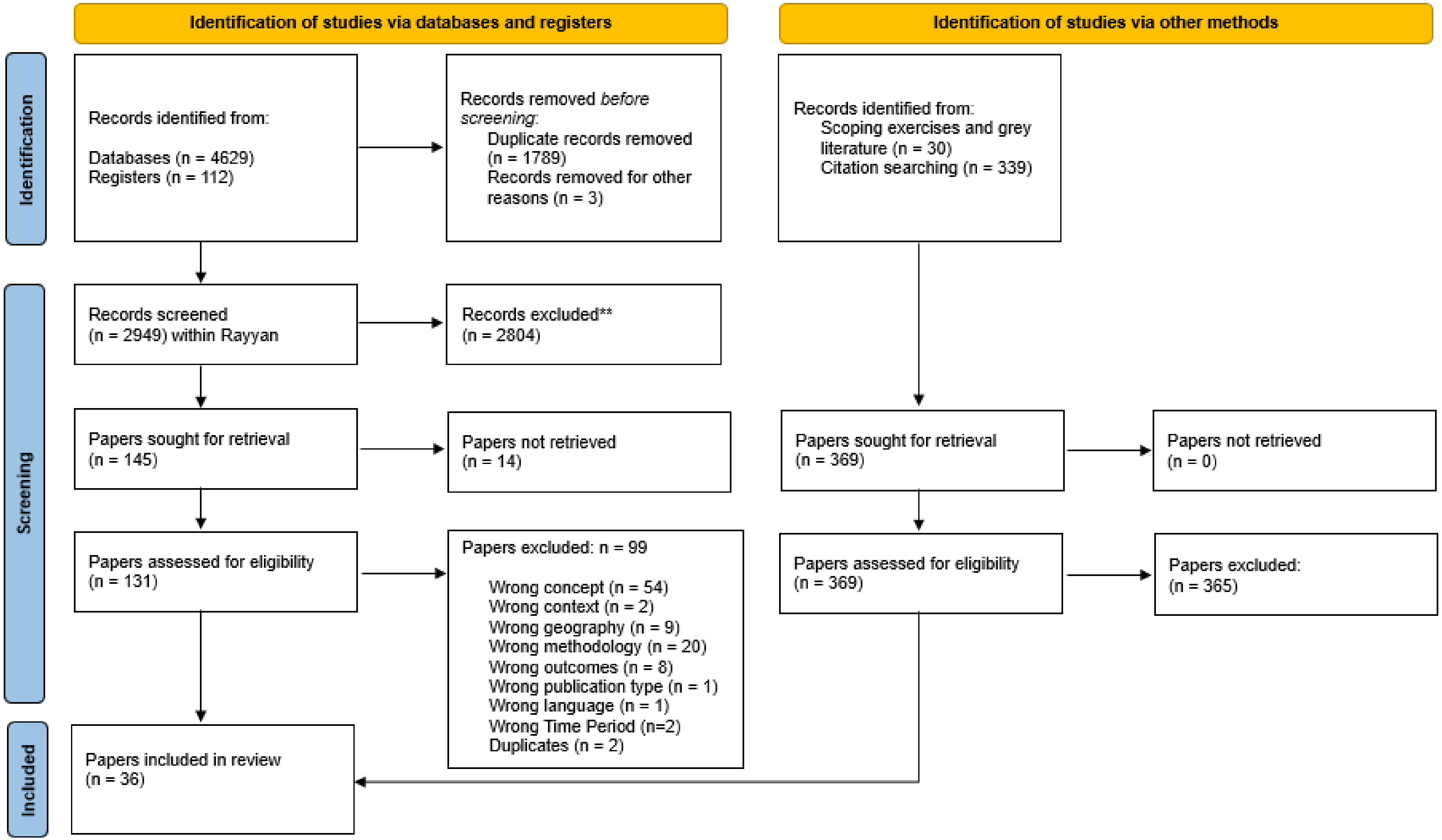
The small number of papers and their heterogeneous nature, as well as not being able to conduct a meta-analysis, limit the scope of tools typically used for certainty assessment (such as GRADE). When assessing the certainty of the evidence, we consider the following factors:

- **Precision of synthesis findings:** We calculate and report a confidence interval and p-value around our vote-counting estimate, which is the form of quantitative synthesis that we use in this review. In our narrative synthesis, when discussing the results of individual studies, we report their tests of statistical significance.
- **Risk of bias of the studies:** We present the number of “Yes” scores in the MMAT quality assessment for each study. We also summarise how results vary according to the methodology employed.
- **Directness of the evidence:** We report the number of papers that examine the link between skills and productivity specifically in the public sector (one). We also report whether the study set out to uncover the relationship between skills and productivity, or whether the result was secondary in a paper focused on a different relationship (e.g., where human capital is used as a control variable, rather than the main independent variable of interest).
- **Potential publication bias**, via the albatross plot as described above.

Results

Paper selection

Figure 1. **PRISMA Flow diagram**



As shown in Figure 1, our searches yielded 4,629 initial results from databases and 112 results from grey literature sources. After deduplication using Zotero, 2,949 records were screened according to their titles and abstracts. We used Rayyan to manually screen these records (Rayyan also contains automation features, such as deduplication, but we do not use these features). In addition, 30 records were identified through our scoping exercise and the call for evidence, and 339 records were identified through the targeted searching of citations in the included papers. Thus, a total of 369 sources of literature were identified through other methods and sought for retrieval.

Upon thoroughly screening this literature, 36 papers were found to meet our inclusion criteria.

Risk of bias

The methodological quality of included papers was evaluated using the **Mixed Methods Appraisal Tool (MMAT)**. The results of the assessment for all of the quantitative descriptive papers are presented in Figures 3 and 4, first as a summary plot, and then as a "traffic-light" plot showing the assessment for each paper and each quality category.

Figure 2 highlights in red two papers that were excluded from the synthesis on the basis of inappropriate measurement. Juruss et al. (2023) use measures that (according to their description) conflate annualisation with the use of logarithms, which means we cannot interpret the estimate. Martin and Alejandro (2016) convert a continuous human capital measure into a discrete variable and represent it with dummy variables, but do not state what the reference group is, which prevents any interpretation of the estimate. Removing these papers leaves us with 34 papers that contribute to the synthesis.

Most papers meet all of the MMAT quality criteria. The quality appraisal assessment for the one quasi-experimental paper (Cammeraat et al. 2024) in our included list, which is not shown in Figure 2, also returned a "Yes" on all the questions posed by the tool.

Figure 2. MMAT assessment for included quantitative descriptive papers

Paper title	Risk of bias				
	4.1	4.2	4.3	4.4	4.5
Ali et al., 2019	Y	Y	Y	Y	N
Bender et al., 2018	Y	Y	Y	Y	Y
Braunerhjelm and Lappi, 2023	Y	Y	Y	Y	Y
Calvino and Fontanelli, 2023	Y	Y	Y	Y	Y
Cammeraat et al., 2021	Y	Y	Y	Y	Y
Cardoso and Ravishankar, 2015	Y	Y	Y	Y	Y
Costa et al., 2019	Y	Y	Y	Y	Y
Cubel et al., 2014	Y	Y	Y	Y	Y
Egert, 2022	Y	Y	Y	Y	N
Escriba-Perez and Murgui-Garcia, 2014	Y	Y	Y	Y	N
Fanti et al., 2021	Y	Y	Y	Y	Y
Grundke et al., 2017	Y	Y	Y	Y	N
Juruss et al., 2023	N	Y	Y	Y	N
Koch and Smolka, 2019	Y	Y	Y	Y	Y
Lombardi et al., 2022	Y	Y	Y	Y	Y
Madzik and Sieber, 2024	Y	Y	Y	Y	Y
Martin and Mungaray, 2016	Y	Y	Y	Y	Y
Máté, 2014	Y	Y	Y	Y	Y
Máté, 2015	Y	Y	Y	Y	Y
McGowan and Andrews, 2015	Y	Y	Y	Y	Y
Molinari and Torres, 2017	Y	Y	Y	Y	Y
Morris, 2015	Y	Y	Y	Y	Y
Nguyen et al., 2024	Y	Y	Y	Y	Y
Ohlsbom, 2021	Y	Y	Y	Y	Y
Olomola and Osinubi, 2018	Y	Y	Y	Y	Y
Pini et al., 2023	Y	Y	Y	Y	Y
Querio, 2021	Y	Y	Y	Y	Y
Rico and Cabrer-Borras, 2020	Y	Y	Y	Y	Y
Sasso and Ritzen, 2019	Y	Y	Y	Y	Y
Skorupinska and Torrent-Sellens, 2017	Y	N	Y	N/A	N
Suarez-Varela et al., 2016	Y	Y	Y	Y	Y
Torrent Sellens et al., 2014	Y	Y	Y	Y	N
Veltri et al., 2016	Y	Y	Y	N/A	Y
Wixe, 2015	Y	Y	Y	Y	Y
Yigiteli and Sanli, 2024	Y	Y	Y	Y	Y

Study characteristics

We now describe the characteristics of the literature that we synthesise. The 34 papers included in the synthesis contain 41 statistically independent analyses of the skills-productivity relationship (and hence our reductionist procedures for selecting independent results, described in "Dependent effect sizes," identified 41 such results). For example, the same paper might perform the same analysis in more than one country. We consider this as two different studies (with the same methodology), though they are analysed in the same paper. The analogue in experimental literature would be where the same intervention is conducted in more than one country, which would be counted as two studies.

Below, we describe the characteristics of these studies.

Methodology for estimating the skills-productivity link

The included papers use a range of methodologies to study the association between skills and productivity. The most common category, used in 20 studies, is cross-sectional regression with control variables. Eight studies use panel regression techniques, meaning that changes over time in skills are associated with changes over time in productivity. One study uses an Instrumental Variables technique, and one is based on a simple correlation without control variables. There are 11 "other" studies that employ methodologies including data envelopment analysis (DEA), structural equation modelling (SEM), and stochastic frontier analysis (SFA).

Geography

As per our protocol, we included papers conducted within OECD countries only. Four studies conducted their analysis within the UK. Twenty-two are from European countries, excluding Eastern Europe. Common European countries analysed include Italy, Spain, and Sweden. There are two studies from Eastern Europe and one from the USA. Eight are from analyses conducted using data from multiple OECD countries. The four remaining studies analyse the relationship between skills and productivity in Turkey and Mexico. As described above, a single paper can conduct analysis separately across multiple geographies. For example, Molinari and Torres (2018) contribute independent results for the UK, the EU, and the USA.

Unit of analysis

Different studies measure skills and productivity at the level of different units. The most common unit of analysis is the firm (19 results). There are two results at the sector level, five at the region level, and eight at the country level. Seven studies combine different units (for example, relating firm-level productivity to measures of human capital at the local area level) or define units based on the intersection between variables (e.g., measuring skills and productivity at the country-sector level). There is one paper that examines the skills–productivity relationship within the UK public sector, specifically the NHS (Ali et al. 2019).

Measures of skill

Many papers analysed multiple measures of or proxies for skills. Very few studies use measures of skill that are directly assessed, in the sense that they come from responses to a survey or test. All four of these (Sasso and Ritzen 2018; Cammeraat, Samek, and Squicciarini 2024; Egert et al. 2022; Grundke et al. 2017) employ the internationally comparable PIAAC data[10]. Only a minority of studies focus on specific skill types, and those skill types constitute a small subset of the full list of types that we identified as part of the scoping exercise for this review (see Appendix A)—split between core skills (e.g., higher order thinking and numeracy), digital and STEM skills, and managerial skills. A large majority of the skills measures are of non-specific skills and are inferred indirectly, very often using the language of "human capital." Major examples are years of schooling, earnings level, and experience.

Measures of productivity

Productivity is the outcome we focus on in this review. Labour productivity is by far the most common and is examined in 24 papers. Outcome variables that fall into this category include value added per employee, GDP per worker, and employee task performance. The next most common is total factor productivity (TF), examined by eight papers. Finally, three papers use efficiency measures based on a comparison of outputs to the sum of inputs. This is conceptually similar to TFP in taking into account all inputs, rather than only labour (these efficiency measures are common in operational research, whereas TFP is standard within economics). Only Ali et al. (2019) consider more than one measure of productivity.

[10] The Programme for the International Assessment of Adult Competencies (PIAAC) is an OECD survey that assesses key cognitive and workplace skills of adults aged 16-65 across participating countries.

Results of synthesis

Research question 1

RQ1: Is there a relationship between the skills of government and public sector workers and public sector productivity, and what is the nature and magnitude of this relationship?

Summary of results:

- There exist 38 statistically independent estimates of the relationship between skills and productivity.
- The evidence strongly suggests a positive association between skills and productivity: 33 of 38 (87%) of estimates found a positive association between skills and productivity.
- It is challenging to convincingly establish the causality of the skills-productivity relationship. Different papers use different methods in an attempt to do this. Reassuringly though, the pattern of results does not look very sensitive to the method employed.
- Limited evidence suggests that:
  - The skills productivity-relationship may take time to fully materialise.
  - The relationship may be stronger in high-skilled sectors.

The vast majority of the included papers—31 out of 34—include results we can use to address RQ1. These papers provide 38 independent estimates of the skills-productivity relationship. Table 1 extracts results from these and reports i) whether the estimated association is positive or negative (based purely on whether the central estimate is above or below zero and taking no account of statistical significance) and ii) whether that relationship is statistically significantly different from zero at the 95% confidence level.

Thirty-three (33) of the 38 results find a positive association between skills and productivity, implying that higher skills are related to higher productivity. In 17 of these, the positive association is statistically significant, and an additional seven positive results do not have statistical significance reported. Only five of the 38 independent estimates find a negative association between skills and productivity (Cammeraat et al. 2021; Lombardi et al. 2022; Rico and Cabrer-Borras 2020; Cardoso and Ravishankar 2023; Escriba-Perez and Murgui-Garcia 2014; and the estimate for Mexico (but not that for Turkey) in Olomola and Osinubi 2018). These suggest that higher skills lead to lower productivity. Three of those are statistically significant.

Table 1. Effect direction in individual studies (primary results only)

Paper	Effect direction	Statistically significant at 95% level
Sasso and Ritzen 2019	Positive	No
Skorupinska and Torrent-Sellens 2017	Positive	Yes
Bender et al. 2018	Positive	No
Nguyen et al. 2024	Positive	Yes
Torrent Sellens et al. 2014	Positive	Yes
Cammeraat et al. 2021	Positive	No
Pini et al. 2023	Positive	Yes
Braunerhjelm and Lappi 2023	Positive	Yes
Cammeraat et al. 2024	Negative	No
Egert 2022	Positive	No
Calvino and Fontanelli 2023 - Denmark	Positive	Yes
Calvino and Fontanelli 2023 - France	Positive	Yes
Calvino and Fontanelli 2023 - Germany	Positive	Yes
Calvino and Fontanelli 2023 - Israel	Positive	No
Yigiteli and Sanli 2024	Positive	Yes
Lombardi et al. 2022	Negative	Yes
Querio 2021	Positive	Yes
Koch and Smolka 2019	Positive	No
Costa et al. 2019	Positive	Yes
Máté 2014	Positive	Yes
Rico and Cabrer-Borras 2020	Positive	No
Olomola and Osinubi 2018 - Mexico	Negative	Yes
Olomola and Osinubi 2018 -Turkey	Positive	Yes
Ohlsbom 2021	Positive	No
Suarez-Varela et al. 2016	Positive	N/A
Veltri et al. 2016	Positive	Yes
Cardoso and Ravishankar 2015	Negative	Yes
Grundke et al. 2017	Positive	Yes

Paper	Effect direction	Statistically significant at 95% level
Molinari and Torres 2017	**Positive**	N/A
Cubel et al. 2014 - Germany	**Positive**	N/A
Cubel et al. 2014 - UK	**Positive**	N/A
Cubel et al. 2014 - France	**Positive**	N/A
Cubel et al. 2014 - Spain	**Positive**	N/A
Cubel et al. 2014 - USA	**Positive**	N/A
Wixe 2015	**Positive**	Yes
Escriba-Perez and Murgui-Garcia 2014	**Negative**	No
Madzik and Sieber 2024	**Positive**	Yes
Ali et al. 2019	**Positive**	No

Quantitative synthesis: Vote counting

Formal statistical testing confirms that there is very strong evidence from these results that skills and productivity are positively associated.

The results reported in Table 1 are not uniform, with five negative results, three of which were statistically significant at the 95% confidence level. However, outlier results in both directions are to be expected given that each individual study produces estimates that are subject to error. For example, if the true associations in the underlying populations were all zero, one in 20 results would be expected to be statistically significant at the 5% level.

To interpret the weight of evidence from this literature more precisely, we employ vote counting as a formal statistical synthesis. This uses information on the direction of effect found in each individual study, but not the statistical significance of any individual estimated effect. The vote-counting procedure aggregates the directions of effect from across the whole body of evidence—reducing the statistical noise generated by each paper considered in isolation—and then performs a statistical test on that aggregated set of information. The null hypothesis tested is that the true skills-productivity association is positive in one-half of the studies. This is what would be expected if there is no systematic association and no publication or reporting bias.

The null hypothesis is strongly rejected ($p<0.01$). There is very strong evidence of a positive association between skills and productivity from these 38 results.

Table 2. Results of vote counting

Number of included results	38
Percentage with a positive effect	86.8%
Confidence Interval at 95% level	73-94%
P-value of binomial test	0.0000004

As a sensitivity test, we checked the proportion of positive results among those we excluded through our reductionist approach for selecting independent estimates, to check whether this inadvertently introduced bias. 82.8% of those estimates were positive.

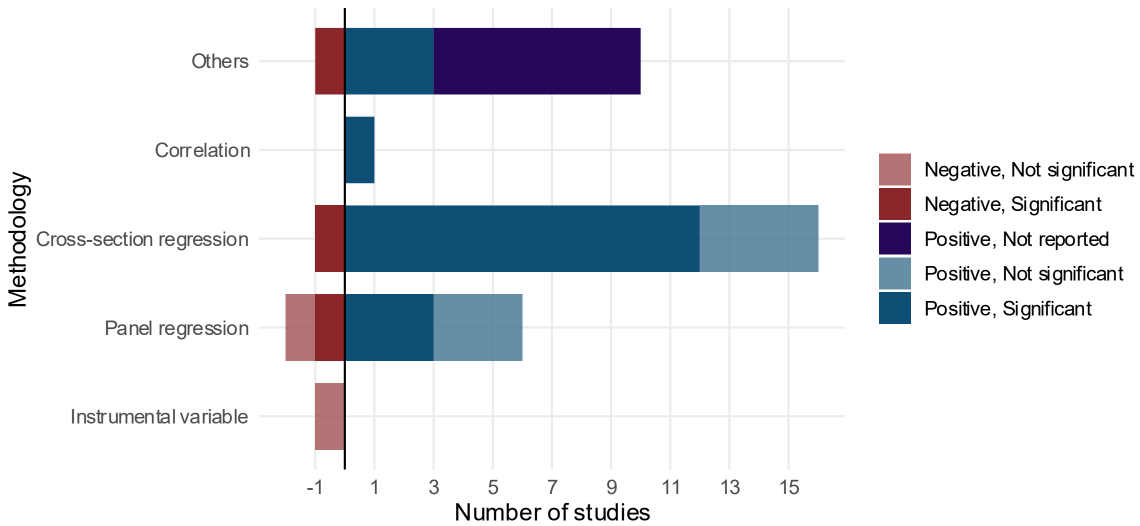
The skills-productivity relationship by methodology used

RQ1 addresses not only the evidence for a skills-productivity relationship, but also the causality in the nature of the relationship. Our results show that the findings are the same across a range of methodologies, suggesting consistency across the literature, even though not all methods examine causality.

The literature included is mostly comprised of quantitative descriptive studies, which offer correlational results. While these can follow the right steps and meet the required quality standards (such as those laid out by the MMAT), it is still debatable whether the relationship identified between skills and productivity is purely causal in nature. The effect direction plot in Figure 3 documents how the range of results in the literature maps onto the broad methodologies employed. This cannot establish causality, but it could provide reason to doubt it, because different methodologies require different sorts of assumptions for the links identified to be causal ones. For example, an unobserved time-invariant variable that correlates with skills and affects productivity would cause the skills-productivity association estimated from a cross-sectional regression to deviate from the causal effect, but this need not be the case if a panel technique is employed. To continue that example, if we were to find that the tendency towards positive associations is driven by cross-sectional approaches, and that no such tendency is seen in panel-based approaches, this would provide reason to doubt a causal interpretation.

Across all the methodologies employed in more than one study, most estimates are of a positive association between skills and productivity. There is not complete uniformity in the extent of this tendency: panel-based methods return positive estimates in six out of eight cases, whereas cross-sectional regression methods return positive estimates in almost all (16 out of 17) cases. Given the small number of papers involved, we cannot draw strong conclusions from this. It does, however, demonstrate that the broad findings are not highly sensitive to the methodology we look at.

Figure 3. Effect direction plot of skills-productivity associations, by methodology used



Level of skill

Another aspect of the nature of the skills-productivity relationship is its shape—for example, whether the relationship is linear or whether the impact of skills on productivity differs depending on the baseline level of skill. We find some evidence that the skills-productivity relationship may be stronger in sectors where skills are already high – although this needs careful interpretation, as explained below.

This issue is implicitly addressed in two papers by Domician Máté using OECD panel data at the country-sector level. The results in these papers are not independent, as the data they use is heavily overlapping (and hence only one of these papers—Máté 2014—contributed to our quantitative synthesis above). Using data from 1985 to 2007, Máté 2014 categorises country-sectors into four groups based on the average years of schooling among workers in the country-sector. In terms of common public sector professions, public administration is included in the "high-skilled" sector, and health and social work are included in the "high-intermediate skilled" sector. The paper finds a positive and statistically significant association between skills and productivity for the high and high-intermediate skilled sectors, while there is a negative and statistically significant association in the lower skill sectors. Results are similar in the non-independent analysis conducted in Máté (2015). These results suggest a tendency for the skills-productivity relationship to be more positive in higher-skilled sectors. However, this represents a very thin evidence base, so we cannot draw confident conclusions.

In addition, it is important to interpret the results carefully. They may reflect that increases in skill levels lead to greater increments in productivity in contexts where those skills are required more (i.e., high-skilled sectors); in other words, they may reflect that the utilisation of additional skill is greater in higher-skilled workplaces. Given the focus of this review on skills within the workplace (and not at the individual level), this would be a relevant insight. It would not, however, imply that increases in skill would bring greater productivity gains for people who are already highly skilled.

Indeed, one of the potential benefits of an improvement in skill levels for an individual is precisely access to work in higher-skilled sectors.

The timing of the skills-productivity link

Most papers study the contemporaneous link between skills measured at a particular point in time and productivity measured at the same point in time. However, two papers provide some evidence that changes in skill levels can take time to fully feed through into changes in productivity levels.

Egert et al. (2022) construct a measure of the stock of human capital across OECD countries, combining cohort-level data on school test scores of the working-age population and their years of schooling. Using this, between 1987 and 2018, they estimate a long-run elasticity of TFP with respect to human capital of 2,838—meaning that a 1% increase in their measure of human capital is associated with almost a 3% increase in TFP—but a contemporaneous relationship that is smaller and not statistically significant. Olomola and Osinubi (2018) analyse the macroeconomic determinants of Total Factor Productivity (TFP) in Turkey and Mexico. For Turkey, they find a negative and statistically significant relationship between human capital (measured through secondary school enrolment) and TFP in the short run, but a positive and statistically significant relationship in the long run. Estimates for Mexico are negative and statistically significant in both the short and long run (the authors argue that this may arise from poor quality standards within the education system, although this is not empirically tested).

There are two limitations. First, with such a small number of studies that look at this issue, the degree of confidence in the conclusions we can draw from the synthesis is low. Second, it is not clear from either study precisely what time horizon the “long run” is.

The magnitude of the skills-productivity link

RQ1 sought to examine the magnitude of the relationship between skills and productivity. However, it was not possible to coherently summarise the findings on the magnitude of this relationship across studies. As explained more fully in the “Synthesis methods” section, this is because the studies are too heterogeneous – estimating relationships between different variables and in widely-varying ways. This prevented us from conducting a meta-analysis, or from creating statistics or charts which focus on a comparison or summary of the magnitudes of the effect sizes across these very diverse studies. The range of magnitudes estimated across these studies would reflect, in large part, the fact that they are estimating different things.

As a result, estimated magnitudes of effects are best described and understood within the full context of the individual studies that produced them. We refer to, and explain, a number of these estimates through our narrative synthesis for RQs 1 and 2. For example, Egert et al (2022), using data from across OECD countries, estimate that a 1% increase in the level of human capital (based on years of schooling and school test scores) is associated with a 3% increase in total factor productivity. Braunerhjelm and Lappi (2023) find that a 10% increase in the proportion of former entrepreneurs in a firm’s labour force is associated with a 3.9% increase in productivity. Costa et al. (2023)

find that one additional year of experience is found to increase labour productivity by 6.8% increase in small firms, 10.3% in medium-sized firms and 13.2% in large firms.

Estimated effect sizes from all papers, together with details of the measures they used, are reported in Appendix I.

Research question 2

RQ2: What systemic conditions and contexts influence the nature of the relationship between public sector skills and productivity?

RQ2a: What types of skills levers can bring about systemic change towards higher productivity, and through what mechanisms do they have their effect?

Summary of results:

- Several studies, when taken together, suggest that the skills-productivity relationship is context-dependent. However, no single factor is studied in more than three papers, making it difficult to draw strong conclusions.
    - **Firm size:** The association between skills and productivity was found to be larger in bigger firms.
    - **Sector:** The economic sector was identified as a contextual factor influencing the skills–productivity relationship; however, the limited evidence available prevents drawing strong conclusions about how this relationship varies across sectors.
    - **Age of employees:** The association between skills and productivity was found to be slightly smaller for younger populations in the long run, but a limited evidence base prevents drawing strong conclusions.
- Much of the compelling evidence of context-dependence was found for contexts that are potentially within the power of workplaces to influence:
    - **Skill mismatch and utilisation:** The degree of alignment between the skills that workers have and the skills required by their jobs is an important determinant of productivity.
    - **Contractual agreements:** The relationship between skills and productivity was found to be stronger in firms that use fixed-term contracts temporarily (before converting them to permanent contracts) than in firms that use fixed-term contracts for longer periods.
    - **Innovation:** Workplaces with more innovation exhibit stronger skills-productivity relationships.
    - **Management practices:** Human capital and management practices are complementary, with the skills–productivity relationship being stronger in firms with better management practices.

To address research question 2 we examine the evidence base for factors that have been identified as associated with the link between skills and productivity. The first conclusion from this is that empirical evidence on the role of variables that can mediate or moderate the relationship is sparse. However, we identify seven factors that have been examined across eight papers. Three of these—firm size, sector, and the age of employees—are discussed below as contexts and conditions. The other four—skills utilisation and mismatch, contractual arrangements, management practices, and the innovativeness of the environment—are subsequently discussed as potential "skills levers," on the basis that they are potentially malleable from within organisations.

Contexts and conditions

Firm size

Firm size is examined in two papers as a potential factor influencing the skills-productivity relationship, in different contexts with different measures of skills. In combination these papers provide very preliminary evidence that the skills-productivity relationship may be stronger within larger firms, but without a larger number of studies we cannot draw strong conclusions.

Costa et al. (2023) examine the relationship between the tenure and education levels of employees (used to proxy skills) and labour productivity, for small (10-49 workers), medium (50-249 workers), and large (more than 250 workers) Italian firms in 2019 and 2020. Estimated effects of average years of education and tenure are statistically significant for both small and large firms, but are larger for bigger firms. For example, one additional year of experience is found to increase labour productivity by 6.8% increase in small firms, 10.3% in medium-sized firms and 13.2% in large firms.

Looking at "entrepreneurial human capital" as defined by the proportion of firms' employees who have previous entrepreneurship experience, Braunerhjelm and Lappi (2023) report positive effects on productivity for both small (fewer than 50 employees) and large firms in Sweden. However, only 3% of the sample of firms were large, and the estimates do not provide enough precision for confident conclusions about whether the effect differs by firm size. The central estimate of the skills-productivity relationship was actually larger for large firms than for small firms, but also less precisely estimated (in fact, only the estimate for small firms was statistically significant).

Sector

There is a very small amount of evidence that speaks directly to our research questions, preventing strong conclusions about how the skills-productivity relationship differs by economic sector.

Lombardi, Santini, and Vecciolini (2022), as part of their study of the drivers of servitisation[11] using data from Italy, examine how the presence of local human capital (measured using average years of schooling) impacts manufacturing firm productivity. They find a positive association for "heavy manufacturing" sectors, although it is not statistically significant, and a negative and statistically significant association for

[11] The authors define "servitisation" as the transition from being pure product-centric firms to hybrid product-service providers.

"made in Italy" sectors[12]. To interpret this result, it is important to note that human capital itself is not measured separately by sector, but only at the local level across all sectors. Local changes in human capital would not necessarily be feeding through to changes in human capital in the same way across all sectors. It could cause a relative shift towards higher-skilled sectors and could change who is working in those sectors. This is therefore not the ideal approach for studying the skills-productivity relationship, which indeed was not the primary aim of the study. We would therefore place some caution against a strong interpretation of this result in the context of this systematic review's research questions.

The papers by Domician Máté, using OECD panel data at the country-sector level, were discussed as part of RQ1, but are also relevant to RQ2. These non-independent papers group sectors according to their average skill levels (measured by years of schooling), and as such, they shed light both on whether the skills-productivity relationship is linear (which we consider is relevant to RQ1) and whether it differs by sector. They find that the skills-productivity relationship tends to be larger in sectors with more highly-educated workforces (which, broadly speaking, tends to characterise the UK civil service (Cribb, Disney, and Sibieta 2014).

Age of employees

A single paper suggests that the link between skills and productivity is slightly smaller for younger workers than older workers in magnitude, although it is unclear whether this difference is statistically significant.

In Egert et al.'s (2022) cross-country time series study of the relationship between human capital (measured by years of schooling and test scores) and TFP, estimates are produced using human capital measures specifically for younger workers (aged 16 to 35), as well as for the whole 16-65 population. This does not yield clear evidence of any differences. In the short run, the estimated association is larger for younger workers, but not statistically significant at the 95% level for either the 16-35 or the 16-65 population. In the long run, the estimated association is slightly smaller for younger workers and statistically significant for both groups, and the statistical significance of the difference between age groups is not reported.

Skills levers

We identify four potential moderators of the skills-productivity relationship examined in the literature that can be considered "levers," in the sense that they are potentially malleable within an organisation. These are skills mismatch and utilisation, contractual arrangements, management practices, and the degree of innovation. For each of these, there is evidence that they are positively related to the strength of association between skills and productivity.

[12] The authors define Non-Urban Made-In-Italy as "Local systems of textile and clothing industries; Hides and leather industries; Machine manufacturing industries; Wood and furniture industries; Agri-food industries; Jewels, glasses, and musical instruments." Non-Urban Heavy Manufacturing LMAs include Local systems of transport industries, Metals production and processing, Construction materials industries, Petrochemical and pharmaceutical industries."

Skills utilisation and mismatch

Our review finds three papers that look at skills mismatch and its impact on productivity. Although this constitutes a thin evidence base, it does provide evidence that skills utilisation and mismatch influence the skills-productivity relationship.

Although all three papers consider the impact of skills mismatch on productivity, rather than the impact of skills mismatch on the association between skills and productivity, logic would suggest a close correspondence between the two. The reason why we would expect skills mismatch to affect productivity is that skills that are present but under-utilised cannot translate into productivity as much as skills that are both present and fully utilised.

Fanti et al. (2021) look at skill mismatch in the context of Italian firms. Using a cross-sectional regression analysis, the paper estimates a positive and statistically significant relationship between firms' productivity and their ability to recruit workers whose skills align with their needs. Their estimates suggest that firms who are able to hire workers with the skills they need have productivity about 30% higher than other firms. In a study of 19 OECD countries, McGowan and Andrews (2015) use the OECD Survey of Adult Skills to construct measures of whether workers' education levels are well-matched to their job requirements at the country-sector level. They find that having a greater proportion of workers whose skills are mismatched with their job is associated with lower productivity, after controlling for observable individual and job characteristics. They find that the presence of both over-matched workers and under-matched workers contributes to the reduction in productivity.

Finally, in the UK, Morris (2015) examines firm-level productivity data, linking it to information on skills from the National Employers Skill Survey. The paper finds that skills mismatch, as measured by the proportion of workers that employers regard as not fully proficient at their job, is negatively associated with productivity, although this relationship is not statistically significant.

Contractual arrangements

One paper suggests that the contractual arrangements between firms and workers are related to the strength of the skills-productivity relationship, and argued that this may be linked to the degree of alignment between the skills possessed and the skills required.

Nguyen et al. (2024) use Dutch firm data to study the relationship between contractual arrangements, skills, and productivity. Their primary focus is on the use of fixed-term contracts. They distinguish between firms that primarily use these contracts early in worker tenures for "screening purposes"—to avoid committing to permanent contracts until they have more information about the workers' quality and their fit for the firm—and those firms that use these contracts for other reasons, such as to retain flexibility in the presence of cyclical or seasonal demand. They measure the rate at which firms convert fixed-term contracts to permanent ones, and high conversion rates are interpreted as evidence of the use of these contracts for screening. Their findings suggest that a high firm conversion rate—that is, the use of fixed-term contracts for "screening" new workers—is associated with greater worker productivity, but more so for high-skilled workers than low-skilled workers. Viewed the other way around, this implies that higher levels of skill are more strongly associated with worker productivity in firms that use fixed-term contracts as a screening device (proxied by the conversion rate).

The purpose of screening is to identify those workers who are better suited to the firm. Hence, one interpretation of this result (ours, rather than an interpretation given directly by the authors) is that the use of temporary contracts for screening strengthens the link between skills and productivity by reducing mismatch between the skills possessed and the skills required by the firm, linking to the discussion in the previous subsection.

Innovation and use of technology

Two papers directly examine the link between the skills-productivity association and the level of innovation. Both find that more innovative environments are related to a stronger skills-productivity association.

Koch and Smolka (2019) find that firms in Spain that have been acquired by foreign entities subsequently see a rise in the skill levels of their workforce, the level of innovation, and productivity. Here, the authors focus on process innovations in a firm, such as new methods of organising production. They show that this result is driven by firms that use their foreign parents to facilitate market access in exporting to foreign markets. Their results suggest that the upskilling of the workforce and the increases in firm innovation and technology adoption are complementary in driving the productivity gains—that is, each enhancing the impact of the other.

In another study using Spanish firm data (this time from Girona in north-east Spain), Torrent Sellens and Diaz-Chao (2015) measure human capital within the firm based on education levels of the workforce, and firm innovativeness based on whether innovative processes, such as ICT adoption or new forms of work organisation, had been adopted in the previous two years. Results suggest that human capital and training are significantly and positively associated with labour productivity. but only for the 25% of firms classified as “innovative.”

Braunerhjelm and Lappi (2023) do not directly study the innovativeness of the workplace, but they do produce an analysis potentially related to this synthesis. They examine the role of what they call “entrepreneurial human capital” in driving firm productivity, defined as the proportion of the workforce who are former entrepreneurs. They find that a 10% increase in the proportion of former entrepreneurs in a firm’s labour force is associated with a 3.9% increase in productivity. It is possible that this is linked to the findings discussed above, indicating that the skills-productivity relationship is stronger within innovative firms, since one potential explanation is that entrepreneurs increase the innovativeness of the firm environment and that this in turn allows skills to be leveraged more productively. This remains an open question however, as the mechanisms underlying the link between entrepreneurial capital and firm productivity are not examined empirically by Braunerhjelm and Lappi (2023).

Management practices

Ohlsbom (2021) finds that firms with better management practices have a stronger skills-productivity relationship. The paper studies the relationship between management practices and productivity among manufacturing, mining, and utilities firms in Finland, while controlling for human capital (and hence contributing to our analysis of RQ1). Management practices are measured through a score derived from a survey including questions on management and organisational practices. In addition, the paper analyses the interaction between management practices and human capital and finds evidence that they are complementary: the positive association between the education levels of the workforce and firm productivity is stronger in firms that have high management scores.

Reporting or publication biases

Appendix E presents an albatross plot with the p-values of results in the included papers plotted against their sample sizes. If publication or reporting bias were present, we would expect p-values to cluster just below conventional significance thresholds (such as 0.05), as studies with statistically significant results are more likely to be published, while non-significant findings may go unpublished or selectively reported. The points on the graph are dispersed, with no clear clustering below round-number p-values. This would suggest a limited risk of substantial publication or reporting bias in these studies, although the small number of studies prevents a more definitive conclusion.

Certainty of evidence

To assess how reliable our findings for both RQ1 and RQ2 are, we considered several factors: study quality according to the MMAT criteria, directness (how closely the studies relate to the research question), the precision of results, and potential publication or reporting bias (as described above). We also considered the level of confidence we can have that the skills-productivity associations estimated are causal.

Twenty-seven out of 34 included papers passed all five criteria set out in the MMAT assessment (having excluded two papers due to failures against key criteria).

As shown in Appendix F, only 12 out of 34 papers actually set out directly to study the relationship between skills and productivity. In the other papers, skills measures are effectively entered as control variables during an exploration of the impact of some other independent variable on productivity.

One reason why a lack of “directness” reduces certainty about what to take from the evidence is that the research was not designed to isolate the causal effect of skills. This links to a wider point that we return to in our discussion of “Limitations of evidence:” research designs and methods employed in this literature mean that causality is hard to be sure of. We did, however, document how the prevalence of positive skills-productivity associations varies across methodologies employed. We did not find strong evidence of differences across methodological approaches. This is reassuring, but it is based on a small number of papers, and at the level of each individual paper, it tends to be highly subjective whether its estimate of the link between skills and productivity has isolated a purely causal element.

The vote counting procedure provided a quantitative synthesis with a formal statistical test that allows for a precise estimate of the level of uncertainty. 86.8% of the results in our included studies suggested a positive skills-productivity association (the 95% confidence interval for this statistic ranges from 73%-94%). We can therefore have a high level of confidence that our included studies demonstrate a tendency for the skills-productivity association to be positive.

However, the lack of meta-analysis and heavy reliance on narrative synthesis means that i) we do not gain a precise sense of the strength of the skills-productivity association, and ii) many questions we address are not accompanied by a formal statistical test and quantification of uncertainty.

We conclude that the evidence for a positive skills-productivity association is strong, despite the modest number of included papers. The evidence would be stronger if we had a larger set of more homogeneous literature, which allowed for more precise tests of publication and reporting bias. However, the level of certainty that the links identified are causal is weak, and the papers do not, in combination, provide a precise sense of the magnitudes of the links.

Discussion

We first discuss key findings from our review, including the connections between them and with insights from wider literature. We then discuss the limitations of the evidence base and of our review processes that need to be taken into account when interpreting our findings. Finally, we draw out implications for policy and future research.

Discussion of findings

Strong evidence of a positive association between skills and productivity, but causality is a bigger question mark.

The weight of evidence is strongly in favour of there being a positive association between skills and productivity, despite there being only a modest number of included papers in our review.

However, it is much harder to be confident about the extent to which this relationship is causal—a limitation noted and discussed by other authors (Gambin, Green, and Hogarth 2009). Our included papers included no experimental literature. The most common methodology was cross-sectional regression with control variables. Studies using panel-based methods are able, all else equal, to control for a greater variety of confounding factors (in particular, any unobserved factors that do not change over time). These studies still found positive associations in a majority of the studies we reviewed. However, without more studies, we cannot draw very firm conclusions from this.

The skills-productivity relationship may take time to fully materialise.

Two studies found evidence that the (positive) association between skills and productivity is greater in the long run than contemporaneously, although they did not precisely define or describe how long it took for the full impact to materialise. If correct, these findings would suggest that changes in skills themselves tend to precede changes in factors that mediate (and specifically strengthen) the skills-productivity relationship. The implication would be that upskilling efforts within the civil service could take time to materialise in future productivity improvements.

Indirectly, this would also be evidence that the skills-productivity relationship is context-dependent, which other papers we reviewed provide further direct evidence of, as discussed below. Wider literature also offers clues as to the kinds of mechanisms that could be responsible. In the context of trying to explain long-term stability in the UK's graduate wage premium despite large increases in graduate supply, Blundell et al. (2016) suggest that increases in high levels of skill (measured in their case through degree-level education) lead to changes in the organisation of work, specifically decentralisation of responsibility and decision-making, to make more use of those higher skill levels. This could in fact be described as a particular manifestation of skills mismatch being an important contextual factor for the skills-productivity relationship (since it implies that skill increases translate more into productivity increases once other factors have adjusted to make better use of those new skills)—something that we return to below.

Several pieces of evidence suggest that the skills-productivity relationship is context-dependent and that those contexts are malleable.

No single contextual factor is studied enough in our included literature to draw very strong conclusions on that factor in isolation. However, several different contextual factors are found to matter. This chimes with other arguments and evidence, both that the skills-productivity relationship is context-dependent in general (Keep, Mayhew, and William Payne 2006), and that some of the specific contextual factors examined are important in shaping productivity.

Three papers suggest that the degree of **alignment between the skills workers have and the skills required by their jobs** is an important determinant of productivity. This is presumably because skill utilisation affects the extent to which skills translate into productivity. This fits with wider literature on patterns and drivers of productivity. In particular, some authors have linked concerns over large spatial disparities in UK productivity to the fact that higher levels of skill (and in particular, degree-level education) do not lead to the same wage or productivity gains in much of the UK as they do in London and a few other urban hotspots, because they are not matched by available jobs that would fully utilise those skills (Stansbury, Turner, and Balls 2023; Xu 2023). Evidence of this includes larger proportions of graduates in non-graduate jobs in those less productive areas, and a graduate wage premium that is declining as the supply of graduates increases (rather than remaining stable, as has been the case in London). This implies that, in the context of the public sector workforce, there could be gains to productivity from improving the match between worker skills and the skills required for the tasks performed at their jobs, and that the gains from upskilling would be greater as well.

Skills utilisation may also be indirectly related to the findings of other papers in our review. Two non-independent papers (Máté 2014; Máté 2015) find that the skills-productivity relationship is stronger in high-skilled sectors. This could be because those sectors are better able to make use of increased skill. Nguyen et al. (2024) found that the skills-productivity relationship is stronger in firms that use fixed-term contracts temporarily (before converting them to permanent contracts) than in firms that use fixed-term contracts for longer periods. They interpret the short-term use of fixed-term contracts as a screening device to identify workers who are a better match.

Two studies found evidence that an **innovative environment** strengthens the skills-productivity relationship (Koch and Smolka 2019; Torrent Sellens and Diaz-Chao 2015). In a finding that may be related, Braunerhjelm and Lappi (2023) estimated a positive link between entrepreneurial human capital in firms and their productivity. This, too, has echoes in wider literature. Aghion et al. (2020), focusing on lower-educated workers in the private sector, have found that occupations demanding higher levels of soft skills are associated with a wage premium, but more so within firms that are innovative, as measured by R&D spending (Aghion et al. 2020). To the extent that private sector wages reflect productivity, this is similar to a finding that skills and productivity are more strongly related in innovative environments.

Finally, Ohlsbom (2021) found that the skills-productivity relationship is stronger in the context of **better management practices**. This connects to literature showing that management practices are related to productivity (Bloom and Van Reenen 2010). Importantly, that research also suggests that the quality of management practices varies substantially (and hence can explain a substantial portion of productivity differences across firms and countries), making it a prime candidate for policy focus.

These papers highlight how the civil and public workforce can derive a higher level of productivity from the employees' skills by investing in the workplace environment and management practices.

Limitations of evidence

Likelihood that causal links are identified

Causality of the skills-productivity relationship is hard to establish empirically with high confidence, particularly at the level of large units of analysis, like the regions or sectors commonly studied in the literature we have reviewed. Randomised experiments are never conducted at this level. Neither is it straightforward to find non-experimental variation in skills between large groups of workers that could not plausibly be accompanied by variation in some other factor that could affect productivity—countries, regions, sectors, and even firms tend to differ and change over time in lots of ways besides skill levels. It is therefore unsurprising that none of the papers we review use experimental methods, and only one uses a method that would typically be described as quasi-experimental (an Instrumental Variables approach).

Difficulty in attributing causality applies to many of the most important questions in social science and does not mean that studies have been conducted to a low standard—just that they attempt something difficult. However, it has consequences for what we can take from the evidence:

- There is uncertainty and, importantly, subjectivity about the strength of justification for causal claims.
- Caution is needed in interpreting and comparing the results of different studies, given differences in control variables and methodologies. The assumptions that would need to be satisfied for statistical associations to be causal are different across different studies. This is closely connected to why meaningful quantitative synthesis of the studies is difficult (discussed further in "Limitations of review processes").

Lack of papers meeting eligibility criteria

One challenge encountered was the limited number of papers that fulfilled the eligibility criteria (despite those criteria allowing for a wide variety of quantitative methods). Many papers examine skills and/or productivity separately, but many fewer consider the link between them, and even fewer examine the link empirically. Many of these papers contained several different results relevant to one or both of our research questions (e.g., using different outcome variables), but often these results were not statistically independent from one another due to using overlapping samples of data. The small number of papers was therefore particularly limiting when it came to formal statistical synthesis.

Heterogeneity of studies

A significant limitation across the included studies was their high degree of heterogeneity, primarily in two dimensions: the independent variables and the methodologies. Skills are measured or proxied in a wide variety of ways. The range of methodologies employed means not only that causality is typically highly debatable, but also that different studies are harder to compare. For example, the single most common methodology is cross-sectional OLS regression with control variables, but the sets of control variables differ across studies. In the absence of random variation in skills, skills can be correlated with control variables. This means that estimated associations between skills and productivity, conditional on different sets of controls, are not actually measuring the same statistical quantities. This heterogeneity increases significantly further once one adds in other studies based on other methods. In turn, this makes it harder to meaningfully perform quantitative synthesis of the results of different studies, and harder to draw conclusions from comparisons between the results of different studies.

Relevance to public sector skills policy

Many studies operationalise skills as a level of formal educational qualifications, years of education, or (less commonly) other proxies, like level of experience. These are not easily malleable, specifically within the civil or public service context, as opposed to skills gained through post-education training or the specific capabilities of workers. The education level of its workforce is something that the UK public sector controls largely through choices that go beyond a traditional conception of “skills policy”—for example, the activities that it chooses to undertake (which affect the number of “white-collar” graduate jobs it offers) and its recruitment policies. It is debatable to what extent the impacts of formal education on productivity would be a good guide to the impacts of post-formal education, professional development, or skills training.

In addition, the vast majority of the included literature does not focus specifically on the public sector. It was clear from our exploratory scoping that this would be the case. We deliberately developed a search strategy and inclusion criteria that would allow us to draw insights from evidence in the wider economy, while also being tailored to exclude evidence that was clearly less relevant to a public sector context. Nevertheless, this inevitably requires more judgement and involves more uncertainty than if the evidence came from the same context we are trying to apply it to.

Limited evidence base on contextual factors for the skills-productivity relationship

Research question 2 focused on the role of contextual factors for the skills-productivity relationship; both those that are relatively exogenous to the system within which that relationship operates (which we considered “contexts and conditions”) and those more directly amenable to choices or policies within that system (which we considered “levers”). In both cases, we planned to use pre-defined conceptual frameworks, based on previous literature and evidence, to organise our synthesis. However, the evidence base proved insufficiently granular for this to be the most productive approach. Instead, we structured the syntheses inductively based on the actual content of the literature.

In part, the granularity of insights is fundamentally limited by the relatively large units (e.g., regions or even countries) that are often studied. These naturally aggregate over a wide range of contexts and conditions. Even with smaller units of analysis, like firms, however, the availability of evidence on heterogeneity in the skills-productivity link is not necessarily tightly aligned with the dimensions of heterogeneity that would be predicted by theory. Instead, empirical insights on heterogeneity are limited to those that can be gleaned from the data most readily available.

The available empirical evidence on the skills-productivity relationship provided especially little that could be mapped to the CATWOE framework (see "Conceptual framework") in our discussion of contexts and conditions. Although the evidence base around levers was also small, we do note some correspondence between the levers studied and the set of hypotheses that theory or previous evidence would suggest are worthy of examination. We referred in our protocol for this review to the "Tripod of Work" framework, which describes the conditions and social dynamics of work that allow employees to perform well (Stamp 2013). This consists of "Tasking," "Tending," and "Trusting." **Tasking** refers to the effective allocation of work. Skills utilisation and mismatch fit closely with this. **Trusting** emphasises the importance of interpersonal trust within teams in giving people the freedom and psychological safety to make the best use of their skills. Both the innovativeness of the environment and management practices could relate to this. Finally, **tending** highlights the need for ongoing support, development, and care for individuals and relationships to foster a productive and healthy work environment, which can again relate to aspects of management practices. Nevertheless, with very few studies specifically looking at any one of these factors, it was more transparent and productive to simply consider each factor directly than to attempt to categorise them into these groupings.

Although the nature of evidence did not support a framework-based synthesis, those frameworks do therefore have some utility in helping highlight gaps in the evidence base. We recognise that our review has shed light on only a subset of the features of the whole skills and productivity system that could, in principle, be examined, and that theory could motivate the investigation of a much more comprehensive set of factors.

Implications for policy

There are three main takeaways for policy from this review.

The first is that, on the basis of the evidence we have, improvements in skills may well bring productivity benefits to the public sector. The ability of the empirical evidence to demonstrate causality is less clear and highly debatable in any individual study. One of the benefits of synthesis, however, is that we can see the tendency towards finding a positive association holding up across the main methodologies employed in the literature.

Besides the crucial question mark over causation, the other caveat around this first policy implication concerns the magnitude of the effect. As discussed, the nature of the literature and our resulting choices of synthesis methods mean that we do not have a precise sense of the magnitude of the impact of skills on productivity. Hence, while there is good reason to expect successful skills investment to raise productivity, it is less clear how powerful it is compared to other possible drivers of productivity (e.g., capital). This is an important missing piece to the puzzle, given that policymakers need to decide how to allocate scarce resources between skills investments and other potential productivity drivers.

Second, while the empirical quantitative literature on contextual factors for the skills-productivity relationship is small, a number of different pieces of evidence point to the fact that the relationship is context-dependent. This includes evidence directly looking at the role of specific contextual factors and evidence suggesting that the relationship is stronger in the long run than the short run and in higher-skilled economic sectors. Importantly, several of the specific contextual factors examined—in particular, skills utilisation, innovation, and management practices—can in principle be influenced by policy. The more granular we get by focusing on any one contextual factor in isolation, the thinner the evidence base becomes. Nevertheless, policymakers should take away an emphasis on effectively integrating skills policy with wider policies, like those relating to workforce and management, to get the most out of skills improvements.

The final policy implication is based on the limitations found in the evidence base. The scarcity of causal evidence and the thinness of the evidence base around contextual factors that influence the skills-productivity relationship can both be ameliorated by more rigorous evaluation of interventions to improve workforce skills.

Limitations of review processes

In spite of the use of a long list of skills keywords, our search did not yield papers across all the identified skills. This could be due to variations in terminology across subjects, but also because of a lack of empirical research on specific skills.

Additionally, our search was restricted to titles and abstracts. Abstracts in economics and related subjects are often unstructured and lack the keywords that can communicate the contents of the paper clearly. For instance, our inclusion criteria required papers to specify the country of focus in either the title or the abstract, but these were often missing.

Geographical inclusion criteria (OECD countries) were included. OECD member countries have comparable economic and administrative structures, which could provide insights more applicable to the British context. Our initial testing suggested that a large volume of literature on public sector skills comes from lower-income countries and focuses on workers with relatively low skill levels, which would be less relevant for this project. Nevertheless, it is possible that this excludes some relevant insights.

The synthesis approaches we used also have limitations. Given the heterogeneity of studies, and especially their methodologies, we mostly used narrative synthesis, alongside vote counting, as a method of formal quantitative synthesis. Both deliver key insights, but neither provides rigorous information about or comparisons between the magnitudes of effects, as would have been possible if the literature had allowed for meta-analysis. This naturally limits the richness of what can be inferred from our review.

Implications for future research

Future research would be well-served by data that allows more exploration of how features of the working environment, including those which can be changed, are associated with the skills-productivity link. Empirical research tends to focus on variables measured in secondary data. In the context of this review, this means that specific contextual factors are relatively likely to be examined. For example, firm data is relatively likely to contain administrative information that firms collect for themselves and/or that public administrative bodies, like tax authorities, need to collect. This includes variables like contract types and innovation activities. Meanwhile, measures of skill mismatch can often be derived from population-level or labour force survey data detailing the characteristics of jobs and the education levels of workers. However, more detailed information about what actually happens within the workplace—how workers interact, what they are and are not empowered to do, how they are treated, etc.—is much less likely to be recorded in either of these sorts of data. The increasing availability and use of large-scale administrative records—a general trend in social science research, and one that is enabling much more research—will not tend to solve that particular problem.

As a result, significant progress on these research questions likely relies on the development of new secondary data and/or innovative primary data collection, informed by hypotheses that flow from theory or other empirical evidence. Coordination and collaboration between survey design and provision and academic research from relevant disciplines would be key if this is to happen and be applied effectively.

Developing a richer understanding of the mediating factors that shape the skills-productivity link would bring two broad sets of benefits. First, it would shed light on how to get the most out of the skills of the public sector. Second, it would give us a more precise understanding of how to translate evidence to (particular parts of) the public sector that was generated from another context. There is very little literature on the skills-productivity link specifically within the public sector. We took a decision during the scoping phase of this review to cast the net much wider, on the basis that evidence from the wider economy is of relevance too, but the more precisely we know how to assess that relevance, the more reliable the conclusions we will be able to draw.

Finally, another way of tackling the latter problem is to generate more high-quality evidence on the skills-productivity link from directly within the public sector. A big constraint on this is the availability of robust public sector productivity measures. These are difficult to come by in part because the output of the knowledge economy can be hard to define. However, relative to otherwise similar work in the private sector, there is the additional large complication that the value of the output of the public sector is typically not directly measurable via observed market prices. Here, we make a similar key recommendation to one made in a sister project commissioned by Government Skills that focuses on the components of effective professional learning design in the civil service, which is to focus research resources on developing robust techniques for measuring productivity within the public sector or at least within more key parts of the public sector. The Office for National Statistics (ONS) is aware of this issue and is working on it (e.g., ONS Public Service Productivity). This sort of work should continue, and it is important that it joins up effectively with academics and the potential users of research on productivity within the public sector, including policymakers and learning and development practitioners.

Conclusion

This systematic review finds that skills and productivity have a strong tendency to be positively associated. The relationship also appears to be context-dependent. There are several pieces of evidence suggesting that the skills-productivity relationship can be strengthened by factors that workplaces have some power to change. There are, however, important limitations of the evidence base. It is difficult to confidently establish causality of the skills-productivity relationship at the level of large units of analysis—a challenge that will likely remain hard to overcome. In addition, the evidence base is limited in size and is very heterogeneous, particularly with respect to methodology, which makes comparison of results across studies difficult.

Other Information

Registration and protocol

The protocol was registered on the UK government evaluation registry and is available on the UK government website. Any deviations from the protocol have been reported in the section titled "Deviations from protocol," found below.

Deviations from protocol

We note the following deviations from the protocol in our analysis:

1. For the implementation of the inclusion/exclusion pathways, we amended the order of sequential exclusion based on the nature of studies we found in the final list of papers. This allowed screening to be conducted more quickly, but did not impact the final outcome. The original order in the protocol was "Date of publication, language of publication, type of publication, geographical focus, population of interest, concept, context, methodology, and study design."
2. There was an additional criterion added to the inclusion/exclusion pathways: "time period of analysis." This was done after reviewing papers based on historical data that met the inclusion criteria, but did not meet the purpose of this project, to produce evidence relevant to the modern workplace. We limit the studies to include only those where the last year of analysis is after 1990.
3. We deviated from the data items specified in the protocol due to a lack of available data in the included papers. We excluded items reported by fewer than two papers, and the list of excluded items is in Appendix D.
4. We focused on a "seed" group of included papers to streamline the citation searching exercise while ensuring there are no systematic gaps in our search strategy.
5. In the absence of a feasible meta-analysis, we decided to supplement the narrative synthesis with a vote-counting exercise as recommended by the Cochrane handbook. Vote counting is an alternative quantitative synthesis technique.
6. We moved away from a synthesis structured around the pre-defined frameworks in our protocol for RQ2. This was because the available empirical evidence did not map closely enough onto those frameworks.

Support

This is an independent report conducted by Alma Economics and commissioned by Government Skills, which is part of the UK Cabinet Office. The project is funded by the HM Treasury Labour Market Evaluations and Pilots Fund. The contact email address for Government Skills is gscu.comms@cabinetoffice.gov.uk.

An Expert Advisory Group consisting of members of the civil service and external experts was also established to monitor and oversee the systematic review.

Both Government Skills and the Expert Advisory Group supported the development of the scope, analytic framework, and key questions for this review. However, they will have no role in the selection of studies, quality assessment, or the synthesis of evidence other than giving expert advice.

Competing interests

No competing interests to declare.

Availability of data, code, and other materials

All materials associated with this project will be made available for public use through the Government Skills website. Additional information can be made available on request.

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Julie Glanville, Academic Librarian, provided quality assurance.

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Appendix A: List of Skills

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Core Skills	Working together	team*
Government Skills Taxonomy	Core Skills	Relationship Management	Relationship manag*
Government Skills Taxonomy	Core Skills	Collaboration	collaborat*
Government Skills Taxonomy	Core Skills	Networking	network*
Government Skills Taxonomy	Core Skills	Team working	team*
Government Skills Taxonomy	Core Skills	Making effective decisions	decision*
Government Skills Taxonomy	Core Skills	Defines Problems	problem
Government Skills Taxonomy	Core Skills	Gathers information	information
Government Skills Taxonomy	Core Skills	Stakeholder analysis	analy*
Government Skills Taxonomy	Core Skills	Option Analysis	analy*
Government Skills Taxonomy	Core Skills	Data analysis	analy*
Government Skills Taxonomy	Core Skills	Analyses Risk	risk
Government Skills Taxonomy	Core Skills	Logical reasoning	logic*
Government Skills Taxonomy	Core Skills	Working at pace	deliver*, respons*
Government Skills Taxonomy	Core Skills	Time management skills	time manag*
Government Skills Taxonomy	Core Skills	Resilient	resilien*
Government Skills Taxonomy	Core Skills	Delivering timely outcomes	time manag*

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Core Skills	Developing self and others	lead*, manage*
Government Skills Taxonomy	Core Skills	Managing myself	manage*
Government Skills Taxonomy	Core Skills	Managing my wellbeing	wellbeing
Government Skills Taxonomy	Core Skills	Developing myself	develop*, improv*
Government Skills Taxonomy	Core Skills	Gives & receives feedback	feedback
Government Skills Taxonomy	Core Skills	Coaches others	coach*
Government Skills Taxonomy	Core Skills	Provides mentorship	mentor*
Government Skills Taxonomy	Core Skills	Managing a quality service	manage*
Government Skills Taxonomy	Core Skills	Manages resources	manage*
Government Skills Taxonomy	Core Skills	Performance/Service measurement	"performance measurement"
Government Skills Taxonomy	Core Skills	Quality assurance	quality
Government Skills Taxonomy	Core Skills	Customer Service	customer
Government Skills Taxonomy	Core Skills	Changing & improving	change manag*
Government Skills Taxonomy	Core Skills	Dealing with ambiguity	ambigu*
Government Skills Taxonomy	Core Skills	Adaptable	adapt*
Government Skills Taxonomy	Core Skills	Process improvement	process improvement
Government Skills Taxonomy	Core Skills	Innovative	innovat*
Government Skills Taxonomy	Core Skills	Change Management	change manag*

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Core Skills	Seeing the bigger picture	change manag*
Government Skills Taxonomy	Core Skills	Strategic thinking	strateg*
Government Skills Taxonomy	Core Skills	Systems thinking	systems think*
Government Skills Taxonomy	Core Skills	Horizon Scanning	horizon scan*
Government Skills Taxonomy	Core Skills	Political Insight	politic*
Government Skills Taxonomy	Core Skills	Communicating and Influencing	influenc*
Government Skills Taxonomy	Core Skills	Written Communication	communicat*
Government Skills Taxonomy	Core Skills	Verbal Communication	communicat*
Government Skills Taxonomy	Core Skills	Managing challenging conversations	communicat*
Government Skills Taxonomy	Core Skills	Negotiation	negotiat*
Government Skills Taxonomy	Core Skills	Presenting	present*
Government Skills Taxonomy	Core Skills	Gives advice and guidance	guid*, advic*, advis*
Government Skills Taxonomy	Core Skills	Listening	listen*
Government Skills Taxonomy	Core Skills	Selecting the right format of communication	communicat*
Government Skills Taxonomy	Core Skills	Understanding and explaining complex information	communicat*
Government Skills Taxonomy	Core Skills	Digital confidence	digital
Government Skills Taxonomy	Core Skills	Digital literacy	digital
Government Skills Taxonomy	Core Skills	Digital security	digital

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Core Skills	Managing digital identity	digital
Government Skills Taxonomy	Core Skills	Data management	data
Government Skills Taxonomy	Core Skills	Data security	data
Government Skills Taxonomy	Core Skills	Explores emerging technology	technolog*
Government Skills Taxonomy	Core Skills	Content creation	content
Government Skills Taxonomy	Core Skills	Leadership	lead*
Government Skills Taxonomy	Core Skills	Purposeful	lead*
Government Skills Taxonomy	Core Skills	Business & Risk	risk
Government Skills Taxonomy	Core Skills	Inclusive	inclusi*, divers*
Government Skills Taxonomy	Core Skills	Line Management	inclusi*, divers*
Government Skills Taxonomy	Core Skills	Building an effective and inclusive team culture	manage*
Government Skills Taxonomy	Core Skills	Supporting the wellbeing of my team/s	wellbeing
Government Skills Taxonomy	Core Skills	Prioritising personal and professional development	manage*
Government Skills Taxonomy	Core Skills	Managing people to perform	manage*
Government Skills Taxonomy	Core Skills	Managing challenging and sensitive communications within my team	manage*
Government Skills Taxonomy	Core Skills	Managing performance and delivery	manage*

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Core Skills	Improving productivity to deliver results	manage*
Government Skills Taxonomy	Core Skills	Recognising and celebrating success	motivat*
Government Skills Taxonomy	Project delivery	Project Management	project manag*
Government Skills Taxonomy	Project delivery	Requirements Management	project manag*
Government Skills Taxonomy	Project delivery	Solutions Development	develop*
Government Skills Taxonomy	Project delivery	Project Planning/Scoping	plan*, scop*
Government Skills Taxonomy	Project delivery	Scheduling	project manag*
Government Skills Taxonomy	Project delivery	Resource Management	project manag*
Government Skills Taxonomy	Project delivery	Project budgeting and Cost Management	project manag*
Government Skills Taxonomy	Project delivery	Project Risk and Issue Management	project manag*
Government Skills Taxonomy	Project delivery	Quality Management	quality
Government Skills Taxonomy	Project delivery	Business Change and Implementation	change manag*
Government Skills Taxonomy	Project delivery	Project Governance	project manag*
Government Skills Taxonomy	Project delivery	Project Frameworks and Methodologies	project manag*
Government Skills Taxonomy	Project delivery	Project Assurance	project manag*
Government Skills Taxonomy	Project delivery	Change Control	change manag*
Government Skills Taxonomy	Project delivery	Business Case Development	business
Government Skills Taxonomy	Project delivery	Asset Allocation (portfolio management)	portfolio manag*

Source	Skill group	Skill type	Keywords
Government Skills Taxonomy	Project delivery	Benefits Management	project manag*
Government Skills Taxonomy	Project delivery	Project evaluation	evaluation
Government Skills Taxonomy	Operational delivery	Operational delivery	deliver*
Government Skills Taxonomy	Operational delivery	Connections and communication	communicat*, connect*
Government Skills Taxonomy	Operational delivery	Operational Leadership and management	lead*
Government Skills Taxonomy	Operational delivery	Adaptability to change	adapt*
Government Skills Taxonomy	Operational delivery	Data and insight	data, analy*
Government Skills Taxonomy	Operational delivery	Delivery and decision making at pace	decision*
Government Skills Taxonomy	Operational delivery	Systems leadership	systems think*
Government Skills Taxonomy	Operational delivery	Innovation and risk	innovat*
Government Skills Taxonomy	Operational delivery	Decisions at pace	Decision*
Government Skills Taxonomy	Operational delivery	Learning agility	learn*
Future skills	Higher Order Thinking Skills	Critical thinking	critical think*
Future skills	Higher Order Thinking Skills	Problem solving	problem
Future skills	Higher Order Thinking Skills	Decision making	decision*
Future skills	Higher Order Thinking Skills	Systems thinking	systems think*
Future skills	Higher Order Thinking Skills	Logical reasoning	logic*
Future skills	Higher Order Thinking Skills	Analytical thinking	analy*

Source	Skill group	Skill type	Keywords
Future skills	Higher Order Thinking Skills	Complex problem solving	problem
Future skills	Higher Order Thinking Skills	Learning agility	learn*
Future skills	Higher Order Thinking Skills	Cognitive skills	Cogniti*
Future skills	Higher Order Thinking Skills	Risk management	risk manag*
Future skills	Higher Order Thinking Skills	Systems analysis	systems analy*
Future skills	Higher Order Thinking Skills	Reflective thinking skills (enhanced through digital tools)	Reflect*
Future skills	Dialogue skills	Collaboration	collaborat*
Future skills	Dialogue skills	Communication	communicat*
Future skills	Dialogue skills	Listening/active listening	listen*, communic*
Future skills	Dialogue skills	Teamwork	teamwork
Future skills	Dialogue skills	Negotiation	negotiat*
Future skills	Dialogue skills	Persuasion	persua*
Future skills	Dialogue skills	Cooperation	cooperat*
Future skills	Dialogue skills	Explaining skills	communicat*
Future skills	Dialogue skills	Conversation abilities	communicat*
Future skills	Dialogue skills	Asking questions	communicat*
Future skills	Dialogue skills	Resolving conflicts	conflict resol*
Future skills	Dialogue skills	Collaborative leadership	collaborat*
Future skills	Dialogue skills	Soft skills	soft
Future skills	Dialogue skills	Emotional intelligence	"emotional intelligence"
Future skills	Dialogue skills	Social skills	social
Future skills	Dialogue skills	Instructing	social
Future skills	Dialogue skills	Trust building	social, team

Source	Skill group	Skill type	Keywords
Future skills	Dialogue skills	Ability to communicate properly through ICTs	communicat*
Future skills	Dialogue skills	Multidisciplinary teamwork	team*
Future skills	Dialogue skills	Cultural awareness	cultur*
Future skills	Dialogue skills	Using appropriate ways to communicate	communicat*
Future skills	Digital and STEM literacy	Computational thinking Only	computation*
Future skills	Digital and STEM literacy	Digital literacy	digital
Future skills	Digital and STEM literacy	ICT literacy	ICT
Future skills	Digital and STEM literacy	Digital Citizenship	digital
Future skills	Digital and STEM literacy	Specific programme skills (eg Python)	programming, coding
Future skills	Digital and STEM literacy	Machine Learning	machine learn*
Future skills	Digital and STEM literacy	Business intelligence	business
Future skills	Digital and STEM literacy	Data science	data
Future skills	Digital and STEM literacy	Digital skills	digital
Future skills	Digital and STEM literacy	Technical skills	technical
Future skills	Digital and STEM literacy	Cyber security skills	cyber security
Future skills	Digital and STEM literacy	STEM	STEM
Future skills	Digital and STEM literacy	Data analysis	data
Future skills	Digital and STEM literacy	Data warehousing	data

Source	Skill group	Skill type	Keywords
Future skills	Digital and STEM literacy	Data ingestion and extraction	data
Future skills	Digital and STEM literacy	Digitalization	digital
Future skills	Digital and STEM literacy	Manipulating data	data
Future skills	Digital and STEM literacy	Reading dashboards	data
Future skills	Digital and STEM literacy	Expertise with emerging technologies	technolog*
Future skills	Digital and STEM literacy	Programming skills	programming, coding
Future skills	Digital and STEM literacy	Mathematics	math*, numera*
Future skills	Digital and STEM literacy	Science	scien*
Future skills	Digital and STEM literacy	Professional Social Media usage	social
Future skills	Digital and STEM literacy	Database searching skills	database
Future skills	Digital and STEM literacy	Online learning skills	online
Future skills	Digital and STEM literacy	Content creation skills	content
Future skills	Digital and STEM literacy	Ethical digital behaviour skills	digital
Future skills	Digital and STEM literacy	Online professional identity management skills	online
Future skills	Digital and STEM literacy	Media literacy skills	media
Future skills	Digital and STEM literacy	Digital record keeping skills	digital
Future skills	Digital and STEM literacy	Skills for creating and managing digital content	content

Source	Skill group	Skill type	Keywords
Future skills	Digital and STEM literacy	Accounting	accounting
Future skills	Digital and STEM literacy	Finance	financ*
Future skills	Digital and STEM literacy	Interpreting and evaluating information	Information
Future skills	Digital and STEM literacy	Netiquette	online
Future skills	Digital and STEM literacy	Digital identity management	digital
Future skills	Digital and STEM literacy	Database management	database
Future skills	Self-management	Resilience	resilien*
Future skills	Self-management	Self-motivation	motivat*
Future skills	Self-management	Productivity/planning/ organisation	organisation*
Future skills	Self-management	Time management	time manag*
Future skills	Lifelong Learning	Learning to learn/learning strategies	learn*
Future skills	Lifelong Learning	Willingness to learn	learn*
Future skills	Lifelong Learning	Active learning	learn*
Future skills	Lifelong Learning	Learning agility	learn*
Future skills	Entreprise skills	Entrepreneurship	entrepr*
Future skills	Entreprise skills	Innovation	innovat*
Future skills	Entreprise skills	Commercial skills	commerc*
Future skills	Entreprise skills	Business skills	business
Future skills	Entreprise skills	Creative design skills	creativ*
Future skills	Entreprise skills	Risk taking	risk
Future skills	Entreprise skills	Cross-cutting skills	cross-cutting
Future skills	Leadership	Management	manage*
Future skills	Leadership	Leadership skills	lead*

Source	Skill group	Skill type	Keywords
Future skills	Leadership	Collaborative leadership qualities and practices	lead*
Future skills	Leadership	Motivational leadership	lead*
Future skills	Leadership	Entrepreneurial leadership	lead*
Future skills	Leadership	Vision and strategy	strateg*
Future skills	Leadership	Crisis management skills	manage*
Future skills	Leadership	Win-win negotiations	negotiat*
Future skills	Leadership	Organisational awareness	organisation*
Future skills	Leadership	Leading people, "inspiring and aligning broad networks of professionals"	lead*
Future skills	Leadership	Adaptive leadership for method	lead*
Future skills	Leadership	Strategic and leadership skills	lead*
Future skills	Leadership	Verbal communications to motivate employees	communicat*
Future skills	Leadership	Change management	change manag*
Future skills	Leadership	Contingent workforce management	manage*
Future skills	Leadership	Productivity management	manage*
Future skills	Leadership	Performance measurement	manage*
Future skills	Leadership	Workload management	manage*
Future skills	Leadership	Talent deployment	talent
Future skills	Leadership	Workforce strategy development	strateg*

Source	Skill group	Skill type	Keywords
Future skills	Leadership	Coaching	coach*
Future skills	Flexibility	Adaptability	adapt*
Future skills	Flexibility	Multi-tasking	multi-task*
Future skills	Flexibility	Agility	agil*
Future skills	Flexibility	Tolerance to ambiguity	ambigu*
Future skills	Flexibility	Agile working	agil*
Future skills	Flexibility	Behavioural flexibility	flexib*
Future skills	Outliers	Project delivery skills	project
Future skills	Outliers	Manual skills/dexterity	manual
Future skills	Outliers	Quality control analysis	quality
Future skills	Outliers	Climate change risk assessment	climate
Future skills	Outliers	Emissions reporting	climate
Future skills	Outliers	Transversal skills	transversal
Future skills	Outliers	ESG (Environmental, Social and corporate Governance)	ESG
Future skills	Outliers	ESG (Environmental, Social and corporate Governance)	ESG
Government Campus	Public administration	Foundations of public administration	public administration
Government Campus	Public administration	Customer	customer
Government Campus	Public administration	Data and Analytics	data, analy*
Government Campus	Public administration	Finance	financ*
Government Campus	Public administration	Leadership and Management	lead*, manag*
Government Campus	Public administration	Mental Health and Wellbeing	wellbeing

Source	Skill group	Skill type	Keywords
Government Campus	Public administration	Project Delivery	project
Government Campus	Public administration	Technology and Software	IT, technolog*, software
Government Campus	Public administration	Security	security
Government Campus	Working in government	Diversity, Equality and Inclusion	diversit*, inclus*
Government Campus	Working in government	Finance	financ*
Government Campus	Working in government	Policy	"policy development"
Government Campus	Working in government	Project Delivery	project
Government Campus	Working in government	Recruitment	recruitment
Government Campus	Working in government	Technology and Software	IT, technolog*, software
Government Campus	Working in government	Writing	writing
Government Campus	Leading and managing	Leading and managing	lead*, manage*
Government Campus	Leading and managing	Coaching	coach*
Government Campus	Leading and managing	Commercial	commerc*
Government Campus	Leading and managing	Diversity, Equality and Inclusion	diversit*, inclus*
Government Campus	Leading and managing	Leadership and Management	Lead*
Government Campus	Leading and managing	Mental Health and Wellbeing	wellbeing
General skills	Leading and managing	Workforce skills	workforce
General skills	Leading and managing	Foundational skills	Foundational

Source	Skill group	Skill type	Keywords
General skills	Leading and managing	Functional skills	Functional
General skills	Leading and managing	Technical skills	Technical
General skills	Leading and managing	Non-technical skills	“non technical”
General skills	Leading and managing	Literacy skills	literacy
General skills	Leading and managing	Core skills	core
General skills	Leading and managing	Interpersonal skills	interpersonal
General skills	Leading and managing	Content skills	content
General skills	Leading and managing	Process skills	process
General skills	Leading and managing	Complex problem-solving skills	“problem solv”
General skills	Leading and managing	Resource management skills	“Resource manage”
General skills	Leading and managing	Social skills	social
General skills	Leading and managing	Systems skills	systems
General skills	Leading and managing	Self-presentation skills	present*
General skills	Leading and managing	Skills captured by referencing the unit of analysis:	present*
General skills	Leading and managing	Organisation skills	organisation*
General skills	Leading and managing	Team skills	Team*
General skills	Leading and managing	Firm skills	Firm*
General skills	Leading and managing	Cross-country skills	countr*

Source	Skill group	Skill type	Keywords
General skills	Leading and managing	International	international
General skills	Leading and managing	national	nation*
General skills	Leading and managing	regional	region*
General skills	Leading and managing	sectoral	sector*
General skills	Leading and managing	OECD	OECD
General skills	Leading and managing	Divisional skills	Division*

Appendix B: Search Logic and Implementation

Search logic

Based on the scoping and pilot testing carried out in the initial stages of the project, we used the following logic to create search skills. Details are provided in the protocol.

"We search Title for skills synonyms and productivity synonyms occurring along with skill type, methodology, and macro unit of analysis keywords in the abstract;

OR

We search *Abstracts* for skills synonyms occurring in proximity (within three words) of the skill type keywords, along with productivity synonyms, methodology, and macro unit of analysis keywords;

OR

We search Title for "skill" and "productivity" variants, with methodology and macro unit of analysis keywords in the abstract;

AND

We search Titles OR Abstracts for the keywords related to geographical focus occurring in the title or abstract."

The following keywords were used in the search process:

Table 3. Keywords used in the search

Skills keywords	skill* OR capabilit* OR competenc* OR accreditation* OR qualification* OR "human capital"
Types of skills	Refer to Appendix A
Productivity keywords	productiv* OR efficien* OR output
Unit of analysis keywords	organisation*, firm*, team*, sector*, division*, region*, nation*, countr*
Methodological keywords Papers with quantitative results	empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*

Skills keywords	**skill* OR capabilit* OR competenc* OR accreditation* OR qualification* OR "human capital"**
Geographical keywords OECD countries only	australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica"* OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe* OR EMEA OR america* OR asia*

Search strings

The following table lists the search string used to collect papers from selected academic databases and grey literature sources, along with the outputs for each of the sources.

Table 4. List of search strings used to collect papers

Database or register	Search strings	Filters
Web of Science **Results**: 1796 **Date of search**: 27th Nov 2024	((TI= (skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND TI= (productiv* OR efficien* OR output*) AND ((AB=("emotional intelligence" OR "performance measurement" OR "policy development" OR "non technical" OR "non-technical" OR "problem solv*" OR "problem-solv*" OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR	Language: English, Dates: 01/01/2004-01/09/2024

Database or register	Search strings	Filters
	deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR "ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR "machine-learn*" OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR region* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical" OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing") OR AB=("human capital")) AND AB=("countr"* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND AB=(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*))) OR (AB=((((skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) NEAR/3 ("emotional intelligence" OR "performance measurement" OR "policy development" OR "non	

Database or register	Search strings	Filters
	technical" OR "non-technical" OR "problem solv*" OR "problem-solv*" OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR "ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR "machine-learn*" OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR region* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical" OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing")) OR ("human capital"))) AND AB= (productiv* OR efficien* OR output*) AND AB=(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND AB=(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR	

Database or register	Search strings	Filters
	panel* OR quasi*)) OR (TI= skill* AND TI= productiv* AND (AB=(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND AB=(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*)))) AND (TI=(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe) OR AB=(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR	

Database or register	Search strings	Filters
	hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe))	
Scopus **Results**: 725 **Date of search**: 27 Nov 2024	((TITLE(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND TITLE(productiv* OR efficien* OR output*) AND ((ABS("emotional intelligence" OR "performance measurement" OR "policy development" OR "non technical" OR "non-technical" OR "problem solv*" OR problem-solv* OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR "ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR machine-learn* OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR	Language: English, Year: 2014-2024, Document Type: Article, Language: English

Database or register	Search strings	Filters
	network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical" OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing") OR ABS("human capital")) AND ABS(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND ABS(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*))) OR (ABS((((skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) NEAR/3 ("emotional intelligence" OR "performance measurement" OR "policy development" OR "non technical" OR "non-technical" OR "problem solv*" OR problem-solv* OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR	

Database or register	Search strings	Filters
	"ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR machine-learn* OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical" OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing")) OR ("human capital"))) AND ABS (productiv* OR efficien* OR output*) AND ABS(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND ABS(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*)) OR (TITLE(skill*) AND TITLE(productiv*) AND (ABS(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce)	

Database or register	Search strings	Filters
	AND ABS(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*)))) AND (TITLE(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe) OR ABS(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe))	

Database or register	Search strings	Filters
ERIC – title **Results: 4** **Date: 27 Nov 2024**	title:(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND title:(productiv* OR efficien* OR output*) pubyearmin:2014 pubyearmax:2024	Title only, Dates: 2014-2024
ERIC – abstract **Results: 23** **Date: 27 Nov 2024**	abstract:(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND abstract:(productiv* OR efficien* OR output*) AND abstract:(organisation* OR organization* OR firm* OR team* OR sector* OR division* OR region* OR nation* OR countr*) AND abstract:(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*) pubyearmin:2014 pubyearmax:2024	Abstract only, Dates: 2014-2024
IDEAS/RePEc - Title **Results: 38** **Date: 27 Nov 2024**	(skill* | capabilit* | competenc* | "human capital" | accreditation* | qualification*) & (productiv* | efficien* | output*)	From: 2014, To: 2024, In: Title
IDEAS/RePEc - abstract **Results: 0** **Date: 27 Nov 2024**	(skill* | capabilit* | competenc* | "human capital" | accreditation* | qualification*) & (productiv* | efficien* | output*) & (organisation* | organization* | firm* | team* | sect|* | division* | region* | nation* | countr*) & (empir* | quant* | survey* | regres* | c|relat* | econometr* | multivariate | meta* | statist* | longitud* | panel* | quasi*)	From: 2014, To: 2024, In: Abstract
GOV.UK **Results: 11** **Date: 27 Nov 2024**	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productiv* OR efficien* OR output*) AND (organisation* OR organization* OR firm* OR team* OR sector* OR division* OR region* OR nation* OR countr*) AND (empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*) site:www.gov.uk	-

Database or register	Search strings	Filters
OECD iLibrary - Title **Results: 10** **Date: 27 Nov 2024**	(Title ‘skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*’) (Language ‘en’) AND (Title ‘productiv* OR efficien* OR output*’) AND (‘’) with type(s) subtype/journal OR subtype/article OR subtype/workingpaper published between 2014 and 2024	Dates: 2014 -2024, Content type: Journals, Articles, Paper, Language: English
OECD iLibrary - Abstract **Results: 66** **Date: 27 Nov 2024**	(Abstract ‘skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*’) (Language ‘en’) AND (Abstract ‘productiv* OR efficien* OR output*’) AND (Abstract ‘organisation* OR organization* OR firm* OR team* OR sector* OR division* OR region* OR nation* OR countr*’) AND (Abstract ‘empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*’) AND (‘’) with type(s) subtype/journal OR subtype/article OR subtype/workingpaper published between 2014 and 2024	Dates: 2014-2024, Content type: Journals, Articles, Paper, Language: English
ProQuest **Results: 1,842** **Date: 27 Nov 2024**	((TITLE(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND TITLE(productiv* OR efficien* OR output*) AND ((ABSTRACT("emotional intelligence" OR "performance measurement" OR "policy development" OR "non technical" OR "non-technical" OR "problem solv*" OR problem-solv* OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber	Date: From 01 January 2014 to 01 September 2024 Source type Dissertations & Theses, Government & Official Publications, Reports, Scholarly Journals, Working Papers Language English

Database or register	Search strings	Filters
	security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR "ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR machine-learn* OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical" OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing") OR ABSTRACT("human capital")) AND ABSTRACT(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND ABSTRACT(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*))) OR	

Database or register	Search strings	Filters
	(ABSTRACT((((skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) NEAR/3 ("emotional intelligence" OR "performance measurement" OR "policy development" OR "non technical" OR "non-technical" OR "problem solv*" OR problem-solv* OR "Resource manage*" OR "accounting" OR adapt* OR agil* OR ambigu* OR analy* OR "business" OR "change manag*" OR "climate" OR coach* OR cognit* OR collaborat* OR commerc* OR communicat* OR connect* OR computation* OR "conflict resol*" OR "content" OR cooperat* OR "core" OR creativ* OR "critical think*" OR "cross-cutting" OR cultur* OR customer OR "cyber security" OR "cyber-security" OR "data" OR analy* OR "database" OR decision* OR deliver* OR respons* OR develop* OR improv* OR inclus* OR "digital" OR diversit* OR entrepr* OR "ESG" OR "evaluation" OR "feedback" OR financ* OR flexib* OR "Foundational" OR "Functional" OR guid* OR advic* OR advis* OR "horizon scan*" OR "ICT" OR inclusi* OR divers* OR influenc* OR "information" OR innovat* OR "interpersonal" OR "IT" OR technolog* OR "software" OR lead* OR manage* OR learn* OR listen* OR communic* OR "literacy" OR logic* OR "machine learn*" OR machine-learn* OR "manual" OR math* OR numera* OR "media" OR mentor* OR motivat* OR multi-task* OR "multi task*" OR negotiat* OR network* OR "online" OR organisation* OR organization* OR persua* OR plan* OR scop* OR politic* OR "portfolio manag*" OR present* OR "problem" OR "process" OR "process improvement" OR "programming" OR "coding" OR "project" OR "project manag*" OR "public administration" OR "quality" OR "recruitment" OR Reflect* OR "Relationship manag*" OR resilien* OR "risk" OR "risk manag*" OR scien* OR "security" OR "social" OR "team" OR "soft" OR "STEM" OR strateg* OR "systems" OR "systems analy*" OR "systems think*" OR "talent" OR team* OR "teamwork" OR "technical"	

Database or register	Search strings	Filters
	OR "time manag*" OR "transversal" OR "wellbeing" OR "well-being" OR "writing")) OR ("human capital"))) AND ABSTRACT(productiv* OR efficien* OR output*) AND ABSTRACT(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND ABSTRACT(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*)) OR (TITLE(skill*) AND TITLE(productiv*) AND (ABSTRACT(countr* OR organisation* OR organization* OR Team* OR Firm* OR international OR nation* OR region* OR sector* OR OECD OR workforce) AND ABSTRACT(empir* OR quant* OR survey* OR regres* OR correlat* OR econometr* OR multivariate OR meta* OR statist* OR longitud* OR panel* OR quasi*)))) AND (TITLE(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR	

Database or register	Search strings	Filters
	france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe) OR ABSTRACT(australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica" OR "costa rican" OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe))	
World Bank Open Knowledge Repository **Results**: 0 **Date of search**: 27 Nov 2024	(("skill*" OR "capabilit*" OR "competenc*" OR "accreditation*" OR "qualification*") AND ("productiv*" OR "efficien*" OR "output*") AND ("organisation*" OR "organization*" OR "firm*" OR "team*" OR "sector*" OR "division*" OR "region*" OR "nation*" OR "countr") AND ("empir*" OR "quant*" OR "survey*" OR "regres*" OR "correlat*" OR "econometr*" OR "multivariate" OR "meta*" OR "statist*" OR "longitud*" OR "panel*" OR "quasi*")) OR (("skill*" OR "capabilit*" OR "competenc*" OR "accreditation*" OR "qualification*") AND ("productiv*" OR "efficien*" OR "output*") AND ("organisation*" OR "organization*" OR "firm*" OR	After the search is completed: Date: 2004-2024, Supported language: EN

Database or register	Search strings	Filters
	"team*" OR "sector*" OR "division*" OR "region*" OR "nation*" OR "countr") AND ("empir*" OR "quant*" OR "survey*" OR "regres*" OR "correlat*" OR "econometr*" OR "multivariate" OR "meta*" OR "statist*" OR "longitud*" OR "panel*" OR "quasi*")) AND (australia* OR austria* OR belgi* OR canad* OR chile* OR colombia* OR "costa rica"* OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe* OR america* OR asia*)	
IZA Institute for Labor Economics **Results**: 2 **Date of search**: 27th Nov 2024	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productiv* OR efficien* OR output*) site:https://www.iza.org/	-
Warwick Institute for Employment Research **Results**: 3 **Date of search**: 27th Nov 2024	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productiv* OR efficien* OR output*) site:https://warwick.ac.uk/fac/soc/ier/ Search using Google	-
Campbell Collaboration **Results**: 1 **Date of search**: 27th Nov 2024	site:www.campbellcollaboration.org (("skill*" OR "capabilit*" OR "competenc*" OR "accreditation*" OR "qualification*") AND ("productiv*" OR "efficien*" OR "output*") AND ("organisation*" OR "organization*" OR "firm*" OR "team*" OR "sector*" OR "division*" OR "region*" OR "nation*" OR "countr") AND ("empir*" OR "quant*" OR "survey*" OR "regres*" OR "correlat*" OR "econometr*" OR "multivariate" OR "meta*" OR "statist*" OR "longitud*" OR "panel*" OR "quasi*")) AND (australia* OR austria* OR belgi* OR canad* OR	Note: This search returns 1 paper from 2017, but the link to the paper is itself no longer exists

Database or register	Search strings	Filters
	chile* OR colombia* OR "costa rica"* OR czech* OR denmark OR danish OR estonia* OR finland* OR finnish OR france OR french OR german* OR greece OR greek OR hungar* OR iceland* OR ireland OR irish OR israel* OR ital* OR japan* OR korea* OR latvia* OR lithuania* OR luxembourg OR mexic* OR netherland* OR dutch OR zealand OR norw* OR poland OR polish OR portug* OR slovak* OR sloven* OR spain OR spanish OR swed* OR switzerland OR swiss OR turk* OR "united kingdom" OR UK OR brit* OR "united states" OR USA OR engl* OR scot* OR wales OR welsh OR OECD OR Europe* OR america* OR asia*)	
Cedefop **Results**: 12 **Date of search**: 27th Nov 2024	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productive* OR efficien* OR output*) AND (organisation* OR organization* OR firm* OR team* OR sector* OR division* OR region* OR nation* OR countr*) site:www.cedefop.europa.eu	
Google Scholar (character limit) **Results**: First 200 saved **Date of search**: 27th Nov 2024	(skill* or capabilit* or competenc* or "human capital" or accreditation* or qualification*) and (productiv* or efficien* or output*) and (organisation* or organization* or firm* or team* or sector* or division* or region* or nation* or countr*)	Date: 2014-2024
SKOPE at the University of Oxford **Results**: 0 **Date of search**: 27th Nov 2024	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productiv* OR efficien* OR output*) AND (organisation* OR organization* OR firm* OR team* OR sector* OR division* OR region* OR nation* OR countr*) site:https://www.education.ox.ac.uk	Date: 2014-2024
The Productivity Institute **Results** 8 **Date of search**: 27th Nov 2024	(skill* OR capabilit* OR competenc* OR "human capital" OR accreditation* OR qualification*) AND (productiv* OR efficien* OR output*) site:https://www.productivity.ac.uk/	Date: 2014-2024

Appendix C: OECD Member Countries

Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Türkiye, United Kingdom, United States.

In addition, our search string also looks for commonly used country groups that are found in literature and are relevant to our project. These include:

i) OECD: OECD
ii) Europe (also capturing East/West/North/Central/South Europe): europe*
iii) EMEA: EMEA
iv) Asia (including East/ Pacific): Asia*
v) Americas (including North/South/Latin/Central): America*

Appendix D: Data Items

The following data items were recorded in the research extraction sheet (RES) either during the extraction or synthesis phases of the systematic review.

Data item	Type
Reference number	-
Title	Bibliographic information
Author	Bibliographic information
Year of Publication	Bibliographic information
Publication Type	Bibliographic information
URL	Bibliographic information
Volume	Bibliographic information
Journal/ Publisher name	Bibliographic information
DOI	Bibliographic information
Edition	Bibliographic information
ISBN/ISSN	Bibliographic information
Issue	Bibliographic information
Institution	Bibliographic information
Abstract	Bibliographic information
Country/region of focus	Bibliographic information
Unit of Analysis - Skill	Information on Context
Unit of Analysis - Productivity	Information on Context
Organisation Type	Information on Context
Type of Civil or Public Sector	Information on Context
Population/Demographic Characteristics	Information on Population
Sub-group variable	Information on Population
Subgroup analysis/interaction terms	Information on Population
Methodology	Information on Methodology
Methodology Type	Information on Methodology
Methods to Address Confounding Bias	Information on Methodology
Years of analysis	Information on Methodology
Skill construct identified in vivo	Information on Concept

Data item	Type
Skill measure	Information on Concept
Measurement of skill	Information on Concept
Outcome (productivity) measure	Information on Concept
Measurement of productivity	Information on Concept
Presence of secondary results	Outcomes
Details of secondary results (narrative, if applicable)	Outcomes
Sample Size	Outcomes
Outcome measure	Outcomes
Effect size for relationship between skill and productivity	Outcomes
SE for relationship between skill and productivity	Outcomes
P-value (<0.01, <0.05, <0.1, insignificant)	Outcomes
Standard deviation	Outcomes
Other comments on results	

The following items were listed in the protocol but excluded from the final list of data items:

Column Name	Reason for deletion
Conflict of Interest	Data not available in more than 2 included studies
Type of product (Good or service)	Data not available in more than 2 included studies
Seniority (Junior (Entry-level position, no team or project management), Mid-Level Management (Positions such as team leads or supervisors with moderate experience), Senior Management (Experienced professionals that oversee teams or significant projects), Executive Leadership (High-level executives such as directors, commissioners or C-suite executives), Unclear/Unreported, Mix of levels of seniority)	Data not available in more than 2 included studies
Gender (% female or others | Unclear/Unreported)	Data not available in more than 2 included studies

Column Name	Reason for deletion
Age (Average age | Unclear/Unreported)	Data not available in more than 2 included studies
Role	Data not available in more than 2 included studies
Profession	Data not available in more than 2 included studies
Methods to Address Missing Data	Not useful in practice - covered by RoB tool
Methods to Address Non-response Bias (individuals who do not respond differ systematically from those who do respond.)	Not useful in practice - covered by RoB tool
Methods for Address Sampling or Selection Bias	Not useful in practice - covered by RoB tool
Methods for Address Attrition Bias	Not useful in practice - covered by RoB tool
Sources of Funding	Data not available in included studies
Potential Sources of Conflict of Interest	No relevant reports in the studies that can identify potential sources of conflict (especially since source of funding is not typically listed)
Control or comparison description (if available)	No studies have comparators
Implementation strategies (for programme or intervention, if applicable)	No data as there are no interventions
Outcome (productivity) measure (from the paper)	Deleted as all papers looked at organisational productivity
Presence of secondary qualitative results	Replaced with any secondary results
Details of secondary qualitative results (narrative, if applicable)	Replaced with any secondary results
For Randomised studies: Effect Size (e.g., OR, RR, MD)	No randomised studies in inclusion list
95% CI (Lower - Upper)	No randomised studies in inclusion list
N (Intervention / Control)	No randomised studies in inclusion list

Column Name	Reason for deletion
Mean (Intervention / Control)	No randomised studies in inclusion list
SD (Intervention / Control)	No randomised studies in inclusion list
P-value	No randomised studies in inclusion list
Timing of outcome measurement after intervention (Multiple options possible): Immediate (<24 hours) | 1-<3 months | 3-<6 months | 6 months-< 1 year | 1 year + | Unclear/Unreported	No randomised studies in inclusion list
For quasi-experimental and other non-randomised studies:Effect size and SD for comparison group	No comparison groups
P-value	No comparison groups
If study uses matching, measures used for matching	No matching in included studies
If study uses controls, measures used as statistical controls (if multiple models exist, for primary specification used in narrative)	We focus on the primary model in the narrative, or, if not specified, the model with the highest number of controls

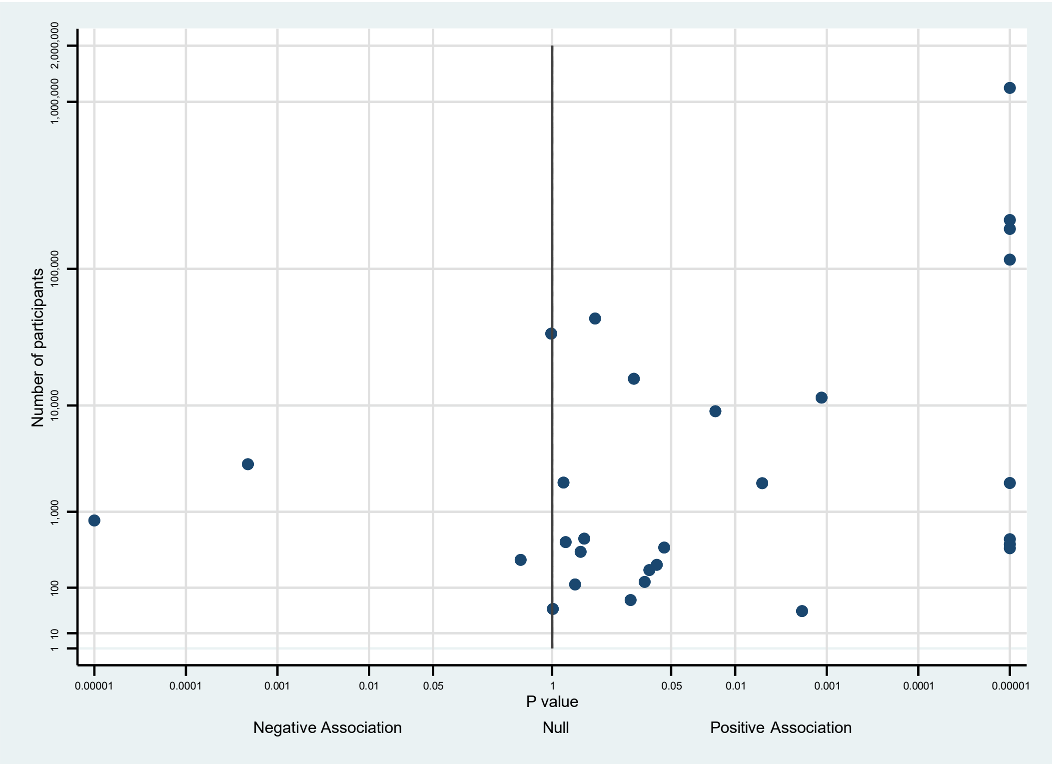
Appendix E: Albatross Plot

In the plot below, we present the albatross plot discussed in the report. An albatross plot is a variation of a forest plot that displays the p-values of individual studies alongside the overall size of the sample. It is designed to visually represent the heterogeneity among the studies that cannot be synthesised using a meta-analysis.

For the purpose of this project, we calculate the p-values using the estimates and standard errors extracted from the included papers. A large number of studies either do not give any indication of p-values or, more commonly, effectively only tell us the upper bound of the p-value (by reporting significance levels). We address this issue by calculating the p-value using the coefficient estimate and its standard error, based on the assumption of a normal sampling distribution for the t-statistic.

We have truncated the p-values that are smaller than 0.00001 for a more accessible visualisation[13]. The clustering on the right-hand edge of the graph represents results that are highly significant at the 99% level.

Figure 4. Albatross plot



[13] We exclude two papers that do not report the sample size of the selected result (Grundke et al. 2017; Escriba-Perez and Murgui-Garcia 2014). We also exclude results with a sample size of 1 (Olomola and Osinubi, 2018; Molinari and Torres 2017; Cubel et al. 2014) as these are typically TFP decompositions for individual countries.

Appendix F: Certainty Assessment Details

The following tables present the list of included papers along with the variables used for the certainty assessment in the main body of the report.

Table 5. Certainty assessment

Paper	MMAT: No of "Yes" results	Sample size	Methodology	Directness: RQ1	Directness: RQ2
Sasso and Ritzen 2019	5	187	Cross-section regression with controls	Yes	No
Skorupinska and Torrent-Sellens 2017	3	41	Cross-section regression with controls	No	No
Bender et al. 2018	5	378	Cross-section regression with controls	Yes	Yes
Fanti et al. 2021	5	16674	Cross-section regression with controls	No	No
Nguyen et al. 2024	5	180560	Cross-section regression with controls	No	Yes
Torrent Sellens et al. 2014	5	124	Cross-section regression with controls	Yes	No
Cammeraat et al. 2021	5	222	Cross-section regression with controls	Yes	No
Pini et al. 2023	5	2000	Cross-section regression with controls	No	Yes
Braunerhjelm and Lappi 2023	5	1191740	Others	No	Yes
Cammeraat et al. 2024	5	260	Quasi-experimental	Yes	No
Egert 2022	5	524	Panel regression	Yes	Yes

Paper	MMAT: No of "Yes" results	Sample size	Methodology	Directness: RQ1	Directness: RQ2
Calvino and Fontanelli 2023	5	11597	Cross-section regression with controls	No	No
Yigiteli and Sanli 2024	5	416	Others	No	No
Lombardi et al. 2022	5	3044	Cross-section regression with controls	No	Yes
Querio 2021	5	128102	Cross-section regression with controls	No	Yes
Koch and Smolka 2019	5	16389	Cross-section regression with controls	Yes	Yes
Costa et al. 2019	5	38552	Cross-section regression with controls	No	Yes
Máté 2014	5	371	Panel regression	Yes	No
Máté 2015	5	61	Panel regression	Yes	No
Rico and Cabrer-Borras 2020	5	35779	Panel regression	No	No
Olomola and Osinubi 2018	5	1	Panel regression	No	Yes
McGowan and Andrews 2015	5	205	Cross-section regression with controls	No	Yes
Ohlsbom 2021	5	333	Cross-section regression with controls	Yes	Yes
Suarez-Varela et al. 2016	5	37	Others	No	No
Veltri et al. 2016	4	475	Others	No	No

Paper	MMAT: No of "Yes" results	Sample size	Methodology	Directness: RQ1	Directness: RQ2
Cardoso and Ravishankar 2015	5	800	Others	No	No
Grundke et al. 2017	5	not reported	Cross-section regression with controls	No	No
Molinari and Torres 2017	5	1	Others	No	No
Cubel et al. 2014	5	1	Others	No	No
Wixe 2015	5	205087	Panel regression	No	No
Escriba-Perez and Murgui-Garcia 2014	5	2040	Panel regression	No	No
Madzik and Sieber 2024	5	443	Correlation	No	No
Ali et al. 2019	5	not reported	Panel regression	Yes	No
Morris 2015	5	1373	Cross-section regression with controls	Yes	Yes

Appendix G: Bibliographic Information for Included Papers

Title	Paper reference	Publication Type	Volume	Journal/ Publisher name
Sectoral cognitive skills, R&D, and productivity: A Cross-country cross-sector analysis	Sasso and Ritzen 2019	Journal article	27	Education Economics
ICT, Innovation and Productivity: Evidence from Eastern European Manufacturing Firms	Skorupinska and Torrent-Sellens 2017	Journal article	8	Journal of the Knowledge Economy
Management Practices, Workforce Selection and Productivity	Bender et al. 2018	Journal article	36	Journal of Labor Economics
Fixed-term contracts and firm productivity: Do workers' skills and firm conversion rates from fixed-term to permanent contracts matter?	Nguyen et al. 2024	Journal article	45	International Journal of Manpower
ICT uses, innovation and SMEs productivity: Modelling direct and indirect effects in small local firms	Torrent Sellens et al. 2014	Report	-	IN3 Working Paper Series
The role of innovation and human capital for the productivity of industries	Cammeraat et al. 2021	Policy paper	-	OECD Science, Technology And Industry Policy Papers
The age of intangibles: empirical evidences of the effects of intangible assets on firm's profitability, productivity and on the post COVID-19 recovery	Pini et al. 2023	Journal article	-	Territori Economie Societa Istituzioni paper
Employees' entrepreneurial human capital and firm performance	Braunerhjelm and Lappi 2023	Journal article	52	Research Policy

Title	Paper reference	Publication Type	Volume	Journal/ Publisher name
Organizational Capital, Skills and Productivity	Cammeraat et al. 2024	Journal article	70	Review of Income and Wealth
A New macroeconomic measure of human capital exploiting PISA and PIAAC: Linking education policies to productivity	Egert 2022	Journal article	-	OECD Economics Department Working Papers
A Potrait of AI adopters across countries	Calvino and Fontanelli 2023	Journal article	-	OECD Science, Technology and Industry Working Papers 2023/02
Decomposition of total factor productivity growth in Turkiye regions: a panel stochastic frontier approach	Yigiteli and Sanli 2024	Journal article	14	Eurasian Economic Review
Drivers of territorial servitization: An Empirical analysis of manufacturing productivity in local value chains	Lombardi et al. 2022	Journal article	253	International Journal of Production Economics
Entrepreneurial Human Capital and Firm Dynamics	Querio 2021	Journal article	89	The Review of Economic Studies
Foreign ownership and skill-biased technological change	Koch and Smolka 2019	Journal article	118	Journal of International Economics
From organisational capabilities to corporate performances: at the roots of productivity slowdown	Costa et al. 2019	Journal article	32	Industrial and Corporate Change
Human Capital, Unions and Productivity in a Labour-skilled Sectoral Approach	Máté 2014	Journal article	36	Society and Economy
Impact of human capital on productivity growth in different labour-skilled branches	Máté 2015	Journal article	65	Acta oeconomica

Title	Paper reference	Publication Type	Volume	Journal/ Publisher name
Intangible capital and business productivity	Rico and Cabrer-Borras 2020	Journal article	65	Economic Research-Ekonomska Istraživanja
Determinants of Total factor Productivity in Mexico, Indonesia, Nigeria and Turkey	Olomola and Osinubi 2018	Journal article	4	Emerging Economy Studies
Management practices drive productivity - but not without human capital	Ohlsbom 2021	Working paper	4	ETLA Economic Research Working Papers
Ownership and Performance in Water Services Revisited: Does Private Management Really Outperform Public?	Suarez-Varela et al. 2016	Journal article	31	Water Resources Management
Measuring Managerial Ability Using a Two-stage SFA-DEA Approach	Veltri et al. 2016	Research article	23	Knowledge and Process Management
Productivity growth and convergence: a stochastic frontier analysis	Cardoso and Ravishankar 2015	Journal article	42	Journal of Economic Studies
Skills and global value chains: A characterisation	Grundke et al. 2017	Working paper	42	OECD Science, Technology and Industry Working Papers 2017/05
Technological sources of economic growth in Europe and the U.S.	Molinari and Torres 2017	Journal article	24	Technological and Economic Development of Economy
The Effect Of Foreign And Domesctic Patents On Total Factor Productivity During The Second Half Of The 20th Century	Cubel et al. 2014	Working paper	24	Working Papers 1404, Department of Applied Economics II, Universidad de Valencia

Title	Paper reference	Publication Type	Volume	Journal/ Publisher name
The Impact of Spatial Externalities: Skills, Education and Plant Productivity	Wixe 2015	Journal article	https://www.tandfonline.com/action/showCitFormats?doi=10.1080/00343404.2014.891729	Regional Studies
Time varying agglomeration effects on total factor productivity in Spanish regions (1995-2008)	Escriba-Perez and Murgui-Garcia 2014	Journal article	14	Regional and Sectoral Economic Studies
The Strategic Path to Success: Key Aspects of Business Digital Transformation in the Post-Pandemic Era	Madzik and Sieber 2024	Journal article	14	IEEE Access
Hospital productivity: The role of efficiency drivers	Ali et al. 2019	Journal article	1	International Journal of Health Planning and Management

Appendix H: Population and Context for Included Papers

Paper reference	Region	Unit of Analysis
Sasso and Ritzen 2019	OECD (multi-country)	Other
Sasso and Ritzen 2019	OECD (multi-country)	Other
Skorupinska and Torrent-Sellens 2017	OECD (multi-country)	Firm
Bender et al. 2018	East Europe	Firm
Bender et al. 2018	East Europe	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Nguyen et al. 2024	Europe (excluding East)	Firm
Torrent Sellens et al. 2014	Europe (excluding East)	Firm
Torrent Sellens et al. 2014	Europe (excluding East)	Firm
Torrent Sellens et al. 2014	Europe (excluding East)	Firm
Cammeraat et al. 2021	OECD (multi-country)	Other
Cammeraat et al. 2021	OECD (multi-country)	Other
Cammeraat et al. 2021	OECD (multi-country)	Other
Cammeraat et al. 2021	OECD (multi-country)	Other
Pini et al. 2023	Europe (excluding East)	Firm
Pini et al. 2023	Europe (excluding East)	Firm
Pini et al. 2023	Europe (excluding East)	Firm
Braunerhjelm and Lappi 2023	Europe (excluding East)	Firm
Braunerhjelm and Lappi 2023	Europe (excluding East)	Firm
Braunerhjelm and Lappi 2023	Europe (excluding East)	Firm

Paper reference	Region	Unit of Analysis
Cammeraat et al. 2024	OECD (multi-country)	Other
Cammeraat et al. 2024	OECD (multi-country)	Other
Cammeraat et al. 2024	OECD (multi-country)	Other
Cammeraat et al. 2024	OECD (multi-country)	Other
Cammeraat et al. 2024	OECD (multi-country)	Other
Cammeraat et al. 2024	OECD (multi-country)	Other
Egert 2022	OECD (multi-country)	Country
Egert 2022	OECD (multi-country)	Country
Egert 2022	OECD (multi-country)	Country
Egert 2022	OECD (multi-country)	Country
Calvino and Fontanelli 2023	Europe (excluding East)	Firm
Calvino and Fontanelli 2023	Europe (excluding East)	Firm
Calvino and Fontanelli 2023	Europe (excluding East)	Firm
Calvino and Fontanelli 2023	Others in OECD	Firm
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Yigiteli and Sanli 2024	Others in OECD	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region

Paper reference	Region	Unit of Analysis
Lombardi et al. 2022	Europe (excluding East)	Region
Lombardi et al. 2022	Europe (excluding East)	Region
Querio 2021	Europe (excluding East)	Other
Querio 2021	Europe (excluding East)	Other
Querio 2021	Europe (excluding East)	Other
Querio 2021	Europe (excluding East)	Other
Koch and Smolka 2019	Europe (excluding East)	Firm
Koch and Smolka 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Costa et al. 2019	Europe (excluding East)	Firm
Máté 2014	OECD (multi-country)	Sector
Máté 2014	OECD (multi-country)	Sector
Máté 2014	OECD (multi-country)	Sector
Máté 2014	OECD (multi-country)	Sector
Máté 2015	OECD (multi-country)	Sector

Paper reference	Region	Unit of Analysis
Máté 2015	OECD (multi-country)	Sector
Máté 2015	OECD (multi-country)	Sector
Máté 2015	OECD (multi-country)	Sector
Rico and Cabrer-Borras 2020	Europe (excluding East)	Other
Rico and Cabrer-Borras 2020	Europe (excluding East)	Other
Olomola and Osinubi 2018	Others in OECD	Country
Olomola and Osinubi 2018	Others in OECD	Country
Olomola and Osinubi 2018	Others in OECD	Country
Olomola and Osinubi 2018	Others in OECD	Country
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Ohlsbom 2021	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Suarez-Varela et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm

Paper reference	Region	Unit of Analysis
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al., 2016	Europe (excluding East)	Firm

Paper reference	Region	Unit of Analysis
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Veltri et al. 2016	Europe (excluding East)	Firm
Cardoso and Ravishankar 2015	Europe (excluding East)	Region
Cardoso and Ravishankar 2015	Europe (excluding East)	Region
Cardoso and Ravishankar 2015	Europe (excluding East)	Region
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Grundke et al. 2017	OECD (multi-country)	Other
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country

Paper reference	Region	Unit of Analysis
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	UK	Country
Molinari and Torres 2017	USA	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	Europe (excluding East)	Country
Molinari and Torres 2017	UK	Country
Molinari and Torres 2017	USA	Country
Cubel et al. 2014	Europe (excluding East)	Country
Cubel et al. 2014	UK	Country
Cubel et al. 2014	Europe (excluding East)	Country
Cubel et al. 2014	Europe (excluding East)	Country
Cubel et al. 2014	USA	Country
Wixe 2015	Europe (excluding East)	Firm
Wixe 2015	Europe (excluding East)	Firm
Wixe 2015	Europe (excluding East)	Firm
Wixe 2015	Europe (excluding East)	Firm
Wixe 2015	Europe (excluding East)	Firm
Wixe 2015	Europe (excluding East)	Firm
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region

Paper reference	Region	Unit of Analysis
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region
Escriba-Perez and Murgui-Garcia 2014	Europe (excluding East)	Region
Madzik and Sieber 2024	East Europe	Other
Madzik and Sieber 2024	East Europe	Other
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm
Ali et al. 2019	UK	Firm

Appendix I: Measures and Results from Included Papers

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Sasso and Ritzen 2019	Measure of specific skill	Labour productivity	Human capital	187	1.059	0.62	Yes
Sasso and Ritzen 2019	Education	Labour productivity	Human capital	187	0.0763	0.38	No
Skorupinska and Torrent-Sellens 2017	Education	Labour productivity	-	41	0.019	Not mentioned	Yes
Bender et al. 2018	Measure of specific skill	TFP (residual)	-	378	0.113	0.06	Yes
Bender et al. 2018	Measure of specific skill	TFP (residual)	-	378	0.052	0.03	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	180,560	0.387	0.01	Yes
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	77,594	0.455	0.02	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	102,966	0.336	0.02	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	180,560	0.235	0.01	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	77,594	0.266	0.02	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	102,966	0.226	0.02	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	180,560	0.126	0.01	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	77,594	0.133	0.01	No
Nguyen et al. 2024	Earnings	Labour productivity	Firm conversion rate	102,966	0.123	0.01	No
Torrent Sellens et al. 2014	Education	Labour productivity	Firm innovation	124	0.382	Not reported	Yes
Torrent Sellens et al. 2014	Education	Labour productivity	Firm innovation	77	0.203	Not reported	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Torrent Sellens et al. 2014	Education	Labour productivity	Firm innovation	55	0.503	Not reported	No
Cammeraat et al. 2021	Measure of specific skill	Labour productivity	Skill	222	0.009	0.01	Yes
Cammeraat et al. 2021	Measure of specific skill	Labour productivity	Skill	222	0	0.01	No
Cammeraat et al. 2021	Measure of specific skill	Labour productivity	Skill	222	0.015	0.02	No
Cammeraat et al. 2021	Proportion of workers with skills	Labour productivity	Skill	222	0.031	0.02	No
Pini et al. 2023	Skills investment	Labour productivity	Effect type (direct)	2,000	0.088	0.03	No
Pini et al. 2023	Skills investment	Labour productivity	Effect type (indirect)	2,000	0.035	0.01	No
Pini et al. 2023	Skills investment	Labour productivity	Effect type (total)	2,000	0.123	0.03	Yes

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Braunerhjelm and Lappi 2023	Experience	Labour productivity	Firm size	1,191,740	0.039	0.01	Yes
Braunerhjelm and Lappi 2023	Experience	Labour productivity	Firm size	1,162,093	0.042	0.01	No
Braunerhjelm and Lappi 2023	Experience	Labour productivity	Firm size	29,647	0.083	0.13	No
Cammeraat et al. 2024	Measure of specific skill	Labour productivity	Skill	260	0.018	0.01	No
Cammeraat et al. 2024	Measure of specific skill	Labour productivity	Skill	260	-0.003	0.00	Yes
Cammeraat et al. 2024	Measure of specific skill	Labour productivity	Skill	260	0.014	0.01	No
Cammeraat et al. 2024	Measure of specific skill	Labour productivity	Skill	260	-0.242	0.11	No
Cammeraat et al. 2024	Measure of specific skill	Labour productivity	Skill	260	0.302	0.13	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Cammeraat et al. 2024	Proportion of workers with skills	Labour productivity	Skill	260	-0.843	0.60	No
Egert 2022	Test scores	Labour productivity	Age & short vs long run	524	2.359	0.60	No
Egert 2022	Test scores	Labour productivity	Age & short vs long run	524	1.426	0.60	No
Egert 2022	Test scores	Labour productivity	Age & short vs long run	113	2.838	0.60	No
Egert 2022	Test scores	Labour productivity	Age & short vs long run	113	0.349	0.60	Yes
Calvino and Fontanelli 2023	Skills investment	Labour productivity	Countries	11,597	0.0924	0.03	Yes
Calvino and Fontanelli 2023	Skills investment	Labour productivity	Countries	8,968	0.0662	0.03	Yes
Calvino and Fontanelli 2023	Proportion of workers with skills	Labour productivity	Countries	1,991	0.169	0.06	Yes

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Calvino and Fontanelli 2023	Skills investment	Labour productivity	Countries	2,019	0.0546	0.17	Yes
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.191	0.03	No
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.901	0.03	Yes
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.0632	0.02	No
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.227	0.04	No
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.146	0.03	No
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.378	0.03	No
Yigiteli and Sanli 2024	Education	Labour productivity	-	416	0.93	0.03	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	3,044	-0.0251	0.03	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	3,044	-0.145	0.04	Yes
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	944	-0.0493	0.03	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	944	-0.0502	0.04	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	424	0.1603	0.10	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	424	0.0421	0.12	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	3,044	0.0303	0.05	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	3,044	0.2216	0.06	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	944	0.0812	0.04	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	944	0.096	0.06	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	424	-0.243	0.14	No
Lombardi et al. 2022	Education	Labour productivity	Nature of firm	424	-0.0559	0.15	No
Querio 2021	Education	Labour productivity	Age of firm	128,102	-0.0057	0.00	No
Querio 2021	Education	Labour productivity	Age of firm	128,102	0.0252	0.01	No
Querio 2021	Education	Labour productivity	age of firm	114,920	-0.0094	0.00	No
Querio 2021	Education	Labour productivity	age of firm	114,920	0.03	0.01	Yes
Koch and Smolka 2019	Education	log(TFP)	age of firm	16,389	0.055	0.04	No
Koch and Smolka 2019	Skills investment	log(TFP)	age of firm	16,389	0.037	0.02	Yes
Costa et al. 2019	Education	Labour productivity	Firm size & year	38,552	0.848	0.04	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Costa et al. 2019	Education	Labour productivity	Firm size & year	12,178	1.421	0.06	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	2,278	1.843	0.14	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	33,564	0.759	0.07	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	9,259	1.324	0.08	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	1,156	1.485	0.21	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	38,552	0.068	0.01	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	12,178	0.103	0.01	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	2,278	0.132	0.03	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	33,564	0.044	0.01	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Costa et al. 2019	Experience	Labour productivity	Firm size & year	9,259	0.088	0.01	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	1,156	0.176	0.04	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	55,163	0.932	0.05	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	55,163	0.087	0.01	No
Costa et al. 2019	Education	Labour productivity	Firm size & year	45,885	0.793	0.07	No
Costa et al. 2019	Experience	Labour productivity	Firm size & year	45,885	0.065	0.07	Yes
Costa et al. 2019	Education	Labour productivity	New outcome variable	45,627	-0.138	0.05	No
Costa et al. 2019	Experience	Labour productivity	New outcome variable	45,627	-0.034	0.01	No
Máté 2014	Education	Labour productivity	Skill level	371	0.539	0.11	Yes

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Máté 2014	Education	Labour productivity	Skill level	371	0.562	0.12	No
Máté 2014	Education	Labour productivity	Skill level	371	0.305	0.08	No
Máté 2014	Education	Labour productivity	Skill level	371	-0.179	0.09	No
Máté 2015	Education	Labour productivity	Skill level	61	0.266	0.18	No
Máté 2015	Education	Labour productivity	Skill level	61	-0.212	-0.19	No
Máté 2015	Education	Labour productivity	Skill level	61	-0.326	-0.15	No
Máté 2015	Education	Labour productivity	Skill level	61	-0.359	0.12	No
Rico and Cabrer-Borras 2020	Education	TFP (residual)	-	35,779	0.003	0.12	Yes
Rico and Cabrer-Borras 2020	Education	TFP (residual)	-	35,779	-0.005	0.12	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Olomola and Osinubi 2018	Education	TFP (residual)	Country	1	-0.01	0.00	Yes
Olomola and Osinubi 2018	Education	TFP (residual)	Country	1	0.01	0.00	Yes
Olomola and Osinubi 2018	Education	TFP (residual)	Country	1	-0.01	0.00	No
Olomola and Osinubi 2018	Education	TFP (residual)	Country	1	-0.002	0.00	No
Ohlsbom 2021	Assessed	Labour productivity	human capital	333	0.877	0.22	No
Ohlsbom 2021	Education	Labour productivity	human capital	333	0.061	0.09	Yes
Ohlsbom 2021	Education	Labour productivity	human capital	333	0.69	0.24	No
Ohlsbom 2021	Education	Labour productivity	human capital	556	0.071	0.21	No
Ohlsbom 2021	Education	Labour productivity	human capital	422	0.111	0.11	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Ohlsbom 2021	Education	Labour productivity	human capital	422	-0.06	0.23	No
Ohlsbom 2021	Assessed	Labour productivity	human capital	431	0.843	0.20	No
Ohlsbom 2021	Education	Labour productivity	human capital	431	0.583	0.22	No
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	37	0.669	0.22	Yes
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	37	0.598	0.22	No
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	37	0.539	0.22	No
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	33	0.682	0.22	No
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	33	0.613	0.22	No
Suarez-Varela et al. 2016	Efficiency	Efficiency	human capital	33	0.62	0.22	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	475	0.9064	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	495	0.9096	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	525	0.9174	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	500	0.9093	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	472	0.8994	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	481	0.8997	0.04	Yes
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	475	0.9133	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	495	0.9161	0.05	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	525	0.923	0.05	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	500	0.9157	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	472	0.9062	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	481	0.9082	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	112	0.9249	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	118	0.9374	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	131	0.9516	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	120	0.9313	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	111	0.9197	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	120	0.9099	0.04	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	112	0.9415	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	118	0.953	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	131	0.963	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	120	0.948	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	111	0.9362	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	120	0.9321	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	26	0.9287	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	27	0.9492	0.02	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	33	0.9613	0.03	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	29	0.9453	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	25	0.9348	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	24	0.9228	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	26	0.9415	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	27	0.9627	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	33	0.9727	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	29	0.9518	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	25	0.9488	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	24	0.9351	0.04	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	337	0.8985	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	350	0.8971	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	361	0.9011	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	351	0.8987	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	336	0.89	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	337	0.8944	0.03	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	337	0.9017	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	350	0.9	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	361	0.9039	0.04	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	351	0.9017	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	336	0.8931	0.04	No
Veltri et al. 2016	Efficiency	Efficiency	Year, Bank type, Model	337	0.8977	0.04	No
Cardoso and Ravishankar 2015	Education	Labour productivity	Human capital	800	-0.14	0.02	No
Cardoso and Ravishankar 2015	Education	Labour productivity	human capital education level	800	-0.273	0.04	No
Cardoso and Ravishankar 2015	Education	Labour productivity	human capital education level	800	-0.102	0.02	Yes
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.029	0.01	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.022	0.01	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.032	0.04	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.011	0.01	Yes
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.01	0.01	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.004	0.02	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.008	-0.01	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	-0.004	0.00	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.039	-0.02	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.0335	-0.02	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.028	0.03	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.011	0.00	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.007	0.01	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.007	0.02	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	0.011	0.00	No
Grundke et al. 2017	Measure of specific skill	Labour productivity	Type of skill	not reported	-0.01	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.46	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.47	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.88	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.36	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.3	0.01	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.29	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.89	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.31	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.43	0.01	Yes
Molinari and Torres 2017	Education	Labour productivity	Country	1	0.32	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	20.2	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	25	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	33.6	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	16.8	0.01	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Molinari and Torres 2017	Education	Labour productivity	Country	1	18.9	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	30.2	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	43.4	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	16.5	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	24	0.01	No
Molinari and Torres 2017	Education	Labour productivity	Country	1	20	0.01	No
Cubel et al. 2014	Education	TFP (residual)	Country	1	9.39	0.01	Yes
Cubel et al. 2014	Education	TFP (residual)	Country	1	10.58	0.01	Yes
Cubel et al. 2014	Education	TFP (residual)	Country	1	2.73	0.01	Yes
Cubel et al. 2014	Education	TFP (residual)	Country	1	24.48	0.01	Yes
Cubel et al. 2014	Education	TFP (residual)	Country	1	4.06	0.01	Yes

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0026	0.00	No
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0024	0.00	Yes
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0017	0.00	No
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0041	0.00	No
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0042	0.00	No
Wixe 2015	Named skill share	Labour productivity	skills	205087	0.0029	0.00	No
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	2040	0.214	0.12	No
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	2040	0.162	0.09	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	2,040	-0.287	0.12	No
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	2,040	-0.274	0.13	No
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	unclear/ not reported	-0.339	0.56	Yes
Escriba-Perez and Murgui-Garcia 2014	Education	TFP (residual)	length of time and outcome measure	unclear/ not reported	-0.312	0.47	No
Madzik and Sieber 2024	Measure of specific skill	Efficiency	measures of firm productivity	443	-0.015	0.76	No
Madzik and Sieber 2024	Measure of specific skill	Efficiency	measures of firm productivity	443	0.28	unclear	Yes

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	489	0.331	0.43	Yes
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	489	0.635	0.23	No
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	489	0.249	0.18	No
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	432	0.181	0.45	No
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	432	0.478	0.25	No
Ali et al. 2019	Named skill share	TFP (residual)	hospital type	432	-0.05	0.16	No
Ali et al. 2019	Named skill share	Labour productivity	hospital type	489	1.782	0.69	No
Ali et al. 2019	Named skill share	Labour productivity	hospital type	489	-0.302	0.29	No
Ali et al. 2019	Named skill share	Labour productivity	hospital type	489	-0.225	0.27	No

Paper reference	Standardised Skills measure	Standardised productivity measure	Sub-group variable	Sample Size	Effect size for relationship between skill and productivity	SE for relationship between skill and productivity	Primary Result
Ali et al. 2019	Named skill share	Labour productivity	hospital type	432	2.094	0.72	No
Ali et al. 2019	Named skill share	Labour productivity	hospital type	432	-0.219	0.30	No
Ali et al. 2019	Named skill share	Labour productivity	hospital type	432	-0.401	0.27	No

Appendix J: Systems Thinking Frameworks

As part of the development of the protocol for the systematic review, we drew on approaches based on complexity systems thinking to ensure the search methods took a more holistic view of identifying and interpreting relevant literature. We sought frameworks that could characterise the relevant features of the ecosystems within which workforce skills and productivity are (potentially) linked.

Two existing frameworks were drawn on. The first is the “**CATWOE**” framework (Chowdhury 2021; Óskarsdóttir and Oddsson 2017), which identifies the following in the context of a change:

- **Customer:** Who are the beneficiaries?
- **Actor:** The entities that carry out the main activities within the system or process.
- **Transformation:** The process by which inputs are converted into outputs within the system.
- **Worldview:** The underlying assumptions, beliefs, and perspectives that shape how the system is perceived and judged.
- **Owner:** The people or entities with ultimate control or authority over the system or process.
- **Environmental constraints:** The external factors or limitations that affect the system but cannot be controlled by it.

The CATWOE framework was chosen because it can capture a number of key dimensions of the workplace, including dimensions that have very direct conceptual links to productivity. This includes who the workers’ output is for (the “customers”), who ultimately controls or owns the economic unit in question (the “owner”), and importantly the nature of production (“transformation”)—essentially, the process by which inputs create outputs, the efficacy of which is directly related to productivity.

The second framework that we drew from was the “Tripod of Work” framework for management practices (Stamp 2009). This was chosen because it captures features of the system that, based on theory or past evidence, one might expect to influence the skills-productivity relationship, and which are potentially malleable.

- **“Tasking”** includes delegation and the process of breaking work down into suitable tasks. This is related to the issue of effective skills utilisation, which an emerging body of evidence is investigating (e.g., Warhurst and Luchinskava 2018).
- **“Tending,”** which encompasses the provision of the necessary support to utilise skills, including mentoring and coaching.
- **“Trusting,”** or providing an organisational culture of trust, independence, and psychological safety within which to apply one’s skills[14].

[14] For example, research on ‘Fair Work’ has examined how creating a fairer workspace for employees can have an impact on success, wellbeing, and prosperity (e.g., Findlay et al. 2024).

Our original intention was to use these frameworks to carry out a framework-based synthesis to guide and structure a review (Carroll, Booth, and Cooper 2011; Dixon-Woods 2011; Weightman et al. 2023). The intention was for their purpose to be twofold: i) to structure the synthesis of the literature around groupings of evidence based on the dimensions of these frameworks, and ii) to identify evidence gaps, and hence priorities for future research. In practice, we did not utilise these conceptual frameworks to the degree that we envisaged. Ultimately, they were used as part of our discussion of evidence gaps, but not for structuring the synthesis of evidence. This is because the included literature we reviewed did not turn out to provide the richness and granularity of evidence that would have made these conceptual frameworks a productive way of structuring the synthesis. Instead, we structured the synthesis inductively based on what the literature did contain.

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