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The emerging, non-routine European skills of the future

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Abstract

Purpose – This paper investigates the future of emerging skills and their impact on occupations in the European Union by setting up a powerful paradigm of leveraging the European Skills, Competences, Qualifications and Occupations (ESCO) Delta files to predict future skills in a repeatable fashion, allowing policymakers and educational institutes to easily gain insights into emerging skill needs. This study explores the implications of automation on skill development, addressing key questions regarding the emergence of non-automatable skills across all industries and skills contained in the ESCO dataset.

Design/methodology/approach – The research design is exploratory, quantitative and cross-sectional. This study employed a big data analysis of the ESCO Delta datasets combined with the ALM-hypothesis framework to analyse the emergence of non-automatable (herein called non-routinisable) skills and what this means for future occupations. The proposed methodology provides a replicable framework for analysing future ESCO Delta file releases with regard to emerging, non-routinsable skills.

Findings – Our empirical findings reveal that (1) there is a Self-Automating Effect, i.e. non-routinisable skills are growing more in non-technical industries and technical industries may be automating themselves out of jobs. (2) The Matthew Effect in Skills, i.e. high-skill jobs are requiring more skills (compared to low-skill jobs as measured by educational requirements) and so becoming more specialised, however, counterintuitively, AI may be reducing this gap. (3) The Red Queen Effect: in spite of the effect of AI in (2), we find that in jobs requiring higher educational degrees, the new skill requirements are increasing most (with a few notable exceptions), requiring employees to run just to stay in the same place.

Originality/value – This study contributes to the existing literature in three ways: (1) it shows a practical and easy-to-replicate approach to leverage the high quality, well curated ESCO data set to carry out predictions of future skills (routinisable or not); (2) it answers questions around skill inequalities potentially arising due to technology advancements; (3) it helps governments and educational institutes understand which skills are emerging, "future-proof" skills that future graduates and current employees will likely need in order to remain competitive in the labour markets of the future.

Keywords European skills, Competences, Qualifications and occupations (ESCO), Future occupations, Future skills, Skill gaps

Paper type Research paper

Introduction

The rapid advancement of Artificial Intelligence (AI), particularly the emergence of Large Language Models (LLMs) and generative AI, has fundamentally altered the landscape of work. The automation of cognitive tasks, previously thought to be the exclusive domain of human expertise, is reshaping the composition of skills required across a wide spectrum of occupations. Traditional economic theories on job displacement, such as the Autor–Levy–Murnane (ALM) hypothesis (Autor *et al.*, 2003), have long distinguished between routine and non-routine tasks, predicting that routinisable work – whether cognitive or manual – is particularly susceptible to technological automation by AI. More recent scholarship (Susskind, 2019) has expanded on this framework, arguing that even non-routine

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analytical and interpersonal tasks are increasingly vulnerable as AI systems advance in sophistication, calling tasks that might become susceptible to automation by machines or computers routinisable.

In light of these technological disruptions, there is a clear need to examine shifts in the European labour market, particularly the emergence of new skill requirements. The European Skills, Competences, Qualifications and Occupations (ESCO) database provides a uniquely valuable resource for tracking changes in the skills required across occupations. By systematically analysing the new skills added to ESCO in each major delta update of the database, we can gain critical insights into the evolving demands of the job market. However, merely identifying new skills is insufficient – many of these additions may already be on the path to obsolescence if they remain what is known as routinisable. To address this challenge, our study applies the ALM hypothesis and subsequent refinements by Susskind to filter out skills that are likely to be automated in the near future (we use subjective expert judgement to predict what, in the next five years, could be automated and include the data on the choices with the paper). What remains is a refined set of genuinely emergent, non-routinisable skills that provide a forward-looking perspective on the competencies that will define the future of work.

As well as analysing individual skills, it is equally important to examine how these new competencies are distributed across occupations. A key research gap in labour market studies is the concentration of skill emergence – that is, identifying which occupational categories are experiencing the most significant influx of new skill requirements (Beblavỳ *et al.*, 2016). Are these emerging skills concentrated in high-skill, high-autonomy professions, or are they diffusing across mid- and low-skill occupations as well? Are certain occupations undergoing more profound skill transformations than others? Answering these questions will provide policymakers, educators, and workforce planners with essential guidance on where reskilling efforts should be targeted.

Despite the growing literature on automation and AI-driven labour market shifts (Shellshear and Oh, 2024), there remains a lack of empirical work linking real-world skill updates from easily usable and accessible data sources – as captured in high-quality databases like ESCO – to theoretical models of automation vulnerability. This study addresses this critical research gap by integrating dynamic skill evolution data with established frameworks of task (and skill) routinisation. In doing so, we move beyond broad discussions of automation risk to offer concrete, evidence-based insights into the skills that will define the next generation of European workers.

This research is of urgent relevance. The transformative effects of generative AI are already evident across industries, with sectors such as customer service, software development, legal analysis and office administration experiencing rapid integration of AI tools (Spring *et al.*, 2022). Yet, policymakers remain uncertain about which skills will remain robust in the face of automation. By distinguishing between truly emergent skills and those that are transient placeholders before obsolescence, we provide insights into changing skill demands in the near future.

In the sections that follow, we first present a review of the literature, then a systematic methodology for tracking skill evolution using ESCO Delta files across all skills contained in these datasets, provide a framework for identifying routinisable versus non-routinisable skills, and an empirical investigation into occupational patterns of skill emergence. We discuss these findings, and then finally, we conclude. Our findings offer a forward-looking view of the competencies that will shape the future European workforce and provide actionable insights for education and labour policy in the age of AI-driven disruption.

Literature review and research questions

Studies on ESCO and labour market data

Much has been written about the future of skills, automation and labour markets and we summarise the main research relevant for this paper here beginning with a review of the dataset that forms the core of our analysis, the ESCO (“ESCO Website,” 2025) dataset.

According to its website, ESCO is a European Commission project, run by the Directorate General for Employment, Social Affairs and Inclusion. Its first full version (ESCO v1) was published on the 28th of July 2017. Built on the Simple Knowledge Organization System, ESCO aims to enhance communication between employers and job seekers. De Smedt *et al.* (2015) describe the design and development of the ESCO dataset, a multilingual classification of ESCO, as a building block for a semantic labour market ecosystem.

The ESCO dataset has been used in a variety of studies and can help as a tool for improving labour market efficiency and addressing skill mismatches in the EU. Building on ESCO's purpose as a semantic labour market tool, le Vrang *et al.* (2014) used ESCO data to tackle the problem of semantic interoperability to help address the mismatch between workers' skills and companies' needs in the EU labour market. Thematically, this paper is closely related to the work presented here.

The ESCO dataset has also been used for understanding occupations and skills on a number of occasions. For example Chiarello *et al.* (2021) examine the ESCO skills classification via text mining to see if it can help align the European ESCO skills classification with emerging Industry 4.0 technological trends to provide more up-to-date labour market intelligence. Further on this theme, Caratozzolo *et al.* (2023) proposes a dynamic knowledge, skills and abilities matrix-based taxonomy for the Industry 4.0 workforce using the ESCO dataset. Although these studies show good uses of the ESCO dataset for understanding skills and occupations, they are only tangentially related to the topic at hand.

Additionally, machine learning and big data techniques have been applied to the ESCO dataset to automate resume/skill classification and improve productivity in skill-based labour market mechanics and dynamics, combining massive resume datasets with official statistical surveys (Mrsic *et al.*, 2020). Further on this theme, Mason *et al.* (2023) demonstrate how skills taxonomies like ESCO can be used with machine learning to integrate online data and reveal skills gaps to inform career and training decisions. This work is of relevance to the results presented here in its complementary nature of showing how to extend the ESCO results here to a more global scale.

Although the above papers (and similar ones not cited here) are relevant to our analysis and use the ESCO dataset, they do not address the research questions that we would like to investigate in this study.

Predicting future skill requirements

Predicting future skills is an important task for both policymakers and education institutes and so much has been written on this topic, especially with the current interest in AI and its impact on jobs and employment rates. For example, Eskarne *et al.* (2019) provide a thorough overview of much research on the impact of technology on employment, shifting skills needs and patterns of occupational change. It synthesises an analysis of the automation of skills and jobs and provides references to many studies that analyse these topics. Building on this theme, Ennis (2018) discusses the need to define and develop 21st-century skills for the future workforce and does so by leveraging data from the World Economic Forum in collaboration with the Boston Consulting Group, New Vision for Education: Fostering Social and Emotional Learning through Technology. It provides insights into competencies and character qualities that are essential for the future workforce, as explored in its research sources.

Of relevance to this paper is a study which developed a multilayer data analysis protocol to predict future skills by examining research publications (Telukdarie *et al.*, 2021). This paper uses research publications to predict future skills, rather than relying on current skill demand or economic indicators. This is similar in theme to the current paper but approaches the question from a different direction. Other papers such as Kotsiou *et al.* (2022) synthesise various future skills frameworks into nine meta-categories to inform the conceptualization of skills needed for the future. This allows a predictive framework for discovering future skills but is not based on concrete data that will continue to be refreshed in the future (like the ESCO dataset). On a similar note, Bakhshi (2017) uses a novel method to map likely changes in employment and skills, finding growth in education, healthcare and public sector occupations, contrary to assumptions about automation's impact. These results align with the findings of this paper. Although not using the ESCO dataset, another paper worth noting along this line is (Sousa and Wilks, 2018) which identifies critical and disruptive technological skills needed by organizations in the future, however, the paper focuses on the skills required by small and medium-sized enterprises with their findings identifying the critical skills of importance as complex problem-solving, critical thinking, creativity, people management, coordinating with others, emotional intelligence, judgement and decision-making, service orientation and negotiating and cognitive flexibility. The important disruptive technological skills were artificial intelligence, nanotechnology, robotisation, Internet of Things, augmented reality and digitalisation. Corroborating this work, Vorina *et al*. (2023) predict that adaptability, creativity, critical thinking and digital skills will be important for future jobs due to technological changes.

An earlier paper, Wilson (2010) discusses the need for Europe to generate higher quality and more innovative products and services, requiring new jobs and skills, to compete in the global market, looking at skills supply and demand in Europe, medium-term forecast up to 2020. The focus, however, is on industry-level demand and needs for specific occupations unlike our focus on specific skills. Another paper of a similar theme is MacCrory *et al*. (2014), which examines changes in occupational skill requirements from 2006 to 2014 due to rapid technological advances, finding the expected result of a reduction in skills that compete with machines and an increase in skills that complement machines.

Although extensive research has explored evolution, automation and labour market transformation, what is missing has been the usage of a repeatable and easily updated framework for predicting future skill needs based on an easily available public data source so that the relevant analysis can be repeated in a predictable and reliable fashion as more data are provided or updated. Without such a dataset, many studies that have scraped data from multiple websites (Borbásné Szabó and Ternai, 2018), show that this can lead to data collection methods that become illegal or challenging in the future as organisations protect themselves from data scrapers due to the impact of AI tools consuming data to train their models.

The other half of the skills equation is the jobs side and much has also been written on this topic. As brief examples, Jagannathan *et al*., (2019) provide an overview of global and regional trends impacting emerging jobs and labour markets, the overview collects a number of papers together which examine promising strategies in skills for jobs that address trends around labour markets of the future with a particular focus on Asia. Fareri *et al*. (2021) developed the SkillNER system, a named entity recognition tool, which was created to automatically extract soft skills from text, enabling the detection of job profile communities based on shared soft skills. Leveraging the ESCO dataset, Mirski *et al*. (2017) describe the OpenSKIMR approach to match individual skills with job demands, with the goal of enabling young people to plan and simulate their individual learning and career trajectories. By using ESCO, they are able to provide a consistent understanding of the skills and qualifications of relevant talents, showcasing the possibility of matching data about skills, learning and jobs. Finally, the article (Wilson, 2012) forecasts future job trends in Europe. This Cedefop research paper provides data showing a number of trends, such as most new jobs in Europe being at the higher and lower end of the skill spectrum, bringing a risk of job polarisation. The data presented shows weak employment growth, indicating a possible oversupply of people with high-level qualifications, leading to the most highly-qualified workforce in its history in Europe, relevant to some of the results presented here.

Our work complements the above papers, filling in a number of gaps as mentioned earlier and builds on the work by Wilson (2012) to predict the future job trends in Europe based on the effect of automation on skills needed by jobs.

It is worth noting that outside of the European context, much has been written about workforce adaptation and changing skill demands. For example, the paper (Lokesh *et al*., 2024) explores the intersection of AI and the future of work, with a focus on the imminent technological shifts and the evolution of in-demand skills. This is done via a literature review on the current state of AI in the workforce and identifying gaps in knowledge and training. The paper introduces a novel approach to addressing the identified gaps with a conceptual framework emphasising adaptive strategies for workforce development. Their early results indicated an intricate interplay between AI adoption and skill demands, providing insights for workforce adaptation. The implications are not dissimilar to those arising here.

The paper (Miah, 2024) discusses future AI's implications, among others, on job creation and job displacement and provides recommendations on how workers and companies can prepare for AI. Some key insights presented are around the predicted job market shifts due to AI, suggesting a bifurcation of roles similar to the aforementioned paper's identification with new opportunities emerging alongside potential job displacement. These disruptions highlight the necessity for upskilling and reskilling initiatives, empowering the workforce to adapt and thrive in an AI-driven environment, especially in skill development. The insights from this article are at a higher economic level rather than broad and specific skill focused like this paper.

Theories of automation and routinisation

The final piece of the puzzle which is important for this paper is deciding which jobs, tasks and skills will likely be automated by computers, robots and machines. This is a real effect and studies have observed a reduction in skills that compete with machines, an increase in skills complementing machines, and growth in areas where automation has not yet made significant progress (MacCrory *et al*., 2014). To understand this, a key part of the theory used in this paper is the ALM hypothesis (Autor *et al*., 2003). This hypothesis is built around two key assumptions:

> (1) that computer capital substitutes for workers in carrying out a limited and well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules (what we term routine tasks); and (2) that computer capital complements workers in carrying out problem-solving and complex communication activities (nonroutine tasks).

Although the task-based approach to understanding technological change's impact on labour markets is widely accepted (instead of just a focus on jobs as evidenced by papers citing the aforementioned publication), the classification of tasks as routine has been challenged for underestimating the capabilities of machines (Susskind, 2019). Susskind proposes a new hypothesis that encompasses ALM as a special case, addressing tasks previously thought immune to automation that he calls routinisable, a concept we use in this paper. The complexity of this topic was further explored by (Autor, 2015), who argued that while automation substitutes for labour, it also complements it, increasing productivity and labour demand, hence providing a more nuanced picture of skill and job automation that is corroborated by the analysis in this paper.

Research Questions. This article carries out an exploratory analysis of the ESCO dataset, looking to address three questions:

(1) The **Self-Automating Effect**: Are any industries (such as IT) reducing their own occupational skill requirements through automation-driven skill evolution?

(2) The **Matthew Effect in Skills**: Are high-skill jobs requiring more skills (compared to low-skill jobs, as measured by educational requirements) and so becoming more specialised and further out of reach for the less educated? What impact does AI and automation have on this?

(3) The **Red Queen Effect**: Put bluntly, are some jobs just running to stay in place? In what types of occupations are we seeing the most new skills being required of employees? Is this effect real or just perceived?

Method

Data collection methodology

The ESCO dataset represents an ideal dataset for carrying out the analysis in this paper. Unlike other datasets scraped from websites or collected from private repositories, the ESCO dataset is a professionally curated, high-quality dataset of thousands of skills and occupations (at the point of writing it contained 3,039 occupations and 13,939 skills). It is well maintained and regularly updated, freely available and well documented, as well as funded by the EU, making it perfect for research projects like the one presented here.

To use the ESCO dataset, our first step was to collect the requisite data from the ESCO website. These data can be downloaded freely and as stated on the website:

> Note that other than accepting the privacy statement, there are no additional requirements when downloading ESCO, ("ESCO Website," 2025)

Hence, the data can be used for any purpose, not violating the privacy statements. Once downloaded, the data need to be filtered, joined and selected to be able to carry out the planned analysis; however, before we describe that process, we explain how skills are added and managed in the ESCO database. Our usage of the datasets analysed all occupations and skills subject to the data preparation steps below.

Skills, competencies and ESCO. The first and one of the most important principles to understand is the types of knowledge, skills and competencies included in ESCO as well as what ESCO means by these concepts. This question is answered directly on the ESCO website as follows:

The skills pillar includes knowledge, skills and competences that are defined as follows:

(1) *Knowledge: The body of facts, principles, theories and practices that is related to a field of work or study. Knowledge is described as theoretical and/or factual, and is the outcome of the assimilation of information through learning.*

(2) *Skill: The ability to apply knowledge and use know-how to complete tasks and solve problems. Skills are described as cognitive (involving the use of logical, intuitive and creative thinking) or practical (involving manual dexterity and the use of methods, materials, tools and instruments).*

(3) *Competence: The proven ability to use knowledge, skills and personal, social and/or methodological abilities, in work or study situations, and in professional and personal development.*

While sometimes used as synonyms, the scope of the terms "skill" and "competence" can be distinguished. "Skill" refers to the use of methods or instruments in a particular setting and in relation to defined tasks. "Competence" is broader and refers to the ability of a person, facing new situations and unforeseen challenges, to use and apply knowledge and skills in an independent and self-directed way. However, there is no distinction between skills and competences recorded in the ESCO skills pillar.

In our analysis, we only required skills and so left knowledge and competences out of our analyses.

To ensure that the database is suitable for our analysis, we need to understand how skills are added to the database. To do this, ESCO employs a methodology that blends a data-driven approach with human expertise. Input is received from a variety of sources, including stakeholders, experts, ESCO users, researchers and national classifications who propose improvements or suggest adding new concepts. These suggestions are then validated by checking whether the concepts are being actively used in the EU labour market and education and training fields. For this purpose, ESCO analyses data such as Online Job Vacancies, CVs, other national or international classifications, courses and learning outcomes and similar sources. In addition to user suggestions, ESCO collects data from all these sources in order to analyse if there are new emerging concepts. The process also involves enriching and clustering extracted information, mapping it to ESCO concepts, manually validating the results and consultations (the above description was provided in a personal communication from ESCO and is also detailed in the reference on Figure 1 below).

The exact methodology was presented in a presentation on the recent launch of v1.2 ("ESCO Website," 2025) and is presented in the following diagram:

As mentioned, our analysis focused on skills/concepts, not knowledge in the ESCO classification.

Preparing the ESCO data for analysis. In this section, we give a description of the ESCO data required for the analysis in this paper.

For the analysis, we focused on the so-called Deltas of the ESCO datasets. These are updates to the database which may add new content such as skills but may perform other functions too. Only the major version updates (i.e. an update to the second digit of the version such as 1.2 or 1.1) will contain new content, as stated on the website under FAQs ("ESCO Website," 2025):

(1) *Minor versions: contain changes that do not affect the concept level (i.e. no concepts are added, no concepts are removed and the scope of the existing concepts is not changed). Minor releases refer to typos, adding or removing relations between concepts, making minor changes to the labels and the descriptions, etc. and do not require any update of mapping tables.*

(2) *Major versions: contain changes that affect either the concept level (i.e. concepts are added, concepts are removed and the scope of the existing concepts is changed) and/or the data model.*

Hence, our analysis utilises the major version updates to the ESCO database, of which there were two relevant ones for our analysis, v1.0.9 - > v1.1.0 and v1.1.1 - > v1.2.0 [1]. In terms of timelines:

(1) ESCO v1.2.0 was released on the 13th of May 2024

(2) ESCO v1.1.0 was released on the 28th of January 2022; however, a pre-release was made available in December 2020.

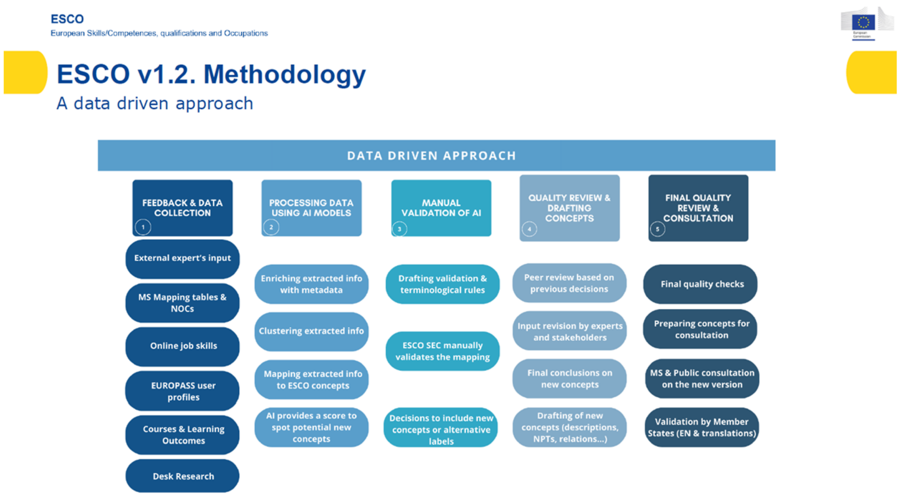

Figure 1. The ESCO methodology for the creation of its database. Used with permission of ESCO. "Source: ESCO version 1.2" (2024)

(3) ESCO v1.0.0 was released on the 28th of July 2017

The major updates to the skills and occupations occurred at the v1.0.9 → v1.1.0 update where 353 new skills/competencies were added. In the v1.1.1 → v1.2.0 update 42 new skills were added.

The size of the datasets used for the analysis are as follows:

(1) The Delta v1.1.0 dataset initially contained 191,734 records, with 23,082 of these being English records, which are the focus of our analysis (the dataset is linguistically diverse, comprising a total of 28 unique languages). Upon reviewing the dataset, out of the 191,734, a total of 64,287 records were there to indicate a removed record, while 22,659 were of existing records that were updated, and finally those of interest were the 104,784 newly added records. Additionally, there were 4 records that remained unclassified.

(2) To analyse the Delta v1.1.0 we required other files as well which were:

- broaderRelationsSkillPillar_en which contained 20,771 total records
- skills_en which contained 13,891 total records
- skillGroups_en which contained 643 total records
- occupations_en which contained 3,008 total records
- occupationSkillRelations_en which contained 123,852 total records

(3) The updated Delta v1.2.0 dataset consists of 140,550 records, with 20,338 of these being English records, which are the primary focus of our analysis. This dataset represents a significant update, with 75,319 of the records indicating they were added, 63,899 records indicating a removal, and 1,332 existing records were updated. Notably, all records have been classified, with no unclassified records remaining. As before, the dataset continued to showcase linguistic diversity, spanning 28 unique languages.

(4) As above, to analyse the Delta v1.2.0 we required other files as well which were:

- broaderRelationsSkillPillar_en which contained 20,822 total records
- skills_en which contained 13,939 total records
- skillGroups_en which contained 640 total records
- occupations_en which contained 3,039 total records
- occupationSkillRelations_en which contained 129,004 total records

Almost a million records in total formed the data source for our analysis. Of these records in the two Deltas, we then selected a subset of them for our analysis by selecting only those records where:

(1) Language is either EN or NONE

(2) conceptURI contains “skill” - To indicated it is skill competence/knowledge record

(3) Action is “Added” - Indicate new records added to the new dataset

Note that the ESCO data classify skills into hierarchies, for example, for the skill “comply with regulations”, it is the final level in the hierarchy: transversal skills and competences → social and communication skills and competences → following ethical code of conduct → comply with regulations.

For our analysis, we choose to work with the L1 and L2 skill levels to be able to aggregate concepts to a sufficient level and analyse larger scale trends instead of, e.g. trying to create our own groupings of terms, we used the natural hierarchies provided by ESCO (to allow easy replicability of our study). Also, going beyond the L1 or L2 skill levels and using the L3 skill level was not an option due to many entries missing and each entry being unique and so not providing aggregated trends. Our process to join the datasets is presented in Figure 2 below.

To validate data integrity, we systematically cross-referenced a subset of records from the Delta file with the online ESCO database using conceptURI identifiers, which served as the primary key. This helped us to understand how new skills were being added and how existing ones were modified over time. Additionally, we examined the broaderRelationsSkillPillar_en file to identify the highest-level skill group each skill belongs to, and based on this, we selected the highest and second highest skill levels for our analyses (i.e. L1 and L2). This step was essential in categorising skills correctly and recognizing overarching trends in ESCO's evolving taxonomy. Once we established the relationships between these datasets, we developed a Python script to extract, process and analyse the relevant data (as mentioned above in the three filtering steps), the results of which we produce in the Data Analysis and Results section below.

In our analysis, we also combined the two deltas into one given that the remaining set of skills in the v1.1.1 → v1.2.0 Delta was only 42. This meant that we were unable to provide a longitudinal time-based analysis; however, it allowed for more robust analysis of the evolution of skills given the larger volume of new skills.

Routinisable skills classification

The second part of our processing of the data analyses the new skills added to the ESCO database via the Deltas and classifies them as routinisable or not. This part of the analysis used the extension of the ALM hypothesis presented in (Susskind, 2019). According to this article, Susskind introduces the concept of routinisable which he defines as follows:

If a task is routinisable, a routine can be composed that allows a machine to perform it – but that routine may not necessarily reflect the way in which a human being performs the task. The concept of "routinisability" nests the concept of "routineness". The latter is focused on whether a task has features that make it more or less feasible to articulate how a human being performs it in a set of rules for a machine to follow. The concept of "routinisability" instead asks whether a task has features that make it more or less feasible to articulate a set of rules for a machine to follow.

To determine which skills are routinisable we used an expert evaluation. Both authors have been developing AI tools for a combined 30+ years and so based on our experiences (working in machine learning, generative AI and optimisation), we classified tasks into routinisable or not based on our experience and predictions. We also found this most appropriate given the recent developments in generative AI and our choice of frameworks (ALM) for deciding on routinisable or not. We see this approach as valid for this publication for two reasons:

(1) Although not perfect (Stevens *et al.*, 2019), it has also been shown in a number of publications and different domains that human expert judgement produces lower error than state of the art machine based approaches in a number of domains (Ärje *et al.*, 2020; EDENBRANDT *et al.*, 1993) or use human experts to form the basis of machine judgement (Yang, 1994).

(2) In addition, we provide the data of what we have classified as routinisable so that others can reproduce our classification easily.

Before choosing this approach, we analysed other approaches such as the one used by Frey and Osborne (2017) who developed a methodology to estimate the probability of computerization for various occupations. They utilized machine learning algorithms to assess tasks based on:

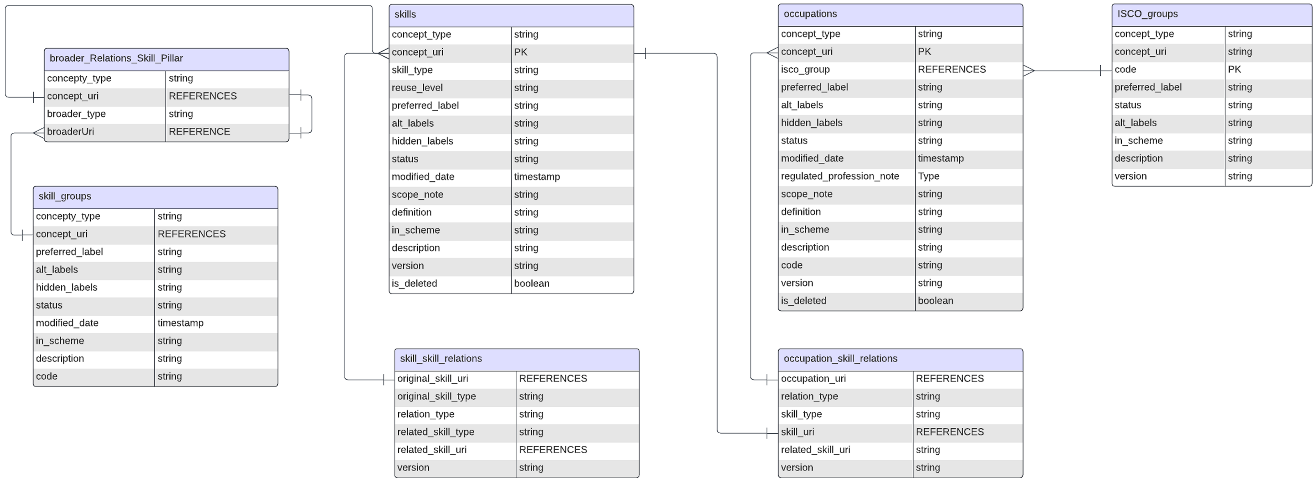

Figure 2. The connections between concepts of the different ESCO tables. The arrows link primary and foreign keys to join tables. Source: Figure by authors

(1) **Perception and Manipulation:** Tasks requiring manual dexterity and complex perception are less likely to be automated.

(2) **Creative Intelligence:** Tasks involving originality and fine arts are less susceptible.

(3) **Social Intelligence:** Tasks necessitating social interaction and negotiation are less prone to automation.

Using these criteria, Frey and Osborne could assign a probability that a task could become automated. This approach wasn't suitable for our scenario due to types of skills provided in ESCO and the skill level we chose to analyse skills on. So in carrying out the classification, we oriented ourselves on the original ALM-Hypothesis paper (Autor *et al.*, 2003) and how it explained what a routine task was and then extended that definition in accordance with Susskind's recommendation. In their paper, Autor *et al.* (2003) categorised tasks into routine and non-routine, as well as cognitive and manual dimensions. According to the authors, routine tasks are characterised by repetitive and rule-based activities, hence are more prone to automation. We used this to guide our classification.

As a part of our classification into routinisable and non-routinisable, we made three additional assumptions:

(1) Our time horizon for deciding on whether a skill is routinisable or not was five years and so it was whether the authors believed that a certain skill or competence would be automatable in the next five years.

(2) Artificial General Intelligence will not become a reality in the next five years, otherwise it would render almost all skills (if not all skills) routinisable.

(3) The 30+ years of experience of the authors was a sufficient basis to classify skills as routinisable.

Once our classification of the skills was complete, we then removed any routinisable skills from the skillsets and analysed the L1 categories to understand which industries and areas we expected to be impacted most, leaving a non-routinisable set of skills for the future which allowed us to answer Research Question 1 above. The results of this are explored in the next section.

After carrying out this analysis, we moved on to Research Questions 2 and 3. For this, we took this remaining list of skills and examined the occupations that required these non-routinisable skills. To do so, we removed rows from the table of skills (a sample of which is provided in Table 1) for L2 skills that we deemed to be routinisable. Note that all

Table 1. An example of an occupation and the new skills included in the v1.0.9 – v1.1.0 update

Occupation	L1 skill category	L2 skill category
Mountain guide	Assisting and caring	Counselling
Mountain guide	Communication, collaboration and creativity	Liaising and networking
Mountain guide	Communication, collaboration and creativity	Teaching and training
Mountain guide	Management skills	Allocating and controlling resources
Mountain guide	Information skills	Monitoring, inspecting and testing
Mountain guide	Working with computers	Using digital tools for collaboration, content creation and problem solving

Source(s): Table by authors

the L2 skills were unique, so there were no issues with joining these two datasets to carry out this matching. This left a set of rows and occupations which we used to answer Research Questions 2 and 3.

Data analysis and results

We begin analysing Research Question 1 beginning with both all the new routinisable and non-routinisable skills and then remove the routinisable skills as discussed in the previous section. We present this at the Level 1 (L1) level of granularity to be able to identify trends. Table 2 presents the results for all new skills in the two Deltas as well as the results for all non-routinisable skills with the number in parentheses showing the order of most to least (i.e. (2) indicates this L1 Skill Category has the second largest number of skills in the list).

To answer Research Questions 2 and 3, we need to look at the relationship between occupations with routinisable and non-routinisable skills and then non-routinisable skills separately as well as whether such jobs require a higher education degree. An example of occupations and new L1 skills for the routinisable vs non-routinisable cases is presented in Tables 3 and 4 respectively.

The next step was to combine this data with whether the occupations were deemed to require a higher education degree or not. This analysis was carried out by analysing each role and confirming whether the job required a bachelor's degree or higher. This analysis was guided by the Bureau of Labor Statistics (BLS) Educational and Training Assignments ("Education and training assignments by detailed occupation," 2023). The U.S. BLS assigns typical education levels needed for entry into various occupations. These assignments are based on analyses of job duties and the education and training commonly required and were used to assess the roles (or similar roles) to decide whether a bachelor's (or more advanced degree) was required. We also provide this classification data as part of the submission of this paper.

From the ESCO updates, there was a total of 488 roles that were deemed to require any of the new skills in at least one of the two ESCO Delta updates. Of these, there were 376 roles

Table 2. L1 skills by all and non-routinisable types, the numbers in parentheses indicate the new order from most to least

L1 skill category	All new L1 skills	Non-routinisable L1 skills
Communication, collaboration and creativity	110 (1)	50 (1)
Information skills	73 (2)	12 (6)
Management skills	45 (3)	45 (2)
Assisting and caring	36 (4)	36 (3)
Working with computers	32 (5)	14 (5)
Life skills and competences	23 (6)	23 (4)
Working with machinery and specialised equipment	20 (7)	8 (8)
Handling and moving	11 (8)	1 (12)
Core skills and competences	9 (9)	9 (7)
Social and communication skills and competences	9 (9)	9 (7)
Thinking skills and competences	7 (10)	7 (9)
Self-management skills and competences	7 (10)	7 (9)
Physical and manual skills and competences	4 (11)	4 (10)
Constructing	3 (12)	3 (11)
Inter-disciplinary programmes and qualifications involving engineering, manufacturing and construction	1 (13)	0 (13)

Source(s): Table by authors

Table 3. A list of occupations and counts of all L1 skills

Occupation	All new L1 skills
Energy engineer	68
Architect	59
Mechanical engineer	54
Civil engineer	33
Environmental scientist	27
Chemical engineer	27
Urban planner	26
Chemist	26
Data scientist	26
Microsystem engineer	25

Source(s): Table by authors

Table 4. A list of occupations and counts of all non-routinisable L1 skills

Occupation	Non-routinisable L1 skills
Energy engineer	25
Architect	25
Mechanical engineer	21
Environmental scientist	19
Chemist	18
Toxicologist	18
Civil engineer	18
Behavioural scientist	18
Chemical engineer	18
Economist	18

Source(s): Table by authors

remaining which needed new, non-routinisable skills (so 112 roles did not require new, non-routinisable skills but just had new skills), and of those 249 required a higher education degree and 129 didn't require higher education degrees (i.e. at least a university bachelor's degree).

For both *routinisable and non-routinisable skills*, what we discover is that for all occupations requiring a higher education degree, there are 3,720 new skills across 302 occupations with a mean of 12.32 new skills per occupation and a sample standard deviation of 11.73 (the range of values was from 68 to 1). For occupations not requiring a higher education degree, there were 186 occupations and 613 new skills with a mean of 3.3 and a standard deviation of 3.51 (the range of values was from 22 to 1).

Due to the nature of the skills per occupation distributions being multimodal and non-Gaussian, we also looked at a number of skill cut-offs for the number of occupations requiring a higher degree. For occupations requiring a higher education degree, there were 140 occupations needing 10 or more new skills; for occupations not requiring higher education degrees, it was 17 occupations needing 10 or more new skills.

For *just the non-routinisable skills,* what we discover is that for all occupations requiring a higher education degree, there were 249 occupations with 2,422 new skills with a mean of 9.73 and a sample standard deviation of 7.7 (the range of values was from 25 to 1). For non-higher education occupations, there were 127 occupations and 380 new skills with a mean of 2.99 and a standard deviation of 2.62 (the range of values was from 11 to 1).

Similar to the above, we analysed a skill cut off of 10 or more skills with 126 such occupations requiring a higher education degree and only 3 occupations not requiring a higher education degree.

The main results of the above analysis are summarised in Table 5 below.

Given there were many occupations with a single new skill, we reviewed the data to see if this single new skill was the same skill for all occupations but it was not the case that there was a common skill (i.e. occurring more than half the time) amongst all of these occupations with just one new skill.

To answer Research Question 3, we analysed the data to understand which types of occupations are seeing the most new skills added when we view them from the dimensions of higher education vs non-higher education and also from the routinisable vs non-routinisable perspective.

When looking at all L1 skills, there are 302 occupations that require a higher education degree, and there are 186 occupations that do not require a higher education degree for occupations with new skills being added. When the 488 occupations were ranked in order of the number of new skills being added, occupations 1 to 128 were occupations requiring higher education degrees, with occupation 129 not requiring a higher education degree. From a purely probabilistic perspective, if the order of the appearance of these occupations was random (i.e. the skill distributions came from similar distributions), then using the binomial distribution to model this probability (with $p = 302/488$), the probability of this specific order of the first 128 occupations requiring higher education degrees occurring is equal to 2.1697×10^{-25}, a probability so low (well below standard statistical significance thresholds of $\alpha = 0.01$) so this is highly likely not random. A similar calculation for non-routinisable skills shows a similarly low probability, showing it highly likely not random that occupations requiring higher education degrees all have so many new skills added in the latest two ESCO Delta updates.

Discussion

Research question 1

The above data helps us to answer Research Question 1 by showing that, for skills in the IT sector such as *information skills* and *working with computers*, although there are many emerging skills (of both routinisable and non-routinisable types), the necessity of prioritising of these skills by policymakers and educational institutes requires further investigation due to such skills not even being in the top three most important recently added skills after filtering out routinisable skills.

On average, the overall new skills in the combined deltas were 390, with only 228 skills being classified as non-routinisable, an overall reduction of 162 (roughly 11 per L1 skill category, of which there were 15) or 42%. We see that in the *information skills* category that 61 skills or 83% are routinisable (according to our analysis) and in *working with computers*, 18 skills or 56% are routinisable (both above the L1 skill category average). Another category for which many skills were routinisable is *communication, collaboration and creativity skills*,

Table 5. Summary of skill differences across occupation and skill types

Skill type	Mean	Standard deviation	Diff. Statistically significant
Higher Ed. Occupation All L1 Skills	12.32	11.73	No
Non-Higher Ed. Occupation All L1 Skills	3.3	3.51	
Higher Ed. Occup. Non-routinisable L1 Skills	9.73	7.7	No
Non-Higher Ed. Occup. Non-routinisable L1 Skills	2.99	2.62	

Source(s): Table by authors

with 55% being routinisable. Despite this reduction, there were so many new skills in the *communication, collaboration and creativity skills* category that it remains the category with the most new non-routinisable L1 skills, demonstrating their importance.

The clearly critical L1 skill categories (in addition to *communication, collaboration and creativity* skills) that should remain a focus are *management skills* and the related skills of *assisting and caring*. All are clearly human tasks that require human input and so we see the other half of the question being answered that although many new computer-focused skills are arising, many will become routinisable and so should not be focused on from an education and policy perspective. However, the people skills that have been a focus of many other studies, Josten and Lordan (2022) have shown that not only are they expanding quickly in the new skills required, but these skills are not routinisable. Assuming that the trends discovered here continue, they deserve significant attention from an education and policy perspective.

Research question 2

To answer Research Question 2, we analysed the occupation data and the new skills per occupation. This research question has two parts:

(1) Are occupations for people with higher education degrees becoming more specialised (i.e. requiring more skills) and further out of reach for those without higher education degrees?

(2) What impact does AI and automation have on this difference in required skills?

In analysing the above, the data indicates that the answer to the first part of Research Question 2 would be yes, although the difference presented here is not statistically significant. By looking at occupations from the routinisable and non-routinisable perspective, we see that the mean for higher education degree requiring occupations (12.24) is greater than for occupations not requiring a higher education degree (3.52) (albeit this not being statistically significant).

When analysing the second part of Research Question 2, we see that the automation of certain skills (i.e. routinisable skills) may potentially be reducing the gap between the new skills required, decreasing the mean for occupations requiring a higher education degree from 12.24 to 9.67 (a 21% decrease) more than for those not requiring a higher education degree from 3.52 to 3.21 (a 9% decrease). These initial findings suggest that AI-driven automation may be contributing to a reduction in skill inequality across occupations, although these results are also not statistically significant, however, provide an interesting trend. This is not a totally expected result as some literature seems to indicate a widening gap (Morandini *et al*., 2023), and so suggests an opportunity for further investigation.

The explanation for this counterintuitive result may be due to technical (e.g. IT) industries in which many new skills are created (originally ranked second and fifth in terms of routinisable and non-routinisable new skills respectively) are simultaneously the industry capable of building AI tools and so perhaps the easiest target for their AI tools are to solve their own problems, hence automating away the new skills that are arising to deal with the technology changes. The definitive answer to this question is a research project in itself.

Research question 3

As we saw from the binomial distribution probability calculation in the previous section, if our null hypothesis were that higher education and non-higher education degrees both required an equal number of new skills, then our final calculation in the "Data analysis and results" section leads us to reject the null hypothesis and conclude that occupations requiring higher education degree are truly requiring more new skills than occupations not requiring higher education degrees (albeit noting the above trend in IT industries).

When we combine the results from Research Question 2 and Research Question 3, then the conclusion we can draw is that yes, occupations requiring higher education degrees are adding more skills but when we take into account the question of which skills are routinisable, then this gap shrinks (especially in IT industries) suggesting that, in the limit, automation may be reducing the disparity between the traditionally more cognitive jobs than those requiring more human presence, physical labour or management. Then overlaying Research Question 1 on top of this conclusion, we see this effect on the individual skill level, noting that many of the IT-related new skills are actually ones that are routinisable, leaving the following three L1 skill categories as being the ones with the most new and emerging, non-routinisable skills:

(1) Communication, collaboration and creativity

(2) Management skills

(3) Assisting and caring

Again, this shows the importance of human skills in an AI-automated workplace.

An important point to note in the above that is missing, is the discussion clearly around the needed increase in AI literacy and skills for employees who will likely be expected to be able to use AI tools to automate parts of their work. This may come from external vendors, but nonetheless an ability to work with AI tools is clearly another important and significant conclusion from the above. With an estimated 41.5% of all new skills in the ESCO Deltas predicted to be routinisable in the next five years, it is clearly a pressing matter.

Academic implications

This study contributes to the existing literature on labour market automation, skill evolution and workforce adaptability by introducing a replicable methodology for tracking skill transformations using the ESCO dataset. Unlike previous studies that rely on static analyses or broad theoretical discussions, our approach integrates dynamic, real-world skill updates with established automation frameworks, providing an ability to develop a longitudinal perspective on emerging competencies. Additionally, this research refines the ALM hypothesis by incorporating Susskind's concept of routinisability, offering a more nuanced classification of skills susceptible to automation. The findings also seem to indicate that prevailing assumptions about AI's impact on skill inequality may require further investigation, as the results here suggest that automation may be reducing, rather than exacerbating, disparities between high- and low-skill occupations.

Practical implications

The findings of this study have significant implications for policymakers, educational institutions and industry leaders seeking to navigate the shifting labour market landscape. With over 40% of new skills identified in the ESCO dataset deemed routinisable within the next five years, strategic workforce planning is essential to prevent skill obsolescence. Policymakers should prioritize the integration of future-proof, non-routinisable skills – such as critical thinking, complex problem-solving and interpersonal communication – into educational curricula and lifelong learning programs. Similarly, businesses must reconsider hiring and training strategies, ensuring that employees are equipped to work alongside AI systems rather than be displaced by them. Organizations should also foster a culture of continuous skill development, leveraging AI-enhanced learning tools to upskill workers in emerging, non-automatable domains. By proactively addressing these shifts, European labour markets can better adapt to automation and technological disruption while ensuring a more resilient and inclusive workforce.

Conclusion

This study has provided a data-driven analysis of emerging skills in the European labour market, leveraging ESCO Delta files to identify trends in skill evolution and automation susceptibility across all skills and occupations present in the ESCO datasets. By integrating the ALM hypothesis and Susskind's framework on routinisability, we examined the impact of automation on occupational skill requirements, addressing three key research questions.

Our findings highlight the Self-Automating Effect, demonstrating that technical industries are automating themselves out of jobs, with many newly emerging IT-related skills classified as routinisable. This suggests that while digital competencies remain relevant, they may not provide long-term job security in their current form. The Matthew Effect in Skills was also observed, indicating that high-skill occupations are accumulating new skill requirements at a faster rate than lower-skill roles, reinforcing the trend of occupational specialisation. However, contrary to expectations, AI-driven automation appears to be narrowing this gap by reducing the number of required skills in high-skill professions. Finally, the Red Queen Effect reveals that many occupations, especially high-skill ones, are experiencing an ongoing need for skill adaptation, particularly in areas requiring human-centric competencies such as communication, collaboration, management and caregiving.

The policy and educational implications of these findings are substantial. While technological skills continue to evolve, the future workforce will likely require a stronger emphasis on interpersonal, managerial and problem-solving abilities – domains that remain largely resistant to automation. Policymakers should focus on designing education and training programs that balance digital literacy with these non-routinisable competencies. Similarly, organizations should reconsider their workforce development strategies to ensure employees are equipped with adaptable, future-proof skills.

Ultimately, this study underscores the urgent need for proactive policy interventions and strategic workforce planning in the face of accelerating automation. By anticipating skill trends and adapting educational curricula accordingly, European institutions can better prepare workers for the demands of an AI-driven economy. Future research should continue to explore the intersection of automation, skill inequality, and labour market transformation to ensure that technological progress translates into inclusive and sustainable employment opportunities.

Limitations and future work

Despite its contributions, this study has limitations. The reliance on expert judgement for routinisability classification introduces a subjective element that could be refined through further validation using crowd-based ratings and/or predictive AI models; this would strengthen the external validity of the results. Although the authors have provided their classification, so they can be analysed and reused in the future. Additionally, the analysis is constrained to European skill dynamics, and future research should examine whether similar trends hold in other global labour markets.

One limitation of this work is the limited number of Deltas used in the analysis. It will be an important research project to repeat this analysis when more skill Deltas are released and to plot the changes over time. This will remain as a future task.

Another limitation was our focus on the English language. Although the English language has become the lingua franca for business interactions across Europe ("The Commission's use of languages - European Commission," n.d.; "Surveys - Eurobarometer," n.d.), it is still not the primary language for all inhabitants of Europe. Research indicates that over 80% of Europeans indicate they speak English ("Top English Speaking Countries in Europe (2025)," n.d.). Investigating the other languages available in the ESCO dataset could help confirm (or refute) the results presented here.

Finally, another limitation could be in biases in the selection of new skills, capabilities and occupations by the ESCO team. It is difficult to know who this impacted the selection of new skills, capabilities and occupations but it is likely to have had an impact.

Future work should also be carried out on a regular basis, given the impressive speed with which AI tools are evolving and automating tasks. Skills and tasks once out of reach of AI could quickly come within reach and entirely change the analysis within this article. In addition, subsequent ESCO Delta updates will provide an opportunity to refine and expand this framework, enabling continuous monitoring of skill transformations over time.

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Note

1. After contacting the ESCO team, they indicated that earlier versions would not be appropriate for our analysis due to changes in the data.

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