SkillsPULSE
SKILLS - PREDICTING, UNDERSTANDING, AND LOCATING SHORTAGES IN EUROPE

4.2 Report on tackling research gaps

Dissemination level: PU (public)

Funded by the European Union

UK Research and Innovation

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Call	HORIZON-CL2-2023-TRANSFORMATIONS-01
Type of action	HORIZON-RIA
Project number	101132727
Activity	HORIZON-CL2-2023-TRANSFORMATIONS-01-07
Project acronym	SkillsPULSE
Project full title	Skills Predicting, Understanding, and Locating Shortages in Europe
WP number and title	WP4: Workplace determinants of shortages and gaps
Title of the deliverable	A report on tackling the research gaps
Deliverable number	D4.2
Responsible partner	UTARTU
Contributing partners / fellows	UTARTU, UNIPI, UNILODZ
Document status	Final

Document development track

	Document version	Organisation	Name, Surname	Date
Drafted by:	V.1	UTARTU UNIPI UNIPI	Anastasiia Pustovalova Vito Giordano Filippo Chiarello	23/03/2026
Reviewed by:	V.2	FGB SRL SB UNILODZ FGB SRL SB	Giulia Martorana Ewa Kusidel Chiara Fratalia	27/03/2026 31/03/2026 31/03/2026
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Abbreviations

AI: Artificial Intelligence

CVTS: Continuing Vocational Training Survey

D: Deliverable

ESCO: European Skills, Competences, Qualifications and Occupations

ECS: European Company Survey

ESJS: European Skills and Jobs Survey

ETLS: European Training and Learning Survey

ER: employee representative

EU: European Union

EVTS: European Vocational Teacher Survey

EWCS: European Working Conditions Survey

LFS: Labour Force Survey

NUTS: Nomenclature of Territorial Units for Statistics

PIAAC: Program for the International Assessment of Adult Competencies

PIAAC-EM: PIAAC Employer Module

PU: Public

RE: Restricted

SME: small and medium enterprises

UK ESS: United Kingdom Employer Skills Survey

WP: Work Package

Executive summary

The persistence of skill shortages and skill gaps across European labour markets presents a challenge to productivity growth, innovation capacity and social cohesion. This suggests the need for comprehensive and reliable ways to explain the structural determinants of skill gaps and shortages and predict skill demand. While in the previous report we identified available datasets and summarised the current state of research, significant gaps remain in understanding how firm-level characteristics, organisational practices and innovation dynamics interact with skill needs and deficiencies. The current report addresses these gaps, outlining data-driven solutions to advance empirical research and related policy design.

Building on the findings of Task 4.1 within WP 4 (SkillsPulse 2025a), this report identifies key research gaps in analysing how firm-level factors (chiefly—management practices, working conditions and co-worker complementarity, as well as the diffusion of AI) affect the incidence and persistence of skill gaps. Section 2 proposes several approaches to study design to address the research gaps, as well as extensions to the existing data collection procedures.

The suggestions range from shorter- to longer-term solutions. Examples include improved integration of employer- and employee-side data, the development of better monitoring mechanisms, improved measurement of skill gaps in firm modules, and the incorporation of patent-based foresight techniques for anticipating emerging skill demand areas. The latter is covered in-depth in Section 3, where we undertake an empirical exercise focusing on AI—a sector that is both relevant in terms of the scope of its effects on labour markets in the future and meaningful in the context of patent-skill relationships. This exercise demonstrates the way in which we can extract useful information about the way future skills are affected by utilising the data from patent descriptions.

The result of the analysis in Section 3 is a list of skills mapped onto the current version of ESCO classification with a corresponding score outlining the level to which this skill is affected by the AI technologies. The most affected skills within the digital skill bundle are deep learning and the principles of AI; among non-digital—spatial planning and memorisation of information. It should be noted that this approach largely overlooks “softer” skills, since they are harder to detect in this type of data; moreover, further expert input is needed to distinguish whether and which of the identified skills are substitutable by or complementary to this technology.

2. Firm-level factors, gaps in research and data and the ways to address them

2.1 Data-specific gaps

2.1.1 One-sidedness of existing survey data

Most existing survey datasets offer one-sided perspectives of either employers or employees, and all are cross-sectional in nature. As a result, it is difficult to assess causal mechanisms, track adjustment processes over time, or evaluate the effectiveness of the firms' activities aimed at tackling skill deficiencies, such as training, organisational restructuring or technological adoption. Moreover, emerging technological developments, such as rapid advancements of generative AI, introduce additional uncertainty regarding future skill needs and potential mismatches.

The lack of matched employer-employee data is one of the largest current issues for the skill gaps literature. We know from the existing studies that both sides can report biased results due to the nature of survey data collection: for instance, employers can misinterpret their hiring needs due to growth as skill gaps, underreport the gaps to justify the success of training, or report skill shortages while omitting information about unfavourable working conditions; on the other hand, the workers may overestimate their proficiency or view skill needs for further career progression as skill gaps (see the discussion of conceptualisation issues in Schwalje 2012, McGuinness et al. 2018, SkillsPulse 2025b, Nedelkoska and Neffke 2019). The specific survey questions about skill gaps and definitions of the main categories vary from study to study, which further exacerbates the issue. Importantly, the lack of data on both sides simultaneously constrains the scope of skill gap research, leaving several important questions unresolved or understudied—some of which we discuss further in Sections 2.2 and 2.3.

Table 1 below compares the types of questions around the topic of skill gaps and reports whether they are covered in existing worker- and firm-level surveys. In addition to EU-wide surveys, it includes UK ESS, which is arguably one of, if not the most comprehensive survey of firms' skill gaps in Europe. Another extensive firm questionnaire can be found in Marcolin and Quintini (2023) (PIAAC-EM), which, unfortunately, has only had limited implementation to date. Nonetheless, individual- and firm-level datasets have a number of topics in common that they explore, most notably those concerning training and its characteristics. On the other hand, employee-level datasets generally provide more extensive data on skill gaps and the types of skills used at work. They also collect information on the persistence and/or duration of skill gaps, while for firm datasets this topic is currently a blind spot.

Table 1. Common question types across employee- and employer-level surveys

Type of question	Employee-level datasets	Employer-level datasets
Skills higher than / at / below needed level	EWCS; ESJS; PIAAC (+ actual skill levels)	ECS; UK ESS
Skills match or not	EU-LFS-2024 (limited); EWC(T)S-2021	-
Types of skills lacking	ESJS; PIAAC	UK ESS; Eurobarometer-433 (limited context); PIAAC-EM
Persistence / duration of skill gaps	ESJS	-
Difficulty recruiting / retaining skilled workers	-	Eurobarometer-529 (SMEs); ECS; PIAAC-EM; UK ESS

Type of question	Employee-level datasets	Employer-level datasets
Providing or receiving training	EWCS; ESJS; PIAAC; LFS (core); ECS	CVTS; ECS; PIAAC-EM; UK ESS
Training characteristics (financing, volume, type, barriers)	ESJS (type, financing, barriers, reasons); PIAAC (financing, form); ECS (types, barriers, involvement of employee representatives)	CVTS; ECS (reasons, barriers); UK ESS (financing, type); PIAAC-EM
Other actions addressing gaps, shortages and skill development	ESJS (limited)	ECS, CVTS, PIAAC-EM; Eurobarometer-529 (SMEs); UK ESS
Skills used at work*	ESJS; PIAAC; EWCS	-
Impact of skill deficiencies on firm/worker outcomes	-	PIAAC-EM; UK ESS
Anticipation of future skill needs	-	CVTS; PIAAC-EM; UK ESS

Notes. * - direct questions about skills and tasks at work; technically, occupational data can provide additional indirect information via linkage to ESCO and is present in all worker-level datasets. An alternative firm-level measure of "skills used at work" could be as simple as its occupational composition.

Longer-term, there is a need to expand existing surveys to include reliable and representative data from both the organisations and their workers. ECS is currently the only Europe-wide survey that attempts to collect information from both sides, having separate questionnaires for the employee representatives and the firm representatives. However, the worker representatives' module of ECS is rather limited in the scope of questions, focusing only on certain aspects of reskilling and upskilling. All questions regarding skill gaps, difficulties retaining employees and the share of workers on jobs necessitating continuous training are reserved for the firm representatives' module.

The most immediate improvement to matched data would be to *harmonise the questions* across ECS modules, ensuring that the questionnaires ask equivalent questions about skill gaps and adjacent practices. Currently, all quantitative skill gap questions are reserved for the management module. Adding a mirror question to the ER module—namely, asking to estimate the share of workers with skills below job requirements, and to identify the main skill types affected—would allow within-establishment comparison. While employee representatives might lack the foresight of HR and other managers, they cannot be disregarded as an additional source of this data. In the current version of ECS, ERs are already asked about the firm's reskilling and upskilling programs and the involvement of ER bodies in the determining of training needs, among other things. The degree of (dis)agreement between ER and management's estimates of skill gap prevalence would itself be analytically valuable as a measure of internal information asymmetry within the establishment. This approach would still leave the caveat of only having matching information on firms that have employee representative bodies, however.

On the firm side, the existing skill gap module could be extended in several ways. The most significant gap relative to worker-level datasets is the absence of granular skill-type information: while ESJS and PIAAC ask workers about deficiencies in specific skill categories such as social, technical or digital, ECS only asks managers to estimate the overall share of workers whose skills fall below requirements. Adding a question that asks managers to elaborate on specific skills (similarly to the UK's ESS dataset and PIAAC-EM) would make ECS the first EU-wide survey to provide this type of data at scale. A second extension would be to ask about the distribution of skill gaps across occupational groups within the establishment, adding a layer of information about within-firm heterogeneity. Finally, both the ER and the management module could include a question about the perceived causes of skill gaps—whether they are attributed to insufficient initial training, inadequate within-firm training, technological change outpacing the development of the workforce or difficulties in recruitment.

Finally, a more fundamental longer-term improvement would be to standardise the framing and response categories of skill gap-related questions across ECS, ESJS and any future surveys, so that employer- and worker-reported skill gaps are directly comparable by construction (see Marcolin and Quintini (2023) for the discussion on comparable questions for employees versus employers).

Currently, the most extensive theoretical framework is outlined in Marcolin and Quintini (2023), who introduce a research design under which it could be possible to reconcile individual- and firm-level data. They develop a methodology and a firm questionnaire that is comprehensive in the amount of information it collects about skill gaps, training and the impact of skill gaps and shortages on firms, while also containing questions that are comparable with the existing individual-level PIAAC dataset. Unfortunately, their study design has only been implemented partially thus far, with a pilot study of firms in 6 European countries and a reference year of 2020 (OECD 2024).

Short-term, it is possible to link the existing surveys by aggregating and merging worker- and firm-level data; with most datasets, it is possible to link the data at least at the industry-region-size level (see Table 2 for a breakdown of surveys and their maximum available aggregation levels in these groups). Although this solution suffers from certain limitations–variations in observation years, coverage and definitions of skill gaps, to name a few, –it may nonetheless provide a basis for analysis that is more comprehensive than the ones that focus on only one group of respondents.

Table 2. List of datasets (last 10 years) and their maximum levels of aggregation on the industry-region-size axis

Survey	Firm or worker	Max level of aggregation
ECS 2019	Firm, ER	NACE: 1-digit Country Firm size: 4 groups
UK Employer Skills Survey	Firm	SIC: 13 sectors 9 regions of UK Firm size: 7 levels
Eurobarometer 529 (SMEs, 2023)	Firm	NACE: 1 Country Firm size: 5 levels
CVTS	Firm	NACE: 4 NUTS: 1 Firm size: 6 levels
EWCS	Worker	NACE: 2 NUTS: 2 Firm size: 8 levels
ESJS	Worker	NACE: 2 NUTS: 3 Firm size: 5 levels
EU-LFS	Worker	NACE: 1 NUTS: 2 Firm size: 5 or 2 levels
PIAAC	Worker	ISIC: 4 Country Firm size: 6 levels
ETLS 2024 (in progress)	Worker	TBA
EVTS 2025-2026 (in progress)	Vocational teachers	TBA

Since true matched employer-employee data does not exist at the European level, one way around the issue could be to create synthetic matches via tools like propensity score matching or instrumenta variable modelling. For instance, individual workers from ESJS or PIAAC may be matched with establishments from ECS or CVTS that share similarities across sector, firm size and region/country, with worker observations assigned propensity scores based on their probability to belong in a certain type of establishment. The key advantage over simple cell-averaging is that propensity score matching weighs observations to achieve distributional balance on observed covariates, reducing (though not eliminating) the compositional bias that arises when worker and establishment samples have different distributions of sector, size and country. It also produces standard errors that account for the matching uncertainty, which simple merging does not. The main limitation is that it only controls for *observed* characteristics. If workers in high-skill-gap firms differ from those in low-skill-gap firms in ways that are not captured by sector, size and country (region), the matched estimates would still be confounded. This is very likely to be the case if there are unobserved factors—such as firm wage levels or management quality—that simultaneously determine both how the firm invests in training and how large the workers' skill gap is. Nonetheless, this type of matching could be a valuable robustness check of the results and, to the best of our knowledge, has not yet been implemented in existing studies.[1]

2.1.2 Cross-sectional limitations

One major structural weakness of existing Europe-wide datasets is the cross-sectionality of data collected around the topic of skill gaps. This limits the ability to establish causality, analyse dynamics, or distinguish between cohort and period effects, among other things.

On the firm side, the issue of *causality* manifests in the ability to distinguish between skill gaps that the firm experiences and the firm's performance and skill-related practices. In other words, we cannot distinguish between skill gaps causing decrease in firm performance and whether firms that perform more poorly have a hard time finding and retaining skilled employees. Similarly, the motivation for and results of training remain ambiguous. On the employee side, cross-sectional approach means that there is no way to see whether the skill issue arose from the worker's current employment position lacking the support system for skills development or from skills atrophy due to lack of use or other factors.

Dynamics-wise, we cannot follow the firm's evolving relationship with skill gaps, the way the gaps change depending on the developments of technology, firm growth and training and other practices. Likewise, workers' skills, as well as their employment situation, change over time. A cross-section provides a glance about the skill situation at the moment, but nothing about how gaps form, persist, widen or close.

In addition, *survivorship bias* is severe especially for firms: the companies that closed due to skill deficiencies or were forced to significantly downsize will simply not appear in this kind of data. Furthermore, non-responsiveness itself is non-random: it could be argued that smaller enterprises, enterprises that experience financial difficulties and firms with poorly functioning HR management are less likely to respond or have sufficient knowledge to answer the questions. This creates non-random selection which is difficult to correct for without auxiliary data. At the worker level, existing comprehensive surveys also overrepresent currently employed individuals. People who left employment due to skill deficiencies thus remain less visible (in ESJS and EWCS more so than in PIAAC).

[1] For instance, Fialho et al. (2019) use PIAAC and sector-level OECD STAN to estimate the link between types of training, on the one hand, and productivity and wages, on the other. While the authors do find interesting results at the sector level, they also emphasise the need to reproduce this exercise with firm-level information, acknowledging the lack of datasets that have information both on participation in training and productivity. Morris et al (2019), on the other hand, merge firm-level data with more aggregated skill information. More recently, Jaumotte et al. (2026) introduce multilevel modelling to estimate the relationship between AI and future skill needs, merging Lightcast data with occupational and industry data from other sources .

The possible solutions to this issue are far beyond the scope of this project and might not be attainable in the near future due to administrative and other constraints. Nonetheless, we outline here several ways of approaching this problem, ranging in their levels of feasibility.

Adding questions to cross-sectional questionnaires. The least resource-intensive improvement would be to enrich the existing cross-sectional instruments with retrospective and persistence-oriented questions.

On the firm side, questionnaires should ideally include questions about the outcomes and effectiveness of previous activities—for example, “In the past N years, has your organisation’s investment in training resulted in a measurable reduction in skill gaps?” with response categories ranging from “significant reduction” to “no change” to “gaps have widened despite the training”. An advantage of ECS in this case is that it could provide the perspective from both employer and employee side, reducing the bias that would arise from a one-sided response. To capture persistence, a simple addition such as “Has your firm experienced shortages in any of the following skill groups for longer than 12 months?”, followed by a checklist of skill categories like problem-solving, advanced digital, technical or job-specific skills etc., would allow researchers to distinguish acute shortages from chronic ones without requiring longitudinal design. A standalone Eurobarometer survey on SMEs is currently the only one that collected this kind of information on a European level, with no discerning between skill types.

On the worker side, retrospective questions about skill development trajectories could also add a pseudo-dynamic dimension. While ESJS does ask the individuals about whether their skills in general improved, worsened or stayed the same since starting their current job, this question refers to the overall skill level rather than the gap relative to job requirements and does not distinguish between skill types. A natural extension would be to specify the retrospective question to include each of the types of skills already outlined in the skill gap section (technical, social and numeracy skills and ICT skills).

Longitudinal design with a follow-up survey. A more resource-intensive but substantially more informative approach would be to introduce a follow-up wave to existing surveys after two or three years. This would allow the tracking of whether skill gaps that were identified in the baseline survey persisted, closed or worsened, and whether interim training is associated with gap reduction.

Administrative data linkage. Encouraging linkage of survey data to administrative records (at least at country level) could address several limitations at once. At the firm level, tax records and business registers could provide more reliable information about such important indicators as firm performance, employment levels and dynamics and wages without having to rely on a single person’s knowledge or willingness to disclose. At the worker level, linkage to unemployment registers, training records or earnings histories would significantly enrich the data and allow researchers to observe outcomes after survey.

Follow-up surveys for struggling firms. A targeted follow-up for firms which reported severe or persistent skill gaps and shortages at the baseline—especially SMEs and firms with financial difficulties—would partially address the issue of survivorship bias. If firms have closed at the time of the follow-up, exit interviews with former managers could provide retrospective evidence that is currently lacking.

One-time study of unemployed and underemployed. One of the more direct ways to address survivorship bias on the worker side would be a dedicated one-time survey of individuals who are currently unemployed, underemployed or have recently left employment. Such a study, asking questions about self-assessed skill levels and deficiencies, skill demands on the last job, and the role of skill-related factors in their current employment situation, also does not need to be a large-scale longitudinal project.

2.1.3 SMEs' place in skill gap monitoring and analysis

Despite one of the recent Flash Eurobarometer surveys focusing on the skill difficulties of SMEs, there is little systematic zoom-in on this group of firms. If anything, Euribarometer-529 has made the need to monitor SMEs even more apparent by reporting the extent to which they struggle finding, retaining and training skilled workers: in total, more than 70% of surveyed SMEs reported having difficulty finding workers with the right skills in at least one major occupation group, and over half found it extremely or moderately difficult to retain existing qualified workers (European Commission 2023). These findings make a strong case for closer study of SMEs, but also raise methodological concerns: there is a high variation to the quality and types of HRM practices in smaller firms, which could potentially lead to either under- or overreporting of shortages or misdiagnosis of internal skill gaps. Smaller firms are much more likely to rely on informal human resource management practices, but those that adopt more sophisticated HRM practices report higher resilience (see e.g. Lai et al. 2016). As discussed in the previous section, struggling firms are also more likely to fall under the radar.

The most direct solution for monitoring would be to repeat a survey similar to Eurobarometer-529 longitudinally; however, this approach has organisational limitations, as noted previously. A somewhat more realistic approach is creating and integrating an SME skill gap monitoring module within an existing repeating survey (such as European Company Survey or CVTS), i.e., dedicating additional questions for respondents below a certain size threshold, or expanding the main module to include questions that are more relevant for SMEs.

At minimum, SME module should include questions about *informal learning* as a response to skill deficiencies—something that is currently missing both from the Eurobarometer Flash Survey and the surveys oriented at European firms at large. Prior findings imply that SMEs rely relatively more on informal learning, as it requires little to no cost (Fialho et al. 2019, OECD 2024), with the recent PIAAC-EM data (OECD 2024) showing that small firms tend to change work practices (such as work reallocation) in response to skill deficiencies more than larger firms.[2]

Next, the module could benefit from questions related to the firm's *capacity to diagnose and respond to skill gaps*, such as whether there are established HRM practices or whether the HRM practices are largely informal. Not only would this help capture HR deficit, but also allow to analyse the ways in which small firms without a dedicated human development structure report skill gaps and shortages differently compared to those in which a system is set up. Moreover, an SME module needs a question similar to the one in Eurobarometer about how difficult it is for the company to assess training needs, identify appropriate training opportunities, finance training and find time for it.

Next, a closer look should be given to *digital capabilities* of smaller companies: only 9% of small firms with digital skill gaps have made efforts to mitidate them, in contrast to around one third of medium-sized and large firms (Centeno et al. 2022); in general, SMEs show substantially lower rates of

[2] A less recent ECS (2019) dataset provides partial support for this. In all three firm size groups, most managers stated "learning from colleagues" as the most important process of upskilling, followed by trial and error and only then formal training. Still, small firms ranked "trial and error" as the most (rank 1) or second-most (rank 2) important learning pathway more often than medium and large firms. Although the difference is modest in magnitude, this ECS question asks about general firm practices, rather than practices in response to skill deficiencies like PIAAC-EM, which could have affected the responses. Additionally, it is possible that within-country or within-industry adjustment could show a different picture (as we have seen in the Management quality section, firm size effects can change dramatically after accounting for country weights).

advanced technology adoption, although the share of small firms with basic digital intensity has increased in the last several years (close to 70% in 2024 (Eurofound and Cedefop 2025), compared to 55% in 2021 (Eurostat 2022)). Whether the digital gap reflects a genuine skill deficit, a lack of training provision or a rational response to the scale of operations and sectoral specifics deserves closer attention. Despite the overall numbers, SMEs can be highly heterogeneous in their digital needs and maturity, which could in turn affect the incidence and distribution of skill deficiency issues that they face. At the very least, a research setup incorporating ICT usage information to classify SMEs by digital maturity could extend the understanding of how digitalisation affects and is affected by skill challenges in smaller companies. Identifying "digital laggards" and their specific skill challenges would further help zoom in on this firm group. As noted further in Section 2, country specifics are also important in this context: SMEs across European countries report significantly different levels of being affected by digital skill gaps and shortages (European Commission 2023), levels of internet use and complex digital technology use (Eurofound and Cedefop 2025).

Furthermore, SMEs *awareness of and access to public support mechanisms* should be studied more closely. Around 30% of SMEs expressed the need for better coordination with public employment services (more than half if we count "moderate" level responses); 19% (48% with "moderate") expressed the need for better tools for assessing the skills of prospective candidates; 18% (47%)—for better tools to evaluate their company's skill needs. The majority is not familiar at all with any of the EU funding programmes for skills and other skill initiatives (European Commission 2023). This disparity has significant policy implications but is not monitored systematically.

Finally*, collaboration* with other private organisations and public institutions is an important component of skill strategies in SMEs (Eurofound and Cedefop 2025, European Commission 2023). Only 9% of SMEs reported actually abandoning a business activity in response to skill shortages; most of them collaborated with public organisations (employment, education) or sectoral bodies, adjusted their search strategy or found ways to automate or outsource the tasks (European Commission 2023). The mechanism through which firms' collaborations with other entities translate into skill gap prevalence and mitigation remains an open research question and is largely absent from firm monitoring surveys.

2.2 Organisational practices and skill gaps

2.2.1 Wage-setting, working conditions and skill gaps

One of the major problems in identifying genuine skill gaps and shortages is the imperfect information on working conditions. When employers report skill deficiencies, it is hard to distinguish whether what they report is a genuine skill shortage or only a gap that exists due to insufficient salary levels, poor job quality, lack of benefits etc. On the other hand, workers can provide information about the actual job conditions and their (dis-)satisfaction with them but the information about the challenges their employer might face is hardly available to them.

The best international sources of information on working conditions in the European labour markets are EWCS, the last edition of which was published earlier this year, and PIAAC. Despite the wide variety of questions about job conditions, however, the respondents in EWCS are only asked one general question about the appropriateness of their skills for their job, which makes it hard to compare the results with other sources. PIAAC's background questionnaire includes information about job satisfaction, perceived appropriateness of wage level and whether the respondent is looking for a new job—all proxies for working conditions that drive voluntary turnover and thus add to labour shortages.

The firm-level datasets tend to be less informative on the topic of working conditions, since firms have limited incentive to disclose unfavourable conditions or below-market wages. It is, however, possible to capture wage-adjustment strategies of firms, including whether they are willing to increase wages to attract workers in the first place or if they prioritise other solutions. For instance, ECS asks managers directly whether the firm finds it difficult to recruit employees with required skills and whether monetary rewards are used to motivate and retain employees. Eurobarometer-529 asks SMEs an even more direct question of whether they have increased remuneration or improved conditions in response to hard-to-fill vacancies.

One of the solutions is related to the data-specific issue outlined elsewhere in this Section: having a dataset that allows to compare information from both sides would help reduce the issue of bias and under-reporting. One such survey already exists (ECS), i.e., in the medium term, extending the ECS questionnaire to include more questions about job conditions and the firm's willingness to adjust them seems to be feasible.

Some examples of additional questions that can be asked from the employee representatives in ECS include:

- "In your opinion, are the wages offered at this establishment competitive compared to similar jobs in the local labour market?";
- "In your opinion, to what extent do unfavourable working conditions—such as working hours, insufficient flexibility, physical demands or job insecurity—contribute to difficulties in recruiting and/or retaining employees at this establishment?"
- "Are there occupation groups in this establishment where employees frequently leave for jobs elsewhere?", and, if so, what could be the main reason. This last question parallels the voluntary turnover proxy measure from PIAAC discussed above.

Examples of additional questions for the management representatives in ECS include:

- "Has this establishment increased wages or improved working conditions in the past N years in response to difficulties recruiting or retaining workers?";
- "When you have difficulties filling vacancies, which of the following responses does this establishment typically prioritise? (increase wages; improve non-wage conditions; invest in training existing staff; reduce skill requirements; use temporary workers; leave vacancy unfilled etc.)";
- It might also be useful to include indirect questions and answer options in firm questionnaires, such as: "Which of the following factors do you think contribute to difficulties in recruiting or retaining workers with the right skills in this establishment? (prospective employees have salary expectations that we cannot meet; there is strong competition from other employers in this sector; there are simply not enough people with the right skills on the labour market etc.)“.

Additionally, there is a more short-term solution related to the fact that we know which sectors and occupations tend to be overrepresented when it comes to poor working conditions driving skill and labour shortages. Examples include education, healthcare and social care, construction, hospitality and food services, among others (Eurofound 2021, 2023, 2025, European Commission 2023, UNESCO 2024). The knowledge about specific sectors where structural issues tend to occur more often can help flag and partially correct for the bias in reported data without the need in new matched data. Namely, the analysis of skill gap surveys should introduce a clear distinction of responses in these "problematic" sectors, so that the generalised results are less biased and more clearly summarise the general trends. This could be done via analysing these sectors separately, introducing additional covariates or weights, a matching system, or constructing a proxy index based on several job conditions-related factors. Building upon the previous discussion about multilevel modelling, sector-level aggregates on job quality dimensions from individual-level datasets (work intensity, wage satisfaction, autonomy, physical hazards) can be used for linking with firm-level data on reported skill gaps and recruitment difficulties. The coefficient of job quality would signal whether poor job conditions predict gaps independently of sector skill supply.

2.2.2 The role of management quality

The quality of management is a major determinant of training investments, workforce planning, adoption of new technologies, employee retention and organisational learning (Schwalje 2012). While direct research on management quality and skill shortages is limited, productivity literature (e.g., Bloom et al., 2019, Brynjolfsson and McElheran 2016) shows links between management practices and productivity outcomes—implying that poor management weakens organisational adaptation capacity. This suggests that firms with poor management are more likely to fail to anticipate shortages, have high employee turnover, underinvest in skills and struggle to implement training effectively.

Despite being hard to quantify, managerial capabilities can be proxied through other indicators. An empirical exercise below (Table 3) uses a proxy of managerial quality by combining HR practices, performance management and employee involvement from the employer part of ECS. Ideally, ECS-based proxy allows the option of combining the information from both modules across several dimensions:

- *Performance management and skill orientation* (mostly managerial module): how quickly skill requirements change (a proxy for whether the firm is in a dynamic skill environment); share of workers in jobs requiring continuous training; difficulty finding skilled workers (potentially inversely related to proactive workforce planning); share of new hires not job-ready (a proxy for poor anticipation of skill needs); to what extent management sees employee skills as an important asset (exists both in firm and ER module).
- *HR practices and incentives* (managerial module): motivational strategy (monetary rewards, mission communication, stimulating work, training opportunities); hiring priority ranking (whether candidates' skills, education or cultural fit are prioritised in recruitment—a proxy for skill-orientation of hiring).
- *Employee involvement and voice* (employee representative module): whether workload is adjusted to allow training (a proxy for genuine commitment to development); extent of employee/ER influence on training decisions; to what extent management listens to employees.

Combining these into an index (e.g., via principal component or similar analysis or a simple additive score) would result in a firm-level management proxy ready to use as an input in further analysis. Moreover, for the subset of ECS where both questionnaires were completed, it is possible to construct a *discrepancy measure*—the gap between what the management reports about skill gaps and training and what the ER reports about the management's commitment to developing skills. For instance, a large discrepancy between management's self-reported training investment and the ER's assessment of management's attitude towards skills could itself be a basic indicator of poor management quality (the gap between stated and actual practices).

As an example, we combine several *firm-level* ECS variables (skillch, contr, wpsupp, mmepintrain, motilearn, hirecando, hiratt, hirqual, hirexp, motimon, motimis, motichal, motilearn) in a principal component analysis, taking the first principal component (PC1) as our measure of "management quality". The largest contributors to this measure in our case turned out to be the variables responsible for the firm's *practices used to motivate and retain employees* and the *extent to which employees have influenced* the firm's decisions on training.[3]

We then use this index, alongside country and sector fixed effects, to predict the firm's difficulties in recruitment (Table 3 columns 1-4) and providing training (columns 5-8). We see that our proxy is a somewhat good predictor of reported difficulties in recruitment and an even better (and more consistent) predictor of training provision. The clearest result is the correlation between our first PC—which reflects motivational strategies and employee orientation—and the probability of providing paid training to employees.

Unweighted results also show an additional positive relationship of management quality for small firms[4]. A somewhat counterintuitive result is that a higher management quality index is associated with small firms reporting more problems in recruiting; however, this might simply reflect the fact that better managed small firms are more likely to identify difficulties in the first place. Moreover, since the largest contributing factors to PC1 are non-monetary motivational practices for retaining employees, it might indirectly reflect the lack of monetary incentives that small firms are able to propose to potential hires.

Table 3. Management quality, recruitment difficulty and training provision

	Recruitment difficulty (binary)				**Training provision (binary)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Mgmt quality index (PC1)	-0.001 (0.011)	-0.015 (0.031)	-0.011* (0.006)	-0.051** (0.020)	0.278*** (0.010)	0.357** (0.141)	0.291*** (0.010)	0.355*** (0.068)
Size: small	0.225*** (0.055)	0.216*** (0.055)	0.170*** (0.036)	0.153*** (0.037)	-0.991*** (0.200)	-1.088*** (0.284)	-0.988*** (0.100)	-1.070*** (0.137)
Size: medium	0.123** (0.061)	0.126** (0.062)	0.037 (0.037)	0.020 (0.038)	-0.436** (0.206)	-0.548* (0.290)	-0.401*** (0.104)	-0.479*** (0.143)
Mgmt index × Small	—	0.024 (0.033)	—	0.057*** (0.022)	—	-0.078 (0.141)	—	-0.067 (0.069)
Mgmt index × Medium	—	-0.038 (0.038)	—	0.019 (0.023)	—	-0.093 (0.145)	—	-0.063 (0.072)
Weighted	yes	yes	no	no	yes	yes	no	no
N	18237	18237	18184	18184	18184	18184	18184	18184
Pseudo-R^2	0.203	0.203	0.174	0.174	0.440	0.440	0.441	0.441

Note: Probit estimates (coefficients). Recruitment difficulty: 1 = very or fairly difficult to find skilled workers, 0 otherwise. Training provision: 1 = any share of employees received paid training, 0 = none at all. Weighted models use wgt_EU_final.

[3] The second largest principal component, not used at the moment, represented the priorities in hiring practices.

[4] Unweighted data has a more even distribution of small firms across the countries; weighted results assign more weights to (especially small) firms in Germany, UK and France, most probably to reflect the actual composition within Europe. Weighted results are more representative in general terms; however, we also report unweighted results, in which smaller countries are not overshadowed by the weights. The fact that the interaction becomes significant without weights suggests the management quality effect on small firms is concentrated in countries that are oversampled.
It is worth noting that, in all these models, within-country variation is substantially higher than between-country variation, meaning that the relationship between management quality and firm size is highly sensitive to country context. In other words, this difference in results might reflect the difference in institutional contexts (labour market structures, training systems, industrial relations etc.).

McFadden pseudo-R^2 reported for all models. Standard errors in parentheses. Reference category for firm size: large (250+ employees). Controls include sector and country fixed effects. * p<0.10, ** p<0.05, *** p<0.01.

However, firms are not the only potential source of information about management quality. Employee-level datasets such as ESJS and PIAAC collect data on satisfaction with the immediate supervisor, autonomy to make decisions on how to do one's work and learning opportunities at work. Although not a representative proxy for *firm-level* management quality, this still opens up a way to expand on existing research by linking the (direct, individual-level) management variables to skills-related activities within the organisation. For instance, both ESJS and PIAAC have items on whether the respondent's job has changed due to new technology or organisational changes. A natural extension would be to test the hypothesis of whether workers in jobs that have recently changed due to technology report weaker gaps when their perception of management is satisfactory—the implication being that good managers anticipate and mitigate skill obsolescence through training and task redesign.

Table 4 below investigates the extent to which management quality (proxied by management satisfaction) might mediate the effects of recent technological change on the worker's skill gap in general (columns 1-3) and in ICT skills specifically (columns 4-6), based on the last wave of ESJS. Here we take the proxy of satisfaction with the supervisor or manager to create a binary indicator (columns 2 and 5 – dummy = 1 if satisfaction is above median value; columns 3 and 6 – dummy = 1 if satisfaction is in the top quartile; columns 1 and 3 – dummy = 1 if satisfaction is in the bottom quartile). The coefficient of the interaction term indicates whether or not management satisfaction above a certain threshold increases or decreases the probability of technological change inducing a skill gap.

Recent technological change itself is positively related to reporting a skill gap in general (first row in columns 1-3), and a skill gap in ICT skills especially (columns 4-6). The workers who are less satisfied with their supervisors are even more likely to report having a gap in digital skills after technological change (third row in column 4), but not the need to develop the skills for their job in general (column 1). On the other hand, those who are satisfied with their supervisors to some degree (above median) or very satisfied (top quartile) are less likely to report the need to improve their ICT skills to be able to do their job after their workplace introduces technological change.

This suggests that the same technological change event can have very different skill gap consequences, depending on the quality of management. Although technological change increases the probability of reporting a skill gap for everyone in our sample, poor management further exacerbates this problem, while better (-perceived) management seems to help mitigate part of the technology's effect. Notably, this moderation effect does not extend to general skills (unless management quality is viewed as exceptionally high) and is mostly reserved for digital skills.

Table 4. Technological change at the workplace, management satisfaction and the probability of (reporting) skill gaps

	Dependent variable – skill gap (any skill, dummy)			Dependent variable – skill gap (digital skills, dummy)		
	MS at or below lower quartile threshold	MS above median	MS at or above the top quartile threshold	MS at or below lower quartile threshold	MS above median	MS at or above the top quartile threshold
	(1)	(2)	(3)	(4)	(5)	(6)
Technological change in the last 12 months dummy	0.760*** (0.059)	0.773*** (0.065)	0.822*** (0.062)	0.846*** (0.046)	1.013*** (0.056)	0.981*** (0.051)
Management satisfaction dummy	-0.037 (0.053)	0.116** (0.051)	0.014 (0.052)	0.068 (0.045)	-0.032 (0.042)	-0.135*** (0.043)
Tech change × Mgmt satisfact	-0.033 (0.099)	-0.059 (0.094)	-0.187* (0.095)	0.173** (0.084)	-0.215*** (0.077)	-0.181** (0.077)
Number of observations	46213	46213	46213	46213	46213	46213
Pseudo-R^2	0.467	0.467	0.467	0.5	0.5	0.501

Note. Median - 7, top quartile threshold - 9, lower quartile threshold - 5; the range is from 0 (completely dissatisfied) to 5 (moderately satisfied) to 10 (completely satisfied). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. controls include education (higher, dummy), occupation group, firm size group, country and sector.

In summary, future research should focus more on the relationship between managerial capabilities and skill shortages and gaps, including the identification of whether better-managed firms experience fewer shortages and gaps or simply manage them more efficiently—through better training, more accurate anticipation of needs and lower employee turnover—without necessarily reducing gap prevalence.

There is also a number of approaches to measuring management quality that we have not discussed in this section but which do exist, for instance, in productivity literature (such as firm's digital capabilities and performance measurement practices, to name a few (Brynjolfsson and McElheran 2016)). Furthermore, employee representation itself—from collective bargaining to decision-making structures more broadly—may have an effect on the way companies experience and mitigate skill deficiencies. As discussed in the previous Deliverable 4.1, there is a reason to suspect that worker representation and employee-oriented HR practices impact the firms' decisions regarding training at least when it comes to their lower-skilled employees. A related research question would be whether union presence is associated with reductions in skill gaps for lower-skilled workers through negotiated training and other mechanisms. At minimum, introducing a control factor derived, for instance, from OECD Employment Protection Legislation indicators, in skill gap analysis could serve to check the robustness of results—especially if the analysis is focused on lower-skilled and lower-wage employees.

2.3 Employees and firm composition

2.3.1 Skill gaps in context: skill-skill complementarity

There is a growing literature investigating the interactions between, and the complementarity of, different skills of an employee. For instance, Stephany and Teutloff (2024) show that the utility of a skill is increased the most when combined with skills of different types; Hosseinioun et al. (2025) further document the ways in which skill networks have an increasingly more nested element to them, suggesting that specialised skills act complementary to the more embedded general skills, but the reverse is not necessarily true. However, Stephany and Teutloff (2024) and Hosseinioun et al. (2025), while centering interskill relationships, focus on the more traditional labour market outcomes such as skill wage premium. In recent skill gap literature, McGuinness and Staffa (2025) document the relevance of job complexity for skill gaps in general, although the nature of the relationship between the two remains unanswered. Specifically, it remains unclear whether in more complex jobs skill gaps in one area cascade into others due to interdependence of tasks—or, conversely, whether workers in complex jobs may be better positioned to compensate for gaps in one area by focusing more on another.

Despite the increasing evidence of skill interdependence, the existing research on skill *gaps* still largely treats skills as a list of separate capabilities, rather than an interdependent network. This is a significant omission, especially because co-occurrence of skill deficiencies may not be symmetrical. For instance, a *deficiency* in one of the fundamental skills (e.g., literacy) could be expected to propagate into other areas, since many higher-order capabilities build on it. At the same time, high *levels* of a fundamental skill would not necessarily translate into lower skill gaps in other domains. On the other hand, a *gap* in problem-solving skills could be expected to be associated strongly with gaps in other areas, and we could also expect high *scores* in problem-solving to be associated with fewer or less severe gaps in other areas. For some transversal skills, however, such relationships are less straightforward. For example, the direction and magnitude of the effects of social skills on other skills may depend more heavily on occupational and sectoral context, with social skills acting as complements to other skills in some cases and being largely independent in other ones.

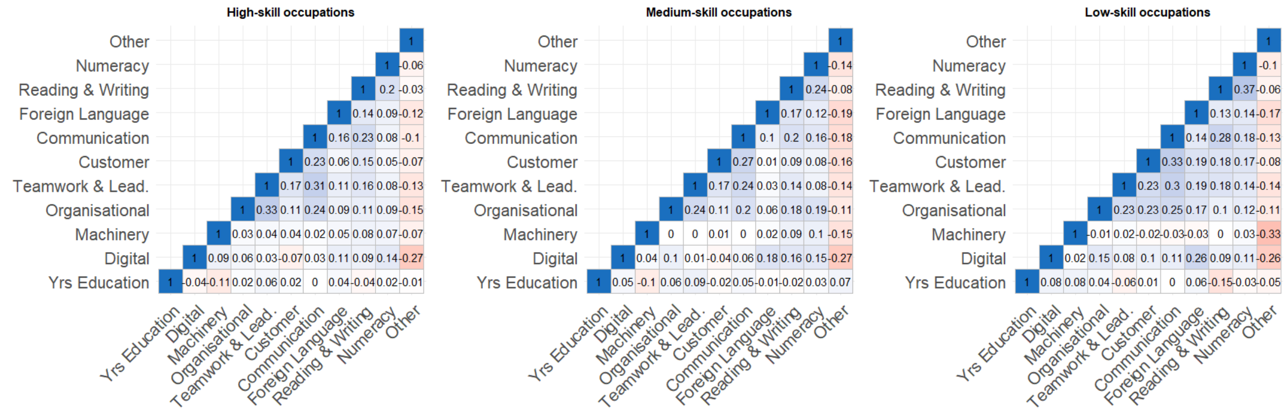
As an illustration, Figures 1 and 2 below document pairwise correlations between the skills in which respondents reported to have gaps, in the second cycles of PIAAC and ESJS, respectively. In both cases, but especially in PIAAC, we see that the skill gap correlations are stronger among the lower-skilled workers than their higher-skilled counterparts, suggesting that the spillover effect outlined above is indeed reasonable to assume. The highest correlation with other skill gaps in ESJS stems from *numeracy* in all employee groups, but especially in the *lower-skilled* one; in PIAAC, both *numeracy and literacy* (Reading & Writing) are strongly associated with skill gaps in other areas and with each other—again, especially for the lower-skilled. For medium- and low-skilled, deficiencies in social skills are also more likely to co-occur with deficiencies in literacy skills.

Interestingly, while a strong relationship between different categories of social skills in Figure 1 is to be expected, it is worth noting that *the lack in some of social skills is also highly interdependent with the lack in organisational skills*. This is worth investigating in further research on the topic. Another notable finding is that skill gaps in operating machinery and equipment appear to be largely independent from other skill gaps, which makes intuitive sense given that this is a rather technical type of skill which does not propagate into other areas the way more foundational skills like communication or literacy do.

Finally, a gap in foreign language skills is associated with a gap in digital ones for lower-skilled, but not so much for other workers. It is possible that this reflects occupational sorting: digitally-intensive jobs being more internationally oriented and concentrating more on the high-skill end of the distribution, leading to most workers have either both or neither gap.

All in all, this exercise demonstrates that considering skill-skill relationships is not only important, but crucial especially for lower-skilled workers.

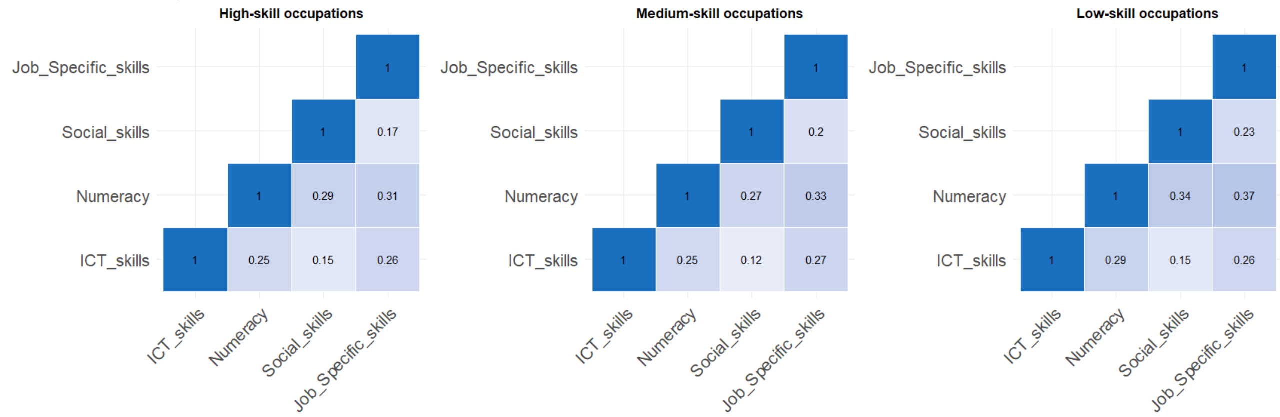
Figure 1. Pairwise correlations between types of skill deficiency among workers whose skills fall below job requirements



Source: Calculations from PIAAC cycle 2 (2023), European countries.

Notes. High-skill occupations – ISCO codes 1 through 3, medium-skill – 4 through 6, low-skill – 7 through 9. Except for years of education, the variables are binary. The row with years of formal education is based on fewer observations due to missing values.

Figure 2. Pairwise correlations between types of skill deficiency among workers whose skills need further development



Source: Calculations from ESJS wave 2 (2021).

Notes. High-skill occupations – ISCO codes 1 through 3, medium-skill – 4 through 6, low-skill – 7 through 9. All variables are binary; ICT skills dummy has the value of 1 if digital skills need to be developed to a great or moderate extent.

There are some important data constraints and further methodological approaches worth discussing. Among existing datasets, granular information on specific skill deficiency types is available primarily from worker surveys. Still, even ESJS is rather limited to a few basic skill groups, which limits the capacity for analysis. Arguably, in the case of ESJS a combination of occupational data and ESCO taxonomy could be used to further improve the analysis on the relationship between skill interdependencies and skill gap. A research setup similar to (the US-based) Alabdulkareem et al. (2018) could be implemented, where a skill relatedness network is mapped to obtain information about skills that are structurally central (and thus more likely to propagate to others), and which are peripheral. This could be used to further compare the skill profiles of workers within occupation-sector groups and the extent to which their skill gap patterns follow patterns typical within the group.

Firm-level surveys rarely address the heterogeneity of skill gaps (see part of the discussion in Section 2 and Table 1). Apart from UK ESS and PIAAC-EM, which are limited to 1-6 countries, and Innobarometer, which captures information only in the narrow context of innovation needs, firm-level European surveys omit the distinction between skill types entirely. This creates a problem, since job-specific, digital, social skills and basic skills like literacy are all considered equally. Ideally, the *skill types should be harmonised across employee- and employer-based datasets*. For instance, PIAAC's classification is one of the most comprehensive and overlaps largely with the skill types outlined in UK ESS and PIAAC-EM.

2.3.2 Co-worker complementarity

Another overlooked topic in the skill gap (and even broader skill-adjacent) literature is the complementarity between co-workers. As discussed in the previous Deliverable 4.1, there is some, albeit limited, literature documenting the complementarity of workers when it comes to labour market outcomes (e.g. Neffke 2019, Moscelli et al. 2025); however, relationship between worker interdependence and skill gaps—both when co-worker profiles are complementary and when they are not—remains largely underexplored.

Meanwhile, teamworking gaps are rather well documented: in European countries, teamworking skills consistently rank among the most significant skill groups in which firms report gaps (OECD 2024) and are among the top emerging skills identified through online job postings (SkillsPulse 2025c). Beyond the prevalence of teamworking gaps, recent firm-level evidence suggests that firms with skill gaps are, on average, likely to have fewer employees who work in teams, to have meetings to improve working practices, or to utilise databases of best practices. The teamworking gaps are especially important for SMEs, where a major way of addressing skill gaps is redistribution of labour within the team (OECD 2024). However, the extent to which task redistribution is used as a response to skill deficiencies, and under which conditions it is effective, is not systematically captured across Europe.

One useful addition to the employee surveys would be a question on whether the respondent works with employees who have substantially different profiles. In some countries, this may be captured indirectly in administrative data via comparing the (occupational) skill profiles of employees working in the same firm; however, this kind of data does not distinguish between those who work on the same projects from those who simply work at the same company. Collecting more direct information on the topic would allow to test, for example, whether skill diversity in the immediate workplace is linked to (lower) prevalence of skill gaps.

On the other hand, firm representatives could be additionally asked to elaborate on ways in which they address skill gaps other than training, such as task redistribution within work teams or placing employees with skill gaps alongside more skilled workers (in a way that is similar to UK ESS and PIAAC-EM).

Continuing the exercise from the previous section, we further look at the ways in which skill gap correlations change, depending on the extent of co-worker cooperation (Figures 3 and 4 below). An initial hypothesis would be that employees with higher co-worker support show weaker skill gap correlations, because co-worker assistance partially compensates for individual deficiencies, weakening the negative spillovers. We again utilise individual-level PIAAC and ESJS, narrowing in on those who reported having skills that are lower than the required level.[5]

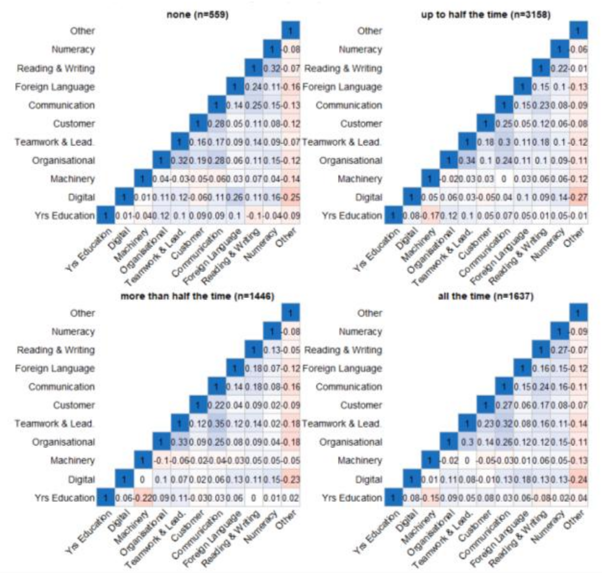
[5] Importantly, ESJS does not provide information on a skill gap in problem-solving. This measure can be constructed from PIAAC based on the actual scores in problem-solving and the individual's occupational profile, but for ESJS this is a rather serious omission. Problem-solving has been consistently one of the most problematic areas reported by employers (see e.g. OECD 2024), and there needs to be a mirror measure in worker questionnaires.

We see that skill gap correlations do change depending on the level of co-worker cooperation; however, PIAAC results suggest that there might be a U-shaped pattern. Low-skill workers (Panel 3b) report skill gaps that are less correlated if they work with others up to half the time or most of the time, partially supporting our hypothesis above. However, the highest skill gap interdependencies for this group are situated on the extremes: both those who do not cooperate with co-workers at all and those who cooperate all the time are more likely to have skill deficiencies from one area be related to deficiencies in another. This pattern is absent from the more general sample (Panel 3a), which may imply that co-worker cooperation is more crucial in mitigating skill gaps for lower-skilled than other workers. The U-shape is especially visible when we look at basic skills. Some of the strongest correlations are between numeracy and literacy skill gaps for the low-skilled workers who either don't work with others at all or work with others all the time.[6]

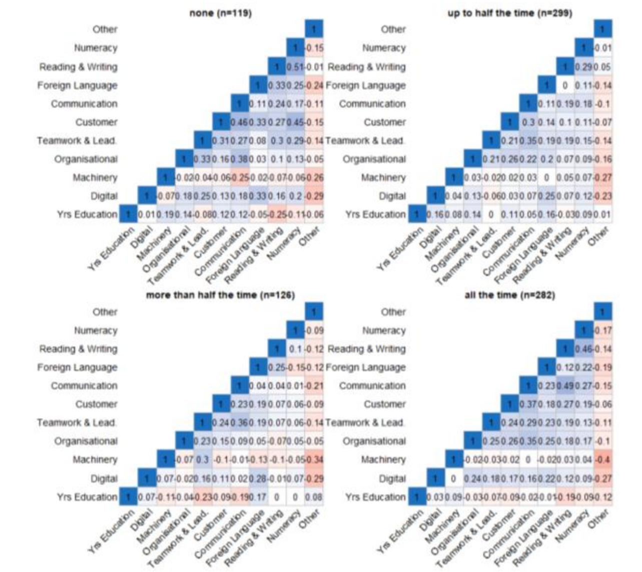
Another notable finding is that for the overall sample there is a relationship between gaps in digital skills and in foreign language skills, but only for those who do not work with others as part of their job (Panel 3a). This pattern is consistent with the selection argument: if workers are more likely to have jobs that simultaneously require both digital and foreign language skills, then having no benefit of colleagues who could compensate for deficiencies in one type of skill creates problems that affect another type of skill. In contrast, in team-based environment digital and foreign language tasks may be distributed across team members with complementary profiles.

Figure 3. Skill gap correlations by extent of co-worker cooperation, PIAAC.

Panel 3a. All occupations



Panel 3b. Low-skill occupations



Source: Calculations from PIAAC cycle 2 (2023), European countries.

Notes. High-skill occupations – ISCO codes 1 through 3, medium-skill – 4 through 6, low-skill – 7 through 9. Except for years of education, the variables are binary. The row with years of formal education is based on fewer observations due to missing values.

ESJS data, on the other hand, tells a somewhat different story (Figure 4). In the lower-skilled occupation group, there is a visible monotone pattern between teamwork, ICT skills and technical skills (Panel 4b): the higher the frequency of working in teams, the stronger the relationship between ICT skill gaps and technical skill gaps. One potential explanation could be that, on low-skill jobs that

Self-assessment of such a skill by an individual has significant limitations, but can be overcome, for example, by anchoring a question in concrete examples and/or splitting it into several components of problem-solving.

[6] Group sizes in this dataset are small for the low-skill group, so any generalisations should be treated with caution.

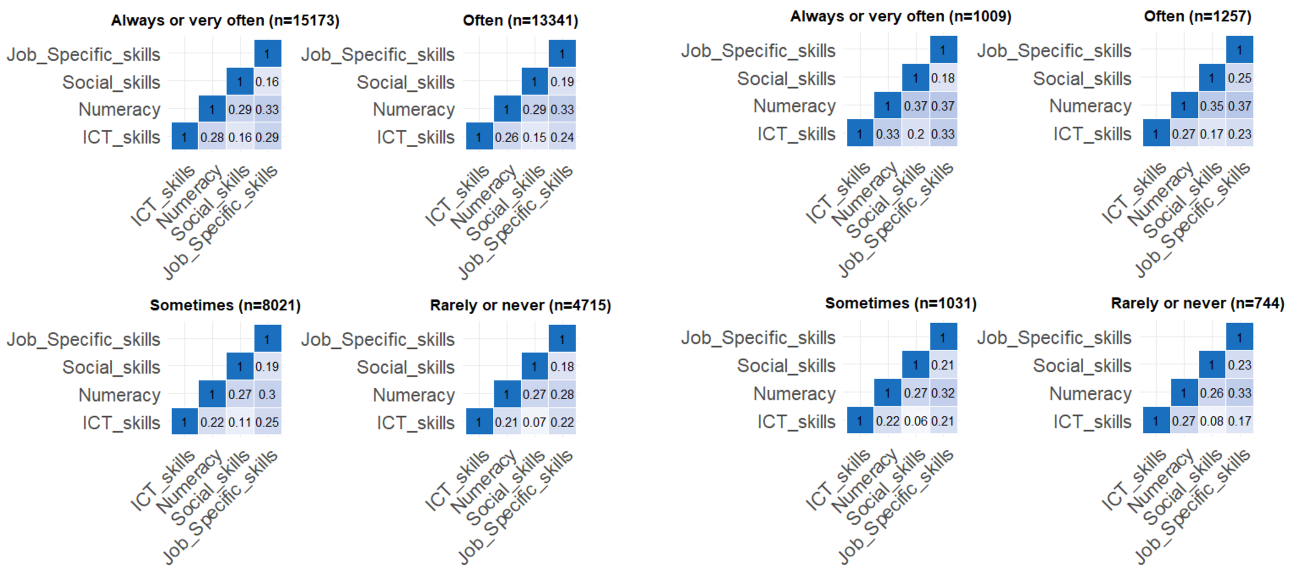
involve frequent teamwork, digital tools are increasingly used for task coordination (scheduling, reporting, communicating with supervisors, logging work completion). In that case, for lower-skill workers who rarely work in teams, job-specific skills and ICT skills would more likely be demanded independently (e.g., a machine operator needs technical skills for the equipment but may never use workplace digital communication tools). The PIAAC figure for the lower-skilled partially supports this reasoning: employees on lower-skill jobs with no teamwork (upper-left in Panel 3b) are less likely to report skill gaps in communication alongside skill gaps in machinery skills.

Across all occupations (Panel 4a), there is also a linear pattern emerging from levels of teamwork—in this case, between ICT skills and social skills. Similarly, the higher the intensity of working in teams as part of one's job, the more skill gaps in one area are likely to be reported together with deficiencies in another one. This pattern holds also for the lower-skilled, except that for them the main distinction is between working in teams sometimes or never (correlations closer to 0) versus often or always.

Figure 4. Skill gap correlations by frequency of teamwork, ESJS wave 2.

Panel 4a. All occupations

Panel 4b. Low-skill occupations



Source: Calculations from ESJS wave 2 (2021).

Notes. High-skill occupations – ISCO codes 1 through 3, medium-skill – 4 through 6, low-skill – 7 through 9. All variables are binary; ICT skills dummy has the value of 1 if digital skills need to be developed to a great or moderate extent.

In both PIAAC and ESJS, there is a notable difference between the lower-skill group and the general sample, which is itself an interesting pattern. Teamwork frequency in both cases affects the distribution of skill gaps for lower-skill workers, but not so much for the workforce as a whole. This preliminarily supports the argument that co-worker complementarity effects are concentrated among workers with lower-complexity jobs where foundational skill deficiencies are more likely to cascade.

Several avenues for further research follow from the findings and limitations discussed in this section. First, the relationship between team autonomy and skill complexity requires further investigation. For instance, teams with higher autonomy might require more advanced coordination, self-management and conflict resolution skills, and skill deficiencies in these areas could have spillover effects on other skills. Testing this would require linking team autonomy measures to individual skill gap outcomes, ideally distinguishing between more technical, job-specific skills and transversal skills. Second, the preliminary finding that workplace cooperation changes the pattern of skill gap co-occurrence raises the question about the underlying mechanisms: for example, whether workers in high-cooperation environments are more likely to report learning from colleagues as their primary skill development route.

2.4 Conclusion

Skill shortages and gaps are shaped not only by labour market dynamics but also by the internal characteristics, practices and strategic choices of firms. In the previous report of this Work Package, we have discussed common topics linking employer characteristics and practices to skill gaps, overviewed Europe-wide datasets that collect data on both and identified gaps in research and data. In this report, we expand on the discussion of gaps in research and data when it comes to the analysis of skill gaps and shortages in the context of firm factors. Section 2 reiterated the gaps and proposed a roadmap of solutions to address them, within and outside the scope of this project.

First, it discussed the structural issues arising from the one-sidedness of existing European datasets and their cross-sectional nature, outlining the ways in which these issues can be mitigated directly in future research (such as linking firm- and employee-level information on the sector-region-size axis) and long-term in survey design (such as by introducing additional modules for collecting granular information, allowing for linkage to administrative data and implementing follow-up modules to overcome survivorship bias).

Next, it discussed several core research gaps and study design limitations in the existing analysis of skill gaps: skill interconnectedness, co-worker complementarities, working conditions and the factor of management quality. Sections 2.2 and 2.3 summarise the methodological limitations associated with these areas and suggest approached to help mitigate them.

The next Section 3 addresses the research gaps that were outlined in Deliverable 4.1 and remained unaddressed in this section: namely, (i) the relationship between Artificial Intelligence technologies and skill gaps and (ii) the overreliance on retrospective data in discussions around skill gaps. To tackle these issues, Section 3 introduces a forward-looking methodology based on patent data, targeting the growing area of AI which, at the moment, is unclear in its future effects on the labour market. Unlike traditional survey-based information discussed in Section 2, patents offer an anticipatory dimension, which can help identify focus areas before the effects manifest in the broader labour markets.

Subsequent work packages of this project will further address the gaps in knowledge surrounding skill gaps and shortages. The survey of employers under WP4, based largely on the UK ESS methodology, will add to the granularity of data on skill gaps from the firm perspective in selected European countries; a skill deficiency index, developed under WP6, will help identify potential skill shortages in a more timely manner than is possible with the current historical data; finally, WP7 will integrate the results of the previous work packages into a comprehensive software tool.

3. Identifying emerging skills through patent analysis: the case of AI-related skills

3.1 Introduction

The purpose of this chapter is to describe and demonstrate how to conduct a **Natural Language Processing (NLP) analysis to identify emerging skills using patent documents** and, in doing so, anticipate current and future trends in industry.

Our analysis builds on a central assumption that technological advancement and skill development are deeply interconnected. Each technological breakthrough generates new requirements in terms of knowledge, expertise, and competencies. Therefore, mapping technological change is a necessary first step to identify the skills that companies and individuals will need to develop in the near future. This relationship between technological change and skills has been widely discussed in the academic literature (Acemoglu, 2002; Acemoglu et al., 2022; Acemoglu, 2025).

Building on these premises, this document illustrates how to analyse technological trajectories and identify emerging technologies in a defined domain, and how to connect these technological dynamics to the skill needs.

Our analysis of technological trends is based on patent documents[7]. It is essential to clarify that patents mainly enable the identification of skills associated with technological development, implementation, and management. They are well suited to capture competencies required to engineer, deploy, maintain and manage technologies, but they are less effective for detecting social, cultural, or organisational skills that emerge from broader transformations in work practices or institutions. To analyse these dimensions, other textual sources—such as course descriptions (Mason et al., 2023) or job postings (Colombo et al., 2019)—are often more appropriate. Nevertheless, patents typically offer strong anticipatory power, meaning they can signal emerging directions earlier than many other sources.

As explained in Deliverable 4.1 (SkillsPulse 2025a), to demonstrate the practical value of the approach, the analysis must be applied to a clearly defined technological field. This is necessary for both methodological and managerial reasons. Methodologically, because the approach relies on patent analysis, applying it without any domain boundary would require analysing the entire global patent corpus. This would be computationally demanding and impractical from a storage perspective, given that the number of patent documents worldwide exceeds ten million. Managerially, without a defined scope, results risk becoming generic or misleading: a skill that is critical in one technological domain may be marginal in another. Domain specificity is therefore essential to generate actionable insights. For these reasons, we apply the method to a specific field: **Artificial Intelligence (AI) technologies**.

We selected AI for three main reasons. First, its relevance has grown dramatically in recent years, especially after the diffusion of Generative AI, which is increasingly pervasive across industries and across multiple aspects of everyday life. Understanding its implications for skills is particularly important to anticipate workforce needs and mitigate adverse phenomena such as skill erosion. Second, the AI field is supported by a rich body of prior research and policy analysis on technologies and skills. This includes both policy-oriented perspectives (e.g., the World Economic Forum[8], WIPO technology trend reports[9]; OECD, 2025) and academic contributions (e.g., Colombo et al., 2019; Giordano et al., 2024a). This enables comparison between our findings and existing evidence, strengthening the interpretation of our findings. Third, the NLP pipeline presented in this document relies on a domain dictionary, namely a curated list of AI-related terms used to identify AI technologies within patents by searching for dictionary terms in patent text. Since the quality of skill identification depends heavily on the precision and completeness of the AI dictionary, it is crucial to rely on a validated resource. Building and validating such a dictionary from scratch would require substantial time, financial resources, and expert involvement, and it falls outside the scope of this deliverable.

[7] A detailed discussion of this methodological choice, and of the type of information patents can provide, is available in Deliverable 4.1 (SkillsPulse 2025a).
[8] See https://www.weforum.org/stories/2026/01/ai-and-human-skills/. Accessed March 2026.
[9] See https://www.wipo.int/en/web/technology-trends/artificial_intelligence/index. Accessed March 2026.

The AI field offers several existing and validated dictionaries and taxonomies (e.g., Liu et al., 2021; Eicke et al., 2025), which can be leveraged as reliable inputs for the analysis.

AI has attracted major academic attention and industrial investment for decades. However, despite more than sixty years of research, AI remains challenging to define in a way that achieves full consensus (Truong & Papagiannidis, 2022). AI is best understood as an umbrella concept that includes a broad set of technologies—such as machine learning, deep learning, natural language processing, computer vision, and Generative Pre-trained Transformer (GPT) systems—rather than a single, well-delimited technology. This document does not aim to provide an exhaustive review of AI definitions. Instead, we adopt a pragmatic definition aligned with the purpose of this deliverable. We define AI as computer systems able to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making, through the use of algorithms that enable machines to analyse data, recognise patterns, and generate predictions or actions without explicit instruction for each specific case (Giordano et al., 2024a). Accordingly, when this document refers to AI, it considers not only Generative AI and not only machine-learning-based systems, but more broadly any system designed to automate or support cognitive processes involved in human decision-making. This also includes rule-based approaches, such as expert systems, where automation is achieved through encoded knowledge and decision rules.

The remainder of the document is organised as follows. Section 3.2 describes the methodology used to extract AI-related technologies from patent documents and to track their technological trajectories over time. Section 3.3 presents the results of the AI technology analysis. Section 3.4 explains how technologies can be linked to skills and illustrates this process in the AI domain, moving from identified AI technologies to the corresponding emerging AI-related skills.

3.2. Methodology

The methodology is structured into four main steps, as illustrated in Figure 5: (1) patent document collection, (2) text preprocessing, (3) text modelling, and (4) text analysis. The following sections describe each step in detail, with specific reference to the AI domain.

3.2.1 Patent document collection

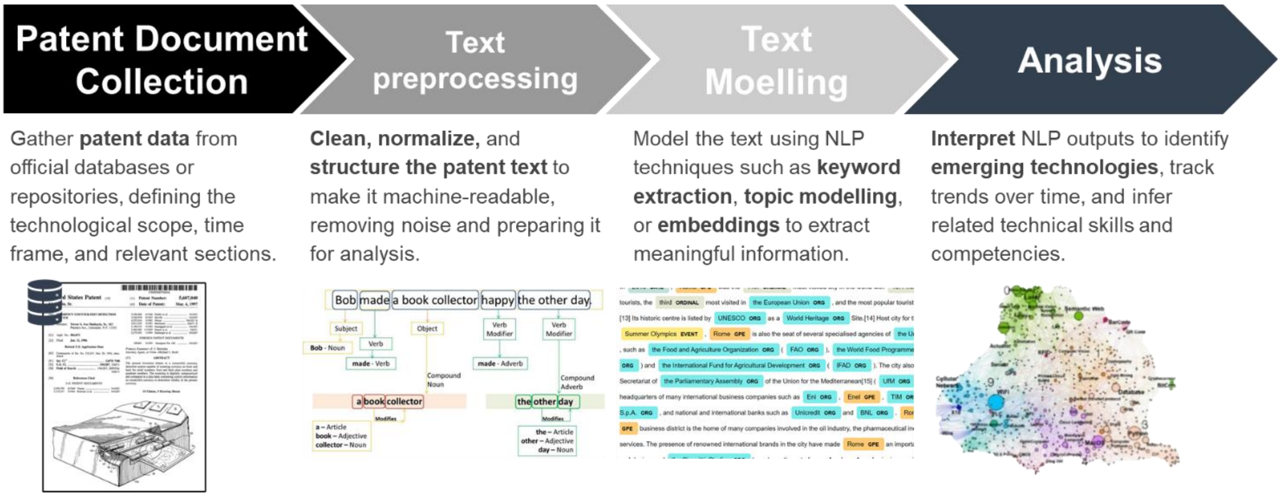
The first stage, **Patent Document Collection**, consists of retrieving patent data from authoritative sources such as patent offices and major patent databases (e.g., EPO, USPTO, and WIPO). In our case, the objective is to collect patents related to Artificial Intelligence.

In recent years, substantial efforts have been devoted to building large-scale textual datasets on AI, particularly from scientific publications and patents. The availability of these data is crucial because it enables empirical analyses of how AI technologies evolve and how they influence skill requirements. At the same time, because AI displays typical characteristics of an emerging technology—radical novelty, rapid growth, internal coherence, potentially high impact, and uncertainty (Rotolo et al., 2015)—defining its boundaries remains challenging (Fujii & Managi, 2018).

Several initiatives have addressed this issue by developing robust approaches for identifying AI-related documents. Liu et al. (2021) proposed an extensive search strategy to retrieve AI-related scientific publications and associated concepts. Similarly, the World Intellectual Property Organization (WIPO, 2019) developed comprehensive queries to identify AI-related patents and publications, covering more than 340,000 patents and 1.6 million scientific papers. More recently, Pairolero et al. (2025) introduced a machine-learning-based method to detect AI patents within the United States

Patent and Trademark Office (USPTO) database, resulting in the Artificial Intelligence Patent Dataset (AIPD).

Figure 5. NLP pipeline for patent analysis.



In this deliverable, we rely on the AIPD to retrieve AI-related patents for two reasons. First, the dataset is described in a peer-reviewed publication (Journal of Technology Transfer) and has been developed in close connection with the USPTO, providing a strong level of credibility and methodological transparency. Second, it is openly available and can be linked to other USPTO resources, including titles, abstracts, descriptions, and bibliographic information. The AIPD includes both granted and pre-grant publications from 1976 to 2023, for a total of 2,628,504 documents. For each patent, it provides a probability score (ranging from 0 to 1) indicating the likelihood that the document belongs to a given AI technology component, with separate scores provided for different components. Following Pairolero et al. (2025), patents are classified as AI-related when the score exceeds 0.500.

From this corpus, we extracted AI patents published between 2010 and 2023, resulting in **727,245 patent documents**. For each patent, we collected the title and abstract, which constitute the textual material used in the subsequent NLP analysis. Table 5 provides an illustrative example of patents included in the resulting dataset.

3.2.2 Text preprocessing

The second stage, **Text Preprocessing**, prepares patent text for machine-readable analysis. In our case, we begin by merging the patent title and abstract into a single text field. This choice reflects the fact that both sections provide concise and highly informative descriptions of the invention, and relevant technological concepts may appear in either one. Treating them jointly ensures that we do not miss signals simply because they are mentioned in the title rather than in the abstract (or vice versa).

Table 5. Example of patents

Patent ID	Year	Title	Abstract
7640673	2010	Calibration and operation of wheel alignment systems	A method is provided for calibrating a sensor pod of a wheel alignment system, the sensor pod including a housing rotatably mounted on a spindle, and an image sensor in the housing having a viewing axis oriented in a direction substantially normal to an axis of rotation of the spindle for imaging a target affixed to an object such as a vehicle wheel. An example of the method includes mounting the pod on a fixture via the pod spindle such that the pod spindle is stationary, and positioning a target to allow imaging of the target with the pod image sensor. The pod is rotated such that its image sensor obtains images of the target in at least two rotational positions, and

Patent ID	Year	Title	Abstract
			the images of the target at the at least two rotational positions are processed to determine the location of the axis of rotation of the spindle relative to the image sensor.
7640746	2010	Method and system integrating solar heat into a regenerative rankine steam cycle	A method to integrate collected solar thermal energy into the feedwater system of a Rankine cycle power plant is disclosed. This novelty uses a closed loop, single phase fluid system to collect both the solar heat and to provide the heat input into the feedwater stream of a regenerative Rankine cycle. One embodiment of this method of integrating solar energy into a regenerative Rankine power plant cycle, such as a coal power plant, allows for automatic balancing of the steam extraction flows and does not change the temperature of the feedwater to the boiler. The concept, depending on the application, allows for the spare turbine capacity normally available in a coal plant to be used to produce incremental capacity and energy that is powered by solar thermal energy. By “piggybacking” on the available components and infrastructure of the host Rankine cycle power plant, considerable cost savings are achieved resulting in lower solar produced electricity costs.
7640747	2010	Method for converting thermal energy into useful work	A method for providing the interaction of the working medium with the heat energy source and also the interaction of the working medium with the additional low-temperature energy source, wherein the positron state of the Dirac's matter is used as said additional low-temperature energy source, and the interaction of the working medium with the additional low-temperature energy source is performed by bringing the working medium into the quantum-mechanical resonance with said state of matter. That is, in order to convert the heat energy into useful work, the capabilities of the quantum-mechanical resonances of the system ‘working medium—additional low-temperature energy source’ are used, i.e. in this case capabilities of the system ‘working medium—positron state of the Dirac's matter’ are used.
7640755	2010	Dynamic process control	A method and apparatus for defining the processing of an ingredient of a manufactured product, particularly one that is manufactured “one-the-spot” to a consumer's specification, such as ice cream, among other products. A tag encoded on a container for the product carries indicia that, directly or indirectly, define one or more formulations for the product. Apparatus into which the ingredient is loaded sets the processing of ingredients in accordance with the formulations so specified. By connecting the apparatus which is to process the ingredients to a control station, the formulations may be changed at will.
7640793	2010	Systems and methods for determining airflow parameters of gas turbine engine components	Systems and methods for determining airflow parameters of gas turbine engine components are provided. In this regard, a representative method includes: receiving information from multiple test systems regarding a first airflow parameter of a gas turbine engine component; and using the information to establish a desired performance parameter that is to be exhibited by a repaired component.
7640899	2010	Adjusting electrically actuated valve lift	A system and method for controlling electromechanical valves operating in an engine is presented. According to the method, valve operation can be adjusted in a number of ways.
7641080	2010	Dispensing mechanism using long tubes to vary pressure drop	A fountain-style carbonated soft drink dispenser includes a housing adapted to attach to a beverage container, an actuator for selectively opening a fluid conduit, and one or more long tubes that vary a pressure drop across the dispensing assembly and convey fluid. The resistance through the tube(s) is decreased as the pressure within the container decreases so as to maintain a substantially constant flow rate throughout dispensing.
7641107	2010	Fault monitoring and notification system for automated banking machines	An automated banking machine includes a card reader operative to read data from user cards and to use the data read by the card reader in operation of the machine. Status messages are received from automated banking machines operating in a network. The messages are received by an event management system operating at least one computer in operative connection with a data store. The data store includes information representative of the banking machines in the network, status messages generated by the banking machines and actions to be taken including entities to be notified of conditions which cause status messages to be sent by the various banking machines.

We then convert the text to lowercase so that the analysis is not influenced by differences in capitalisation. For example, “Robot” and “robot” are treated as the same token, improving consistency in term matching.

Unlike many NLP pipelines, we do not apply stop-word removal or lemmatisation. The reason is that the approach adopted in the next stage (Section 3.2.3) is dictionary-based: the core task is to detect whether specific AI-related terms from a predefined dictionary appear in the text. In this context, removing stop words does not improve performance, because the dictionary terms of interest are typically content-bearing expressions rather than common function words. Similarly, lemmatisation is not strictly necessary because the dictionary is designed to include the relevant variants of each term (e.g., singular/plural forms or closely related lexical variants). More importantly, aggressive normalisation may distort multi-word expressions and technical phrases, potentially reducing the accuracy of the matching.

3.2.3 Text modelling

Once the text has been prepared, the **Text Modelling** phase defines how patent content will be represented for subsequent analysis. Different modelling strategies can be adopted depending on the research objective. In this manuscript, we operationalise technological content by identifying technology appearance in patent text through Named Entity Recognition (NER) and then analysing how the occurrence of these technologies changes over time. This representation enables us to detect signals of emerging technologies and to track their growth dynamics within a specific domain.

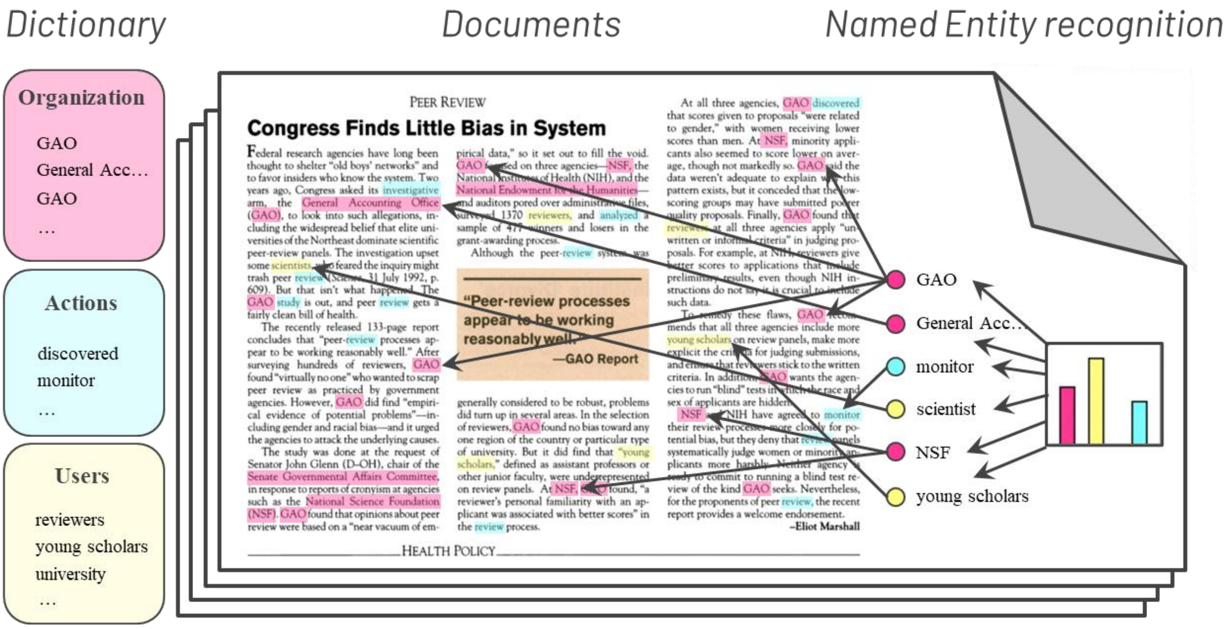
Examples of how NER can be used to identify technologies in patent documents are discussed in Puccetti et al. (2023). Approaches for assessing technological emergence and, more broadly, for analysing technological growth trajectories are described in Giordano et al. (2021; 2024b).

NER is an Information Extraction technique aimed at detecting and classifying meaningful units of information (entities) in unstructured text. Entities may refer to people, organisations, places, or, as in our case, technologies and technical concepts. In the literature, three main approaches to NER are typically distinguished: (1) Dictionary-based NER; (2) Rule-based NER; (3) Machine Learning-based NER.

- **Dictionary-based NER** uses external knowledge bases or dictionaries that contain lists of known entity names. The algorithm scans the text and maps terms that match the entries in the gazetteer (for example, from Wikipedia or domain-specific lists). This approach is semi-supervised, as the creation and maintenance of the gazetteer often require manual curation and domain expertise. It is fast and reliable when the knowledge base is comprehensive.
- **Rule-based** approach relies on manually defined linguistic rules—such as regular expressions or grammatical patterns—designed to capture specific entity types. Rule-based systems are unsupervised and top-down, since they use expert knowledge encoded as rules rather than relying on training data. They are accurate in well-defined domains but may lack flexibility when applied to broader or evolving contexts.
- **Machine Learning-based NER** uses supervised learning, where a model is trained on a manually annotated dataset to recognise and classify entities. These methods represent the state of the art in many NLP applications because they can generalise beyond predefined examples, though they require large, high-quality labelled datasets to perform effectively.

In this work, we adopt a dictionary-based NER approach. Figure 6 illustrates the logic of the procedure. A set of predefined dictionaries contains known entities grouped by category; the system scans the patent text and detects words or phrases that match dictionary entries; the output is a structured list of recognised entities, each assigned to a category. This transformation is essential because it converts unstructured text into analysable data, enabling quantitative assessments such as term frequency analysis, trend detection, and comparisons across time periods.

Figure 6. Example of the dictionary-based Named Entity Recognition (NER) process.



Dictionary-based NER relies on an expert-driven list of keywords that represent relevant technologies, components, or processes in the domain of interest. In the AI case, typical entries include terms such as "neural network," "deep learning," "computer vision," and "reinforcement learning". A key advantage of dictionary-based NER is that it is fast, transparent, and easy to replicate across domains. At the same time, its performance depends directly on dictionary quality. Missing terms can lead to false negatives, whereas overly broad terms may introduce noise. For this reason, as anticipated in Section 3.1, we rely on validated AI dictionaries already developed in prior work. Specifically, we build on dictionaries and taxonomies from WIPO (2019), Liu et al. (2021), Eicke et al. (2025), and OECD (2025).

Starting from these sources, we merged the dictionaries and then manually revised the resulting list to improve consistency and reduce ambiguity. In this step, we removed duplicates, added relevant variants (e.g., alternative spellings and closely used formulations), and grouped terms that refer to the same concept but are expressed differently. This process produced an initial dictionary of 561 AI-related terms, grouped into 215 labels (i.e., conceptual categories).

We then enriched the dictionary using a bottom-up procedure inspired by Bai and Qu (2025), with the goal of capturing additional expressions that occur in AI patents but may not be present in the initial expert-driven list. Specifically, we tokenised the patent text into unigrams, bigrams, and trigrams, keeping only tokens that do not contain stop words. We filtered this token set by retaining only those appearing in at least 0.0005% of the patents (approximately 350 occurrences given a corpus of around 700,000 documents), yielding 9,273 candidate tokens.

Next, we searched for candidate tokens that are semantically equivalent or very close to existing AI terms but expressed in a different way. To do so, we computed semantic similarity using BERT (Devlin et al., 2018). Each AI term and each candidate token was mapped into a 1024-dimensional vector representation in a semantic space, where distances reflect conceptual relatedness. Similarity between vectors was measured via cosine similarity: the closer the vectors (i.e., the smaller the angle between them), the more similar the underlying concepts. The similarity values range from 0 (not similar) to 1 (very similar). For each candidate token, we computed similarity against all AI terms and retained only those with a similarity score of at least 0.65 to at least one dictionary term. This procedure identified 138 additional tokens, which were subsequently integrated into the dictionary after verification. The final dictionary therefore contains **699 AI-related terms** that are grouped into **215 different AI-technologies**. The dictionary is available in the Appendix A.

This dictionary is then used to identify AI technologies in the titles and abstracts of the AI patent corpus.

3.2.4 Text analysis

The final stage, **Text Analysis**, focuses on interpreting the outputs of the modelling phase in order to produce actionable insights. In our case, once technology appearances have been identified in the patent corpus, we can compute indicators that describe how each technology evolves over time and how its dynamics compare with those of other technologies. A particularly informative indicator for this purpose is growth, as it captures whether a technology is expanding in inventive activity and therefore potentially gaining relevance.

In this section, we measure the growth of technologies to identify emerging ones. To detect technological trends within the AI patent set, we assess how the number of patents associated with each technology changes over time. Our underlying assumption is that a rapid increase in patenting activity signals a technology with strong growth potential. The literature proposes several approaches to study technological growth. Growth curves and S-curves are widely used because they help position a technology along diffusion stages such as emergence, growth, maturity, and saturation. However, these approaches are less suited to our objective, which is to obtain a synthetic index that enables direct comparisons across multiple technologies within the same domain. A related stream of work, often referred to as Technology Trend Analysis, focuses on capturing and comparing temporal patterns of technological development and diffusion.

Building on this literature, we adopt a synthetic indicator known as the Relative Development of Growth Rates (RDGR), originally introduced by Ernst & Soll (2003). For each technology, RDGR measures relative growth by comparing recent patenting intensity with earlier patenting activity. Specifically, RDGR is computed as the ratio between the number of patents related to a given technology published in the most recent four-year period and the number of patents published in the preceding ten-year period. Given that our dataset covers 2010–2023, in our case the index contrasts activity in the last three years of observation with activity in the earlier eleven years.

In some cases, RDGR[10] cannot be computed in a standard way because of zero counts. If a technology has no patents in the most recent three years, the numerator is zero, indicating a lack of recent activity. If a technology has no patents in the earlier eleven-year period, the denominator is zero, meaning that the technology is not observed historically in the dataset. To handle these cases consistently, we classify technologies with no patents in the first eleven years but patent activity in the last four years as “emerging technologies”, as they appear only in the recent period. Conversely, technologies that are present in the first eleven years but have no patents in the last four years are labelled “obsolescent technologies”, as they show historical activity but no recent development.

3.3. AI Technologies

Patents containing at least one AI-related technology amount to 184,458 (corresponding to 25% of the overall dataset). Within these patents, we identified 169 distinct AI technologies out of the 215

[10] For ease of reading and interpretation, in the remainder of this document we refer to the RDGR indicator simply as the “**growth index**”.

technologies included in our dictionary, indicating that most of the predefined technology concepts are actually observed in the patent corpus.

Figure 7 reports the top 15 AI technologies by number of associated patents. This ranking provides a first indication of where inventive and patenting activity is most concentrated, and therefore which technological areas appear to attract the greatest attention from organisations. In our case, the most frequently identified technologies include Image Processing, Machine Learning, Graph Learning, and Intelligent Agents. The figure also shows that broad, umbrella labels such as "Artificial Intelligence" occur less frequently than more specific technology terms. This is consistent with expectations: patent texts tend to describe inventions through concrete methods and components rather than using generic field-level descriptors.

Figure 7. Top-15 AI-technologies.

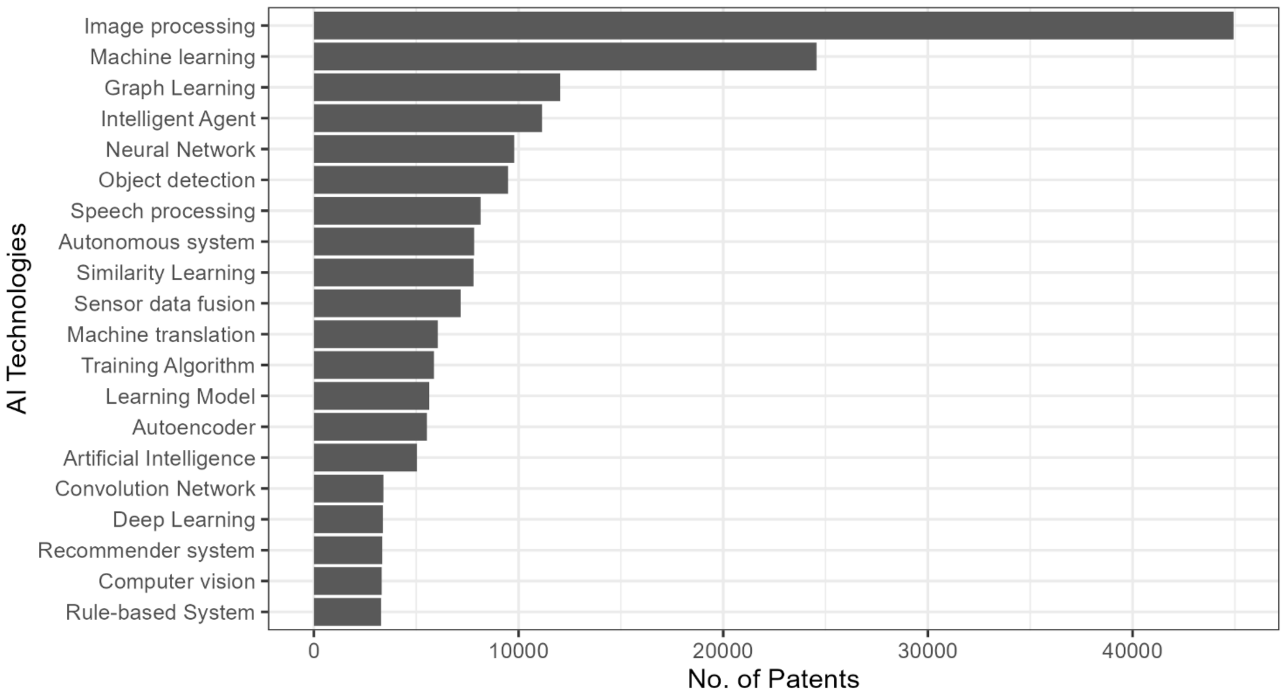


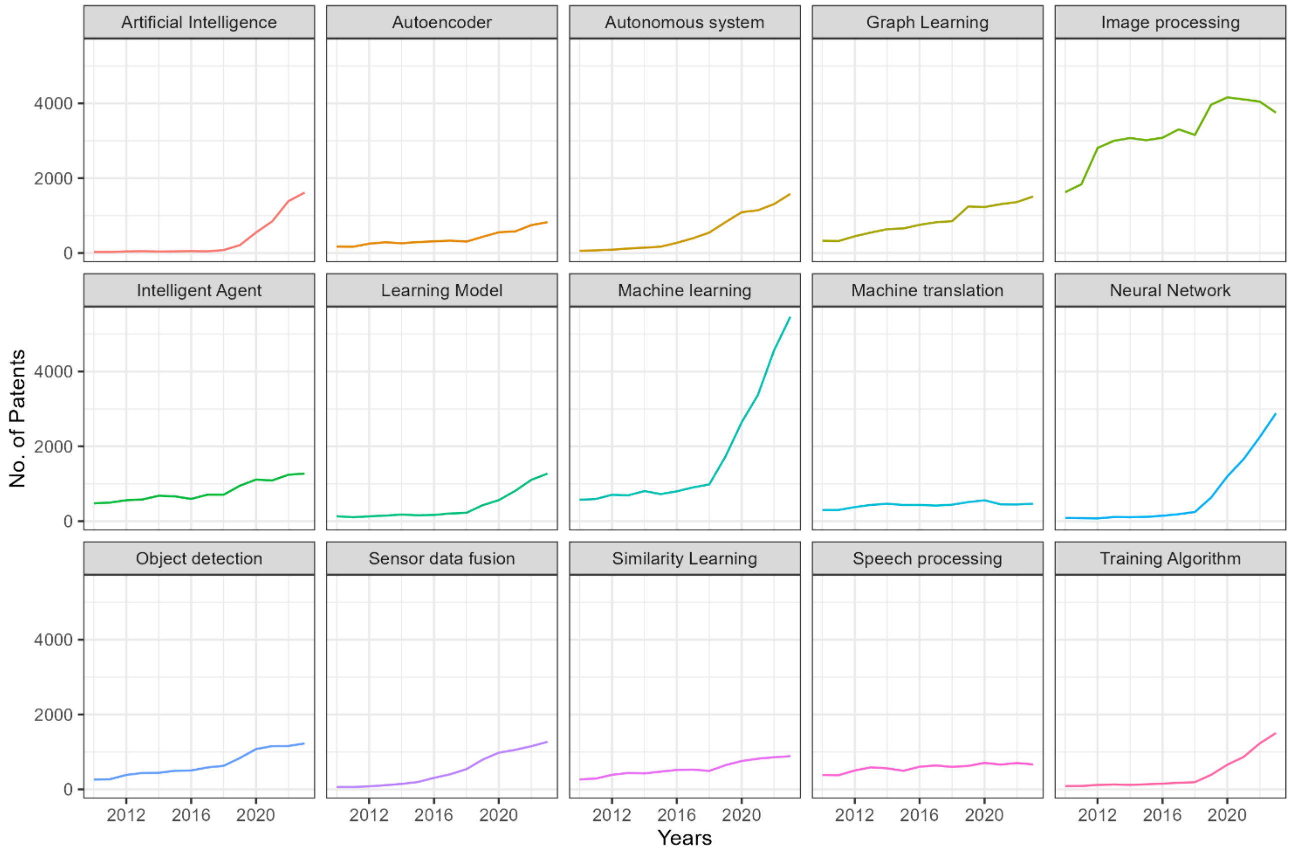
Figure 8 shows the trend analysis for the top-15 AI technologies by the highest number of patents. Each panel reports, year by year (2010–2023), how many patents mention the corresponding technology, providing a clear picture of how patenting activity evolves over time across different technological areas.

Overall, the figure highlights a strong acceleration in AI-related patenting, especially from the late 2010s onward, but with meaningful differences across technologies. Machine learning displays the most pronounced growth, with a sharp take-off after 2018–2019 and a steep increase through the most recent years, signalling a broad and rapidly expanding technological focus. Neural network follows a similar trajectory, with limited activity in the early period and a strong surge after 2019, consistent with the diffusion of neural approaches in multiple application domains. Related concepts such as Learning model and Training algorithm also show clear upward trends, suggesting increasing attention not only to AI applications but also to model development and optimisation processes.

Some technologies exhibit sustained growth over the full period but with a smoother slope. For instance, Graph learning, Autonomous system, and Intelligent agent increase steadily, indicating a progressive consolidation rather than a sudden take-off. Others, such as Image processing and Object detection, reach high patent volumes early and remain consistently prominent; their curves suggest that these areas represent more established application domains of AI, with continued but comparatively less explosive growth in the last years.

Finally, a few technologies show more stable or moderate dynamics. Machine translation and Speech processing remain relatively flat compared to the strongest growth areas, suggesting a technological maturity.

Figure 8. Trend analysis.



As explained in Section 3.2.4, to capture in a synthetic way whether a technology is growing or not, we compute a growth index for each technology. Table 6 presents detailed information about the top-15 faster-growing and slower-growing technologies for growth index identified using our NLP method. For each technology, the table includes several key metrics. The table provides the number of patents published in two distinct periods: from 2010 to 2019 and from 2020 to 2023. This division allows us to see the historical and recent interest in each technology. The growth index measures the growth rate of the technology. It is calculated by dividing the number of patents published in the last four years (2020–2023) by the number of patents published in the preceding ten years (2010–2019), as explained in Section 3.2.4. A higher growth index indicates a faster-growing technology. The Appendix 2 provides the full table.

Table 6. Top-15 faster-growing and slower-growing AI technologies for growth index.

AI Technology	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Generative Adversarial Network	18	342	19.00	Faster-growing
Transfer Learning	14	110	7.86	

AI Technology	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Deep Learning	402	2,968	7.38	
Artificial Intelligence	628	4,402	7.01	
Activation Function	27	132	4.89	
Generative AI	20	95	4.75	
Neural Network	1,798	7,988	4.44	
Reinforcement Learning	164	709	4.32	
Natural Language Generation	15	56	3.73	
Motion planning	29	103	3.55	
Recurrent neural network	118	395	3.35	
Convolution Network	808	2,588	3.20	
Long Short Term Memory	15	42	2.80	
Training Algorithm	1,601	4,262	2.66	
Supervised Learning	119	279	2.34	
…	…	…	…	…
Swarm optimization	47	23	0.49	Slower-growing
Gesture recognition	587	287	0.49	
Collaborative filtering	111	54	0.49	
Machine translation	4,127	1,926	0.47	
Conditional Random Field	52	24	0.46	
Human-AI interaction	44	20	0.45	
Fuzzy system	554	245	0.44	
Pattern recognition	1,093	471	0.43	
Sparse representation	50	21	0.42	
MapReduce	79	33	0.42	
Evolutionary algorithm	57	18	0.32	
Graphical model	183	56	0.31	
Classifcation Algorithm	28	8	0.29	
Hidden markov model	160	45	0.28	
Adaptive Boosting	29	8	0.28	

AI Technology	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Radial Basis Function Network	11	2	0.18	

Among the faster-growing technologies, the strongest signal comes from Generative Adversarial Networks (GANs), which move from only 18 patents in 2010–2019 to 342 patents in 2020–2023, producing the highest growth index (19.00). This pattern is consistent with a technology that was relatively marginal in the earlier period and then rapidly diffused across applications. Other technologies with very strong growth include Transfer Learning (7.86), Deep Learning (7.38), and the broader label Artificial Intelligence (7.01). Together with Neural Network (4.44), these results confirm that recent AI patenting is heavily shaped by modern learning paradigms and neural architectures, with a particular emphasis on techniques that improve performance and reuse of models across tasks (transfer learning).

The table also highlights a cluster of fast-growing technologies that align with the current Generative AI wave. Generative AI shows a high index (4.75), and Natural Language Generation (3.73) increases sharply as well, although both start from relatively small baseline counts.

Other technologies with strong growth are more specific building blocks of neural systems. Activation Function (4.89), Recurrent neural network (3.35), Convolution Network (3.20), and Long Short-Term Memory (2.80) all show expansion, indicating that patents increasingly refer to particular neural components and architectures rather than only broad labels. Reinforcement Learning (4.32) also stands out, pointing to growth in relation to Large Language Models.

At the opposite end, the slower-growing group is dominated by technologies that were prominent earlier but expand much less in the recent period. Machine translation illustrates this clearly: despite very large absolute volumes, it drops from 4,127 patents in 2010–2019 to 1,926 in 2020–2023, yielding a growth index below 0.5. Similar patterns appear for Pattern recognition, Fuzzy systems, and classic probabilistic sequence models such as Hidden Markov Models, as well as methods such as Conditional Random Fields.

In the Appendix 2, an *emerging* technology in our results is the Graph Neural Network. In the dataset, this technology has zero patents in 2010–2019 and 52 patents in 2020–2023. This pattern is exactly what we expect for an emerging trajectory: the concept is essentially absent in the earlier period and then appears only in the most recent years, signalling a new and rapidly forming technological niche rather than a mature field.

This emergence is coherent with what has happened in both the technology domain and the market. Over the last few years, graphs have become a central way to represent complex, relational data—such as social networks, knowledge graphs, chemical molecules, supply chains, fraud rings, and communication networks—where the value lies not only in individual data points but also in the structure of their connections. Graph Neural Networks are specifically designed to learn from this kind of relational structure, making them a natural extension of deep learning to domains where interactions, dependencies, and topology matter.

From a market perspective, the rise of Graph Neural Networks aligns with the growing industrial focus on applications that require reasoning over relationships and networks. Examples include recommendation and personalisation systems, fraud detection, cybersecurity, drug discovery and materials science, and knowledge-graph-based search and enterprise analytics. In parallel, the broader diffusion of deep learning platforms and the availability of graph-oriented tooling have lowered adoption barriers, enabling companies to integrate graph-based learning into products and decision systems more quickly than would have been possible a decade ago.

3.4. From AI Tech to AI Skills

The objective of this section is to explain how we move from the technologies identified in Section 3.3 to the skills and knowledge associated with them. Specifically, starting from the list of AI technologies extracted from patent documents, we identify which skills, competences, and knowledge concepts in the ESCO classification (https://esco.ec.europa.eu/en) are most closely related to each technology in semantic terms. This procedure builds on the approach proposed by Fareri et al. (2023), who use semantic similarity methods to connect technologies to ESCO concepts in the context of sustainable manufacturing.

The purpose of this "technology-to-skills" step is to construct a structured mapping between AI technologies and relevant ESCO skills[11], enabling a clearer understanding of how technological innovation translates into changing skill requirements. Importantly, this mapping also allows us to transfer the information derived from the technology analysis, the growth index, to the skills domain. In other words, once a technology is linked to a set of ESCO skills, the technology's growth dynamics can be used as an early signal of whether demand for those associated skills is likely to increase. Accordingly, technologies classified as "emerging"—because they appear primarily in the most recent period and exhibit strong growth signals—are interpreted as potential drivers of new or rapidly increasing skill needs. Conversely, technologies showing declining or absent recent patent activity may be associated with skills whose relevance is stabilising or decreasing over time.

The input of this task consists of:

1. The list of **AI technologies** identified from patent analysis that is composed of 169 different technologies.
2. The **ESCO database** provides a comprehensive taxonomy of skills, competences, and knowledge relevant to the European labour market. The last version of ESCO (v1.2.1) contains 13,960 skills.

Starting from the Text analysis (Section 3.2.3), only technologies identified in patents are selected. This filtered list serves as the input for the matching process.

The first step is identified AI technologies that exactly match with the preferred or alternative labels of ESCO skills. These Technologies are directly linked with ESCO skills. This step ensures that well-established technologies already present in ESCO are immediately connected to their related competencies. For technologies that do not find an exact correspondence, a semantic similarity algorithm is applied. This approach allows us to move beyond exact textual matching by capturing semantic relationships. For example, recognising that "deep learning" and "neural networks" refer to closely related concepts, despite their differences.

Each technology name and each ESCO skill are transformed into vector representations in a high-dimensional semantic space. Specifically, each term is mapped into a 1024-dimensional vector using the Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al., 2018). The BERT model encodes the contextual meaning of each word or phrase, allowing it to capture linguistic nuances and domain-specific relationships. For instance, the technology "Artificial Intelligence" could be represented by a 1024-dimensional vector such as:

[-0.6113, -0.4964, -1.9548, …, 0.9718, 0.3563, 0.2444]

[11] For simplicity of reading, when we refer to **ESCO skills** throughout this section, we include both **skills** and **knowledge** as defined in the ESCO framework. In ESCO, these two categories are conceptually distinct. Skills describe the ability to apply knowledge and use know-how to complete tasks and solve problems, while knowledge refers to the body of facts, principles, and theories related to a field of work or study. However, in the context of our analysis, both are considered jointly, since they are equally relevant for understanding the competences associated with emerging technologies.

Structuring technologies and skills as semantic vectors enables the identification of conceptual similarity between them. To measure the similarity between technologies and skills, we compute the cosine similarity between their respective vectors. For each technology, the cosine similarity is calculated against all ESCO skills, and the pairs with a similarity higher than 0.55 are selected. This process enables the automatic identification of the closest ESCO concepts for each AI technology, even when no direct or exact match exists. The process lead to obtain 273 potential skills connected to AI technologies. An extraction of the output of this process is shown in Table 7.

In the second step, the results of the semantic similarity step are manually reviewed by experts to ensure the coherence and accuracy of the matches. Experts verify whether each linked ESCO skill truly reflects the capabilities required to work with the given technology. After the revision, we identified 108 ESCO skills that are connected to AI technologies. These skills are connected to 41 of technologies. In Appendix 3, we provided the list of 108 skills with related AI technologies.

It is important to emphasise that the technology-skill links obtained through semantic similarity can be interpreted in at least two ways. First, technological change may increase the demand for the skills and knowledge required to develop, implement, operate, or manage the technology. For instance, the strong growth of Deep Learning-related inventions is associated with the ESCO skill “Deep learning.” Here, increased patenting activity plausibly indicates that organisations will need more people able to design and train neural architectures, evaluate model performance, and integrate deep learning models into products and processes. Second, technological change may substitute some of those skills and knowledge areas, reducing their relative importance by automating related tasks or embedding expertise into systems. A representative example of the second interpretation is the link between “Machine translation” and several translation-related skills in ESCO (e.g., “Translate texts” and “Translate foreign language”). As machine translation technologies improve and become embedded in work tools, routine translation tasks can be increasingly automated, potentially reducing demand for basic translation while shifting remaining demand toward higher-value activities such as post-editing, quality assurance, and specialised translation in high-stakes domains.

Because our approach is based on textual relatedness, it cannot determine which of these mechanisms is at work for a given technology–skill pair. Interpreting the direction of the effect therefore requires domain expertise. Nonetheless, the mapping remains valuable because it signals that technological change is likely to influence the associated skills and helps anticipate which specific competencies are most exposed to future impacts. **In general terms, the technology-skill relationship can be interpreted as evidence that a given technology is likely to “impact” the associated skill**.

Table 7. Example of semantic similarity between emerging technologies and ESCO skills.

ESCO Skill	AI Technology	Similarity
Cognitive computing	Brain computer interface	0.5805
Computational biology	Genetic Programming	0.5844
Computational linguistics	Large Language Model	0.5616
Computer graphics	Computer vision	0.6335
Control systems	Autonomous system	0.6244
Create digital images	Image processing	0.5572
Computer vision	Gesture recognition	0.5597

ESCO Skill	AI Technology	Similarity
Data analytics	Machine Learning	0.5904
Data mining	Machine Learning	0.7204
data mining methods	Machine Learning	0.5953

The proposed methodology makes it possible to extend the technology growth index to the skills domain. Because each skill is linked to one or more technologies, it can be analysed through the growth dynamics of those associated technologies. This enables the construction of an indicator of skill emergence and growth, intended as a quantitative proxy of how quickly a skill is becoming exposed to, and shaped by, technological change.

From an operational perspective, this requires translating patent counts from the technology level to the skill level. We begin with the time series of patent activity for each AI technology and use the technology–skill mapping (Appendix 3) to connect patents to skills indirectly. Specifically, a patent is associated with a skill if the patent contains at least one technology that is mapped to that skill. Aggregating patents according to this rule produces, for each of the 108 skills, a skill-level patent time series describing how many patents are linked to that skill in each period. This reconstructed series can then be used to compute the same growth index adopted for technologies, yielding a comparable measure that signals whether a skill is emerging and how rapidly the technological context surrounding that skill is changing.

Table 8. Growth index for skills.

Skill	Total No. of patents	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Description
Deep learning	3,370	402	2,968	7.38	The principles, methods and algorithms of deep learning, a subfield of artificial intelligence and machine learning. Common neural networks like perceptrons, feed-forward, backpropagation, and convolutional and recurrent neural networks.
Principles of artificial intelligence	5,030	628	4,402	7.01	The artificial intelligence theories, applied principles, architectures and systems, such as intelligent agents, multi-agent systems, expert systems, rule-based systems, neural networks, ontologies and cognition theories.
Artificial neural networks	9,786	1,798	7,988	4.44	A network of artificial neurons composed for solving artificial intelligence problems. These computing systems are inspired by the biological neural networks that constitute brains. Understanding of its general model and its elements. Knowledge of its use possibilities for automation.
Spatial planning	132	29	103	3.55	An interdisciplinary field of study between engineering and social sciences. It refers to the planning of economic, environmental and social processes for specific aims. These processes are combined with diagrams and visual representation about sociospatial activities.
Memorise information	57	15	42	2.80	Store information such as words, numbers, pictures and procedures for later retrieval.
Memorise large amounts of information	57	15	42	2.80	Retain large amounts of information and take notes for accurate interpretation.
Evaluate training	5,863	1,601	4,262	2.66	Assess the realisation of the training's learning outcomes and goals, the quality of teaching, and give transparent feedback to the trainers and trainees.

Skill	Total No. of patents	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Description
Develop predictive models	5,639	1,888	3,751	1.99	Develop simplified descriptions, mainly mathematical descriptions of processes or systems, in order to assist calculations and predictions.
Automatic control system	7,830	2,704	5,126	1.90	Set of interconnected mechanisms and components, such as controllers or sensing elements, that use programming logic to automate the operation and behaviour of a process or system without a continuous human intervention, to achieve a desired performance such as stability.
Control systems	7,830	2,704	5,126	1.90	Devices or a set of devices that command and manage the performance and behaviour of other equipment and systems. This includes Industrial control systems (ICS) which are used for industrial production and manufacturing.
Robotics	7,830	2,704	5,126	1.90	The branch of engineering that involves the design, operation, manufacture, and application of robots. Robotics is part of mechanical engineering, electrical engineering, and computer science and overlaps with mechatronics and automation engineering.
Data analytics	24,729	8,540	16,189	1.90	The science of analysing and making decisions based on raw data collected from various sources. Includes knowledge of techniques using algorithms that derive insights or trends from that data to support decision-making processes.
Data mining	24,729	8,540	16,189	1.90	The methods of artificial intelligence, machine learning, statistics and databases used to extract content from a dataset.
Data mining methods	24,729	8,540	16,189	1.90	Data mining techniques used to determine and analyse the relationship between different elements of economy and marketing.
Data models	24,729	8,540	16,189	1.90	The techniques and existing systems used for structuring data elements and showing relationships between them, as well as methods for interpreting the data structures and relationships.

Table 8 reports the growth index for skills linked to AI technologies, together with additional descriptive information, including the total number of associated patents, the number of patents in the early observation window and in the most recent years, and the ESCO definition of each skill. Table 8 presents the top 15 skills ranked by growth index, while the full table is provided in Appendix 4.

Overall, the ranking is dominated by core technical AI capabilities, while a second group reflects enabling data and automation competences. A smaller set of skills appears less directly “AI-native” and should be interpreted carefully, as it may reflect broader, cross-domain linkages captured by semantic similarity rather than direct skill demand. Observing Table 8 more in details, the top three positions—Deep learning (Growth Index 7.38), Principles of artificial intelligence (7.01), and Artificial neural networks (4.44)—are fully coherent with the recent expansion of AI innovation. These skills show a sharp shift from relatively modest patent counts in 2010–2019 to very large volumes in 2020–2023. Substantively, they represent the technological core of current AI systems, and their prominence indicates that recent AI patenting is largely anchored in neural approaches and related AI architectures. In interpretive terms, this suggests that the technological scenario around these skills is evolving very rapidly requiring workers to know how to use and manage these technologies.

A second cluster contains skills with moderate growth and substantial patent volumes, such as Develop predictive models (1.99), and a set of closely related engineering/automation skills—Automatic control system, Control systems, and Robotics (all 1.90). These results suggest that AI patenting is strongly intertwined with deployment contexts where prediction and automated control matter, including industrial automation, robotics, and cyber-physical systems. The identical patent counts and growth indices for these three entries likely indicate that, in the mapping, they are linked to the same (or very similar) set of underlying technologies and patents. Practically, this points to an "AI + automation" trajectory in which AI methods are increasingly embedded into systems that sense, decide, and act.

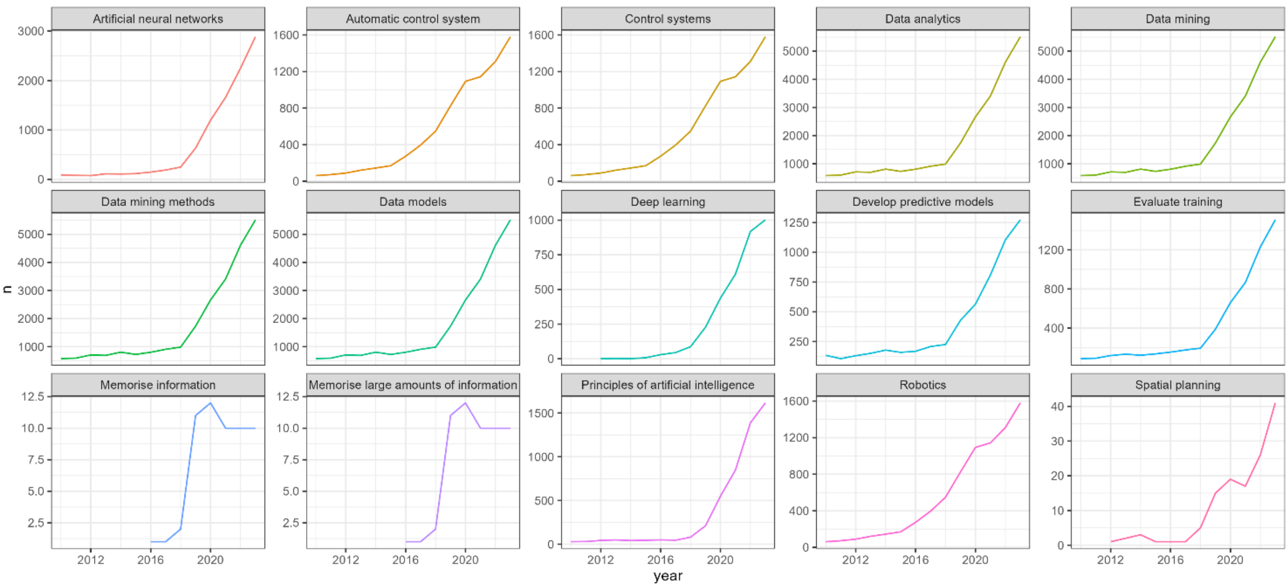
A third, highly visible group concerns data-centric capabilities: Data analytics, Data mining, Data mining methods, and Data models (all with Growth Index 1.90 and the same patent counts). This pattern again suggests a shared technological linkage in the mapping, and it is conceptually consistent: data-related competences are foundational complements to AI development and deployment. At the same time, because these skills are broad and widely applicable beyond AI, their presence in the top-15 should be read as evidence that AI patenting draws heavily on data infrastructures and techniques, rather than as a uniquely AI-specific signal.

It is important to underline that this growth index should not be interpreted mechanically as an indicator of increasing labour market demand for a given skill. As discussed earlier, technologies can affect skills by either complementing them (increasing demand) or substituting them (reducing demand through automation). For this reason, the skill growth index should be interpreted more generally as a measure of how fast the technological scenario related to that skill is evolving, and therefore how quickly the skill is likely to be impacted.

For example, we will take into consideration the skill "Semantics", which is linked to the technology "Natural Language Understanding" (see Appendix 3). The growth index for this pair is 1.60 (see Appendix 4), indicating a strong increase in the volume of patents connected to Natural Language Understanding. However, this does not necessarily imply that demand for human expertise in semantics will rise proportionally. In recent years, advances such as Large Language Models (as filed related to Natural Language Understanding) have significantly expanded the automation of semantic processing. In such cases, the observed technological growth may correspond to an increasing ability of systems to perform semantic tasks, potentially substituting part of the human skill. Therefore, a high growth index should be read as a signal that the impact on the skill domain is likely to intensify and evolve rapidly, rather than as a direct forecast that labour market demand for that specific skill will necessarily increase.

Finally, Figure 9 visualises the time trends for the top-15 items ranked by Growth Index, plotting (on the y-axis) the yearly number of patents associated with each item from 2010 to 2023.

Figure 9. Trend for the top-15 skills.



3.5. Conclusion

In conclusion, this document illustrates how it is possible to anticipate the ways in which technological evolution may affect skills. The proposed approach, based on NLP analysis of patent documents, supports the identification of skills and knowledge areas that are potentially impacted by technological change and enables the calculation of a growth index that captures how rapidly this impact may intensify. We demonstrate the application of the methodology in the field of Artificial Intelligence, which has attracted substantial scientific, industrial, and policy attention in recent years.

It is important to have clear in mind which are the main assumptions and boundaries of the approach. First, because the analysis is based on patents and on the detection of technology appearances, it mainly captures skill implications from a technological perspective. Other dimensions that may shape skill needs, such as social, environmental, political, or broader economic drivers, are not directly addressed through this type of data and would require complementary sources. Second, the technology–skill relationship should be interpreted in an abstract way: the mapping indicates that a technology is likely to affect a given skill, but the direction of the effect need to be assessed separately. In practice, technological change may increase demand for a skill by complementing human work, or it may substitute the skill by automating tasks. Third, the growth index should not be interpreted as a direct measure of labour market demand. Rather, it captures how quickly the technological landscape connected to a skill is evolving and, therefore, how rapidly that skill is likely to be exposed to change.

A key strength of the methodology is that it attempts to quantify the technology–skills link in a systematic way, producing comparable indicators across a large set of technologies and skills. In addition, the approach is highly scalable because most steps are automated once the dictionaries and mappings are defined. These characteristics address important limitations of expert-based approaches that are often used to analyse skills and labour market dynamics. Expert exercises typically require significant time and resources, which constrains scalability, and they may also be affected by cognitive and informational biases, for example, anchoring on familiar technologies, overlooking weak signals, or overemphasising salient trends (Bonaccorsi et al., 2020). Finally, grounding the skill layer in the ESCO framework ensures alignment with a widely adopted European classification system, facilitating interoperability with other EU policies, datasets, and institutional initiatives.

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Appendix 1 – AI dictionary

Term	AI Technologies	Term	AI Technologies	Term	AI Technologies
action recognition	Action recognition	high dimensional model	High dimensional model	relevance vectors machines	Relevance Vector Machine
activation function	Activation Function	hopfield net	Hopfield Network	representation learning	Representation Learning
activity recognition	Action recognition	hopfield nets	Hopfield Network	reservoir computing	Reservoir Computing
actor critic algorithm	Actor-critic Algorithm	hopfield network	Hopfield Network	robot learning	Robot Learning
actor critic algorithms	Actor-critic Algorithm	hopfield networking	Hopfield Network	robotic learning	Robot Learning
adaboost	Adaptive Boosting	hopfield networks	Hopfield Network	robotics learning	Robot Learning
adaboosting	Adaptive Boosting	hough transformer	Hough transformer	robots learning	Robot Learning
adaboosts	Adaptive Boosting	human action recognition	Human action recognition	rough set	Rough set
adaptive boosting	Adaptive Boosting	human activity recognition	Human action recognition	rule based learning	Rule-based System
adversarial learning	Adversarial Learning	human ai interaction	Human-AI interaction	rule based system	Rule-based System
adversarial network	Adversarial Learning	human artificial intelligence interaction	Human-AI interaction	rule based systems	Rule-based System
ambient intelligence	Ambient intelligence	human aware artificial intelligence	Human aware artificial intelligence	rule induction	Rule induction
artificial intelligence	Artificial Intelligence	human computer interaction	Human-AI interaction	rule learning	Rule-based System
artificial intelligences	Artificial Intelligence	human robot interaction	Human-AI interaction	rules based system	Rule-based System
artificial intelligenece	Artificial Intelligence	humanoid robot	Human-AI interaction	rules based systems	Rule-based System
artificial intelligent	Artificial Intelligence	hybrid ai	Human-AI interaction	rules induction	Rule induction
artificial intelligents	Artificial Intelligence	hypergraph learning	Hypergraph Learning	self driving car	Autonomous system
association rule	Association rule	hypergraphs learning	Hypergraph Learning	self organising map	Autonomous system
attention based	Transformer	image classification	Image processing	self organising structure	Autonomous system
attention transformer	Transformer	image processing	Image processing	semi supervised learning	Semi supervised learning
autoencoder	Autoencoder	image recognition	Image processing	semi supervised training	Semi supervised learning
autoencoders	Autoencoder	image retrieval	Image processing	sensor data fusion	Sensor data fusion
automated planning	Autonomous system	image segmentation	Image processing	sensor fusion	Sensor data fusion
automated scheduling	Autonomous system	incremental learning	Incremental Learning	sentiment analysis	Sentiment analysis

autonomic computing	Autonomous system	independent component analysis	Independent component analysis	similarity learning	Similarity Learning
autonomous car	Autonomous system	inductive logic programm	Inductive Logic Programming	simultaneous localisation mapping	Simultaneous localisation mapping
autonomous vehicle	Autonomous system	inductive logic programming	Inductive Logic Programming	single linkage clustering	Single linkage clustering
autonomous weapon	Autonomous system	inductive monitoring	Inductive monitoring	sparse representation	Sparse representation
back propagation algorithm	Backpropagation Learning	instance based learning	Instance based learning	spectral clustering	Spectral clustering
back propagation algorithms	Backpropagation Learning	intelligence augmentation	Intelligence augmentation	speech processing	Speech processing
back propagation learning	Backpropagation Learning	intelligent agent	Intelligent Agent	speech recognition	Speech processing
back propagation net	Backpropagation Learning	intelligent agents	Intelligent Agent	speech synthesis	Speech processing
back propagation nets	Backpropagation Learning	intelligent algorithm	Intelligent Algorithm	speech to text	Speech processing
back propagation network	Backpropagation Learning	intelligent algorithms	Intelligent Algorithm	stacked generalisation	Stacked generalisation
back propagation networking	Backpropagation Learning	intelligent classifier	Classifcation Algorithm	statistical relation learning	Statistical Relation Learning
back propagation networks	Backpropagation Learning	intelligent geometric computing	Intelligent Agent	statistical relational learning	Statistical Relation Learning
backpropagation algorithm	Backpropagation Learning	intelligent infrastructure	Intelligent Agent	statistical relationing learning	Statistical Relation Learning
backpropagation algorithms	Backpropagation Learning	intelligent software agent	Intelligent Agent	statistical relations learning	Statistical Relation Learning
backpropagation learning	Backpropagation Learning	intelligent system	Intelligent Agent	statistical relationship learning	Statistical Relation Learning
backpropagation net	Backpropagation Learning	intuitionistic fuzzy set	Fuzzy system	statistical relationships learning	Statistical Relation Learning
backpropagation nets	Backpropagation Learning	k mean	Cluster analysis	stochastic gradient	Stochastic gradient
backpropagation network	Backpropagation Learning	k means	Cluster analysis	string kernel	String Kernel
backpropagation networking	Backpropagation Learning	kernel learning	Kernel learning	string kernels	String Kernel
backpropagation networks	Backpropagation Learning	label propagation	Label Propagation	supervised learning	Supervised Learning
bayes network	Bayesian learning	language transformer	Large Language Model	supervised training	Supervised Learning
bayesian learning	Bayesian learning	large language model	Large Language Model	support vector machine	Support Vector Machine
bayesian network	Bayesian learning	latent dirichlet allocation	Topic Modelling	support vector machines	Support Vector Machine

bee colony	Bee colony	latent semantic analysis	Topic Modelling	support vector regression	Support Vector Machine
blind signal separation	Blind signal separation	layered control system	Layered control system	support vectors machine	Support Vector Machine
boltzmann machine	Boltzmann Machine	lazy learning	Lazy Learning	support vectors machines	Support Vector Machine
boltzmann machines	Boltzmann Machine	learning algorithm	Learning Algorithm	support vectors regression	Support Vector Machine
boosting algorithm	Boosting Algorithm	learning algorithms	Learning Algorithm	supports vector machine	Support Vector Machine
boosting algorithms	Boosting Algorithm	learning automata	Learning Algorithm	supports vector machines	Support Vector Machine
bootstrap aggregation	Bootstrap aggregation	learning model	Learning Model	supports vector regression	Support Vector Machine
bp learning	Backpropagation Learning	learning modeling	Learning Model	supports vectors machine	Support Vector Machine
bp net	Back-propagation Network	learning modelling	Learning Model	supports vectors machines	Support Vector Machine
bp nets	Back-propagation Network	learning models	Learning Model	supports vectors regression	Support Vector Machine
bp network	Back-propagation Network	learning to rank	Learning To Rank	swarm optimization	Swarm optimization
bp networking	Back-propagation Network	learning to ranking	Learning To Rank	t s fuzzy system	Fuzzy system
bp networks	Back-propagation Network	link prediction	Link prediction	takagi sugeno fuzzy system	Fuzzy system
brain computer interface	Brain computer interface	liquid state machine	Liquid State Machine	temporal diference learning	Temporal Diference Learning
brownboost	Brownboost	liquid state machines	Liquid State Machine	text mining	Natural Language Processing
classifcation algorithm	Classifcation Algorithm	logistic regression	Logistic regression	text to speech	Speech processing
classifcation algorithms	Classifcation Algorithm	logitboost	Logitboost	topic model	Topic Modelling
classification tree	Classifcation Algorithm	long short term memory	Long Short Term Memory	topic modeling	Topic Modelling
cluster analysis	Cluster analysis	lpboost	LPboost	topic modelling	Topic Modelling
co training	Co-training	machine intelligence	Machine Intelligence	totalboost	Totalboost
cognitive automation	Cognitive computing	machine intelligences	Machine Intelligence	training algorithm	Training Algorithm
cognitive computing	Cognitive computing	machine intelligent	Machine Intelligence	training algorithms	Training Algorithm
cognitive insight system	Cognitive computing	machine intelligents	Machine Intelligence	trajectory planning	Trajectory tracking
cognitive modelling	Cognitive computing	machine learned ranking	Machine-learned Ranking	trajectory tracking	Trajectory tracking
cognitive robotic	Cognitive computing	machine learning	Machine learning	transductive learning	Transductive Learning

collaborative filtering	Collaborative filtering	machine learning model	Machine learning	transfer learning	Transfer Learning
collision avoidance	Collision avoidance	machine translation	Machine translation	trust region policy optimisation	Trust region policy optimisation
committee machine	Committee Machine	machine vision	Computer vision	unmanned aerial vehicle	Autonomous system
committee machines	Committee Machine	machines intelligence	Machine Intelligence	unsupervised learning	Unsupervised Learning
community detection	Cluster analysis	machines intelligences	Machine Intelligence	unsupervised training	Unsupervised Learning
computation intelligence	Artificial Intelligence	machines intelligent	Machine Intelligence	variational inference	Variational inference
computation intelligences	Artificial Intelligence	machines intelligents	Machine Intelligence	vconvolutional neural	Convolution Network
computation intelligent	Artificial Intelligence	machines learning	Machine Learning	virtual assistant	Intelligent Agent
computation intelligents	Artificial Intelligence	madaboost	Madaboost	visual servoing	Visual servoing
computational intelligence	Artificial Intelligence	manifold learning	Manifold Learning	xgboost	Xgboost
computational intelligences	Artificial Intelligence	manifold regularisation	Manifold Regularization	xgboosts	Xgboost
computational intelligent	Artificial Intelligence	manifold regularization	Manifold Regularization	foundation model	Foundation Model
computational intelligents	Artificial Intelligence	mapreduce	MapReduce	foundation models	Foundation Model
computationally intelligence	Artificial Intelligence	markovian	Markovian	frontier model	Foundation Model
computationally intelligences	Artificial Intelligence	memetic algorithm	Memetic algorithm	frontier models	Foundation Model
computationally intelligent	Artificial Intelligence	meta learning	Meta learning	gen ai	Generative AI
computationally intelligents	Artificial Intelligence	metric learning	Metric Learning	multimodal model	Multi Modal AI
computer vision	Computer vision	mixture of expert	Mixture Of Expert	multimodal models	Multi Modal AI
concept drift	Concept Drift	mixture of experts	Mixture Of Expert	vision language model	Multi Modal AI
concepts drift	Concept Drift	model testing	Machine learning	vision language models	Multi Modal AI
conditional random field	Conditional Random Field	model training	Machine learning	activity detection	Human action recognition
conditional random fields	Conditional Random Field	model validation	Machine learning	agent	Intelligent Agent
connectionis	Connectionis	motion planning	Motion planning	agents	Intelligent Agent
connectionises	Connectionis	multi agent learning	Multiagent Learning	ai	Artificial Intelligence
convolution net	Convolution Network	multi agent system	Multi agent system	audio processing	Speech processing

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convolution nets	Convolution Network	multi class classifcation	Multiclass Classifcation	automated system	Autonomous system
convolution network	Convolution Network	multi class classified	Multiclass Classifcation	automatic detection	Object detection
convolution networking	Convolution Network	multi class classifier	Multiclass Classifcation	automatic speech	Speech processing
convolution networks	Convolution Network	multi class classifies	Multiclass Classifcation	autonomous driving	Autonomous system
convolutional net	Convolution Network	multi class classify	Multiclass Classifcation	autonomous vehicles	Autonomous system
convolutional nets	Convolution Network	multi class classifying	Multiclass Classifcation	bayesian	Bayesian learning
convolutional network	Convolution Network	multi instance learning	Multi-instance Learning	character recognition	Optical character recognition
convolutional networking	Convolution Network	multi kernel learning	Multi Kernel Learning	classification model	One class Classification
convolutional networks	Convolution Network	multi label classifcation	Multilabel Classifcation	classification system	One class Classification
convolutional neural net	Convolution Network	multi label classification	Multi label classification	collision	Collision avoidance
convolutional neural nets	Convolution Network	multi label classified	Multilabel Classifcation	collisions	Collision avoidance
convolutional neural network	Convolution Network	multi label classifier	Multilabel Classifcation	component analysis	Independent component analysis
convolutional neural networks	Convolution Network	multi label classifies	Multilabel Classifcation	computing systems	Cognitive computing
convolutionalneural net	Convolution Network	multi label classify	Multilabel Classifcation	convolution	Convolution Network
convolutionalneural nets	Convolution Network	multi label classifying	Multilabel Classifcation	convolutional	Convolution Network
convolutionalneural network	Convolution Network	multi label learning	Multilabel Learning	convolutional neural	Convolution Network
convolutionalneural networks	Convolution Network	multi layer perceptron	Multi layer perceptron	data mining	Machine learning
convolutionary net	Convolution Network	multi objective evolutionary algorithm	Multi objective evolutionary algorithm	data model	Learning Model
convolutionary nets	Convolution Network	multi objective optimisation	Multi objective optimisation	data models	Learning Model
convolutionary network	Convolution Network	multi sensor fusion	Multi sensor fusion	data processing	Machine learning
convolutionary networking	Convolution Network	multi task learning	Multitask Learning	detect objects	Object detection
convolutionary networks	Convolution Network	multiagent learning	Multiagent Learning	detected objects	Object detection
decision forest	Decision Forest	multiclass classifcation	Multiclass Classifcation	detecting objects	Object detection
decision forests	Decision Forest	multiclass classified	Multiclass Classifcation	detection algorithm	Object detection
decision model	Decision model	multiclass classifier	Multiclass Classifcation	detection method	Object detection
decision tree	Decision Forest	multiclass classifies	Multiclass Classifcation	detection methods	Object detection

deep belief net	Deep Belief Network	multiclass classify	Multiclass Classifcation	detection model	Object detection
deep belief nets	Deep Belief Network	multiclass classifying	Multiclass Classifcation	detection system	Object detection
deep belief network	Deep Belief Network	multi-instance learning	Multi-instance Learning	detection systems	Object detection
deep belief networking	Deep Belief Network	multikernel learning	Multi Kernel Learning	digital image	Image processing
deep belief networks	Deep Belief Network	multilabel classifcation	Multilabel Classifcation	digital images	Image processing
deep learning	Deep Learning	multilabel classified	Multilabel Classifcation	embed	Embedding
deep net	Deep Learning	multilabel classifier	Multilabel Classifcation	embeddings	Embedding
deep nets	Deep Learning	multilabel classifies	Multilabel Classifcation	emotion	Emotion recognition
deep network	Deep Learning	multilabel classify	Multilabel Classifcation	encode	Autoencoder
deep networking	Deep Learning	multilabel classifying	Multilabel Classifcation	encoder	Autoencoder
deep networks	Deep Learning	multilabel learning	Multilabel Learning	ensemble	Ensemble Learning
deep neural	Deep Learning	multilayer perceptron	Multilayer perceptron	eye tracking	Computer vision
deep neural network	Deep Learning	multinomial naïve Bayes	Multinomial naïve Bayes	facial features	Face recognition
deep reinforcement learning	Deep Learning	multiple kernel learning	Multi Kernel Learning	facial image	Face recognition
dictionary learning	Dictionary learning	multitask learning	Multitask Learning	facial recognition	Face recognition
differential evolution algorithm	Differential evolution algorithm	naive bayes classification	Naive bayes Classification	feature vectors	Feature Learning
diffusion model	Diffusion model	naïve bayes classification	Naive bayes Classification	federated	Federated learning
dimensionality reduction	Dimensionality reduction	naive bayes classified	Naive bayes Classification	fuzzy	Fuzzy system
driverless car	Autonomous system	naïve bayes classified	Naive bayes Classification	gesture based	Gesture recognition
driverless vehicle	Autonomous system	naive bayes classifier	Naive bayes Classification	graph	Graph Learning
dynamic time warping	Dynamic time warping	naïve bayes classifier	Naive bayes Classification	graphics processing	Graph Learning
echo state net	Echo State Network	naive bayes classifies	Naive bayes Classification	graphs	Graph Learning
echo state nets	Echo State Network	naïve bayes classifies	Naive bayes Classification	image acquiring	Image processing
echo state network	Echo State Network	naive bayes classify	Naive bayes Classification	image acquisition	Image processing
echo state networking	Echo State Network	naïve bayes classify	Naive bayes Classification	image analysis	Image processing
echo state networks	Echo State Network	naive bayes classifying	Naive bayes Classification	image capturing	Image processing

echostate net	Echo State Network	naïve bayes classifying	Naive bayes Classification	image coding	Image processing
echostate nets	Echo State Network	natural gradient	Natural gradient	image compression	Image processing
echostate network	Echo State Network	natural language generation	Natural Language Generation	image correction	Image processing
echostate networking	Echo State Network	natural language processing	Natural Language Processing	image detecting	Image processing
echostate networks	Echo State Network	natural language understanding	Natural Language Understanding	image determining	Image processing
embedding	Embedding	nearest neighbour algorithm	Nearest neighbour algorithm	image enhancement	Image processing
emotion recognition	Emotion recognition	neocognitron	Neocognitron	image extracting	Image processing
ensemble learning	Ensemble Learning	neocognitrons	Neocognitron	image features	Image processing
evolutionary algorithm	Evolutionary algorithm	neural architecture search	Neural architecture search	image generation	Image processing
evolutionary computation	Evolutionary algorithm	neural gas	Neural Gas	image matching	Image processing
evolutionary robotic	Evolutionary algorithm	neural model	Neural Model	image processor	Image processing
expert system	Expert System	neural modeling	Neural Model	image sensing	Image processing
expert systems	Expert System	neural modelling	Neural Model	image sensor	Image processing
extreme learning machine	Extreme Learning Machine	neural models	Neural Model	image signals	Image processing
extreme learning machines	Extreme Learning Machine	neural net	Neural Network	images captured	Image processing
extreme machine learning	Extreme Learning Machine	neural nets	Neural Network	images systems	Image processing
face recognition	Face recognition	neural network	Neural Network	intelligence system	Intelligent Agent
facial expression recognition	Face recognition	neural networking	Neural Network	kernel	String Kernel
factorisation machine	Factorisation machine	neural networks	Neural Network	learning engine	Learning Model
feature engineering	Feature Learning	neural turing	Neural turing	learning system	Learning Model
feature extraction	Feature Learning	neuro computing	Neuro-Computing	learning techniques	Learning Model
feature learning	Feature Learning	neuro dynamic programming	Neuro dynamic Programming	machine learned	Machine Learning
feature selection	Feature Learning	neuro evolution	Neuro-evolution	method of monitoring	Inductive monitoring
federated learning	Federated learning	neuro fuzzy	Neurofuzzy	motion detection	Object detection
feed forward net	Feed-Forward Network	neuro robotic	Neuro-robotic	multi modal	Multi Modal AI
feed forward nets	Feed-Forward Network	neuro robotics	Neuro-robotic	multiple sensors	Multi sensor fusion

feed forward network	Feed-Forward Network	neurocomputing	Neurocomputing	network cnn	Convolution Network
feed forward networking	Feed-Forward Network	neurodynamic programming	Neuro dynamic Programming	neuromorphic	Neuromorphic computing
feed forward networks	Feed-Forward Network	neuroevolution	Neuro-evolution	object determining	Object detection
feedforward net	Feed-Forward Network	neurofuzzy	Neurofuzzy	object identification	Object detection
feedforward nets	Feed-Forward Network	neuromorphic architecture	Neuromorphic computing	object tracking	Object detection
feedforward network	Feed-Forward Network	neuromorphic computing	Neuromorphic computing	obstacle	Obstacle avoidance
feedforward networking	Feed-Forward Network	neuromorphic engineering	Neuromorphic computing	obstacles	Obstacle avoidance
feedforward networks	Feed-Forward Network	neurorobotic	Neuro-robotic	optical character	Optical character recognition
firefly algorithm	Firefly algorithm	neurorobotics	Neuro-robotic	pattern matching	Pattern recognition
fuzzy c	Fuzzy system	nlp	Natural Language Processing	pedestrian	Pedestrian detection
fuzzy environment	Fuzzy system	non negative matrix factorisation	Non negative matrix factorisation	planning system	Planning algorithm
fuzzy logic	Fuzzy system	non supervised learning	Unsupervised Learning	prediction model	Learning Model
fuzzy number	Fuzzy system	object detection	Object detection	processed image	Image processing
fuzzy set	Fuzzy system	object recognition	Object recognition	processing apparatus image	Image processing
fuzzy system	Fuzzy system	obstacle avoidance	Obstacle avoidance	processing device image	Image processing
gaussian mixture model	Gaussian mixture model	one class classification	One class Classification	processing image	Image processing
gaussian process	Gaussian mixture model	one class classified	One class Classification	processing image data	Image processing
genai	Generative AI	one class classifier	One class Classification	processing images	Image processing
generalisation error	Generalization Error	one class classifies	One class Classification	processing method image	Image processing
generalisation errors	Generalization Error	one class classifying	One class Classification	recommendation based	Recommender system
generalization error	Generalization Error	one class learning	One class Classification	recommendation engine	Recommender system
generalization errors	Generalization Error	one shot learning	One shot learning	recommendation system	Recommender system
generation model	Generative AI	optical character recognition	Optical character recognition	recommendations based	Recommender system
generative adversarial net	Generative Adversarial Network	optimisation for learning	Optimisation for learning	recommending	Recommender system

generative adversarial nets	Generative Adversarial Network	optimization for learning	Optimisation for learning	reinforcement	Reinforcement Learning
generative adversarial network	Generative Adversarial Network	pac learning	Pac Learning	robot control	Autonomous system
generative adversarial networking	Generative Adversarial Network	particle swarm optimisation	Particle swarm optimisation	robot system	Autonomous system
generative adversarial networks	Generative Adversarial Network	pattern recognition	Pattern recognition	robotic system	Autonomous system
generative ai	Generative AI	pcnn	Pulse Coupled Neural Network	rule based	Rule-based System
generative artificial intelligence	Generative AI	pedestrian detection	Pedestrian detection	rule set	Rule-based System
generative pre-trained transformer	Generative AI	perceptron	Perceptron	rules based	Rule-based System
genetic algorithm	Genetic Programming	planning algorithm	Planning algorithm	rules engine	Rule-based System
genetic programming	Genetic Programming	policy gradient method	Policy gradient method	sensor data	Sensor data fusion
gesture recognition	Gesture recognition	probable approximate correct learning	Probably Approximately Correct Learning	sensor information	Sensor data fusion
gradient boosting	Gradient Boosting	probable approximately correct learning	Probably Approximately Correct Learning	sentiment	Sentiment analysis
gradient tree boosting	Gradient Boosting	probably approximate correct learning	Probably Approximately Correct Learning	set of rules	Rule-based System
grammatical inference	Grammatical Inference	probably approximately correct learning	Probably Approximately Correct Learning	set of training	Training Algorithm
graph kernel	Graph Kernel	pulse coupled neural net	Pulse Coupled Neural Network	similarity	Similarity Learning
graph kernels	Graph Kernel	pulse coupled neural nets	Pulse Coupled Neural Network	similarity score	Similarity Learning
graph learning	Graph Learning	q learning	Q learning	speech data	Speech processing
graph neural net	Graph neural network	radial basis function net	Radial Basis Function Network	speech input	Speech processing
graph neural nets	Graph neural network	radial basis function nets	Radial Basis Function Network	speech signal	Speech processing
graph neural network	Graph neural network	radial basis function network	Radial Basis Function Network	tracking method	Trajectory tracking
graph neural networks	Graph neural network	radial basis function networking	Radial Basis Function Network	tracking system	Trajectory tracking
graphical kernel	Graph Kernel	radial basis function networks	Radial Basis Function Network	trained machine	Training Algorithm
graphical kernels	Graph Kernel	random field	Random Forest	trained model	Training Algorithm
graphical model	Gaphical model	random forest	Random Forest	training data	Training Algorithm

graphneural net	Graph neural network	random forests	Random Forest	training system	Training Algorithm
graphneural nets	Graph neural network	rankboost	Rankboost	transformer	Transformer
graphneural network	Graph neural network	rbf net	Radial Basis Function Network	translating	Machine translation
graphneural networks	Graph neural network	rbfnn	Radial Basis Function Network	translation	Machine translation
graphs kernel	Graph Kernel	recommender system	Recommender system	translations	Machine translation
graphs kernels	Graph Kernel	recurrent neural network	Recurrent neural network	video processing	Computer vision
gravitational search algorithm	Gravitational search algorithm	regression tree	Regression tree	voice communication	Speech processing
hebbian learning	Hebbian learning	reinforcement learning	Reinforcement Learning	voice recognition	Speech processing
hidden markov model	Hidden markov model	relational learning	Relational learning		
hierarchical clustering	Hierarchical clustering	relevance vector machine	Relevance Vector Machine		
high dimensional data	High dimensional model	relevance vector machines	Relevance Vector Machine		
high dimensional feature	High dimensional model	relevance vectors machine	Relevance Vector Machine		
high dimensional input	High dimensional model				

Appendix 2 – Growth Index for AI technologies

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Adversarial Learning	3	57	19.00	Increasing
Generative Adversarial Network	18	342	19.00	Increasing
Representation Learning	3	51	17.00	Increasing
Neural architecture search	1	16	16.00	Increasing
Gradient Boosting	3	33	11.00	Increasing
Concept Drift	1	10	10.00	Increasing
Echo State Network	1	8	8.00	Increasing
Transfer Learning	14	110	7.86	Increasing
Deep Learning	402	2,968	7.38	Increasing
Artificial Intelligence	628	4,402	7.01	Increasing
Differential evolution algorithm	1	5	5.00	Increasing
Meta learning	1	5	5.00	Increasing
Activation Function	27	132	4.89	Increasing
Generative AI	20	95	4.75	Increasing
Neural Network	1,798	7,988	4.44	Increasing
Reinforcement Learning	164	709	4.32	Increasing
Graph Kernel	1	4	4.00	Increasing
Link prediction	4	16	4.00	Increasing
Natural Language Generation	15	56	3.73	Increasing
Motion planning	29	103	3.55	Increasing
Recurrent neural network	118	395	3.35	Increasing
Convolution Network	808	2,588	3.20	Increasing
Extreme Learning Machine	2	6	3.00	Increasing
Generalization Error	1	3	3.00	Increasing
Long Short Term Memory	15	42	2.80	Increasing
Robot Learning	4	11	2.75	Increasing
Training Algorithm	1,601	4,262	2.66	Increasing
Variational inference	2	5	2.50	Increasing
Supervised Learning	119	279	2.34	Increasing
Multilayer perceptron	10	21	2.10	Increasing
Machine-learned Ranking	1	2	2.00	Increasing

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Multi Modal AI	5	10	2.00	Increasing
Neural Model	17	34	2.00	Increasing
Learning Model	1,888	3,751	1.99	Increasing
Unsupervised Learning	87	171	1.97	Increasing
Neuromorphic computing	135	263	1.95	Increasing
Autonomous system	2,704	5,126	1.90	Increasing
Machine Learning	8,540	16,189	1.90	Increasing
Reservoir Computing	8	15	1.88	Increasing
Incremental Learning	12	22	1.83	Increasing
Natural Language Processing	728	1,324	1.82	Increasing
Decision model	24	42	1.75	Increasing
Action recognition	49	84	1.71	Increasing
Dimensionality reduction	42	72	1.71	Increasing
Perceptron	20	34	1.70	Increasing
Backpropagation Learning	3	5	1.67	Increasing
Stochastic gradient	20	33	1.65	Increasing
Sensor data fusion	2,715	4,461	1.64	Increasing
Deep Belief Network	8	13	1.62	Increasing
One class Classification	439	705	1.61	Increasing
Natural Language Understanding	133	213	1.60	Increasing
Random Forest	76	118	1.55	Increasing
Relational learning	2	3	1.50	Increasing
Learning Algorithm	197	294	1.49	Increasing
Brain computer interface	11	16	1.45	Increasing
Sentiment analysis	419	593	1.42	Increasing
Naive bayes Classification	5	7	1.40	Increasing
Ensemble Learning	268	372	1.39	Increasing
Embedding	1,254	1,705	1.36	Increasing
Boltzmann Machine	17	23	1.35	Increasing
Multitask Learning	7	9	1.29	Increasing
Dynamic time warping	18	23	1.28	Increasing
Computer vision	1,454	1,856	1.28	Increasing
Metric Learning	20	25	1.25	Increasing

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Emotion recognition	366	453	1.24	Increasing
Logistic regression	66	80	1.21	Increasing
Kernel learning	5	6	1.20	Increasing
High dimensional model	16	19	1.19	Increasing
Markovian	6	7	1.17	Increasing
Manifold Learning	7	8	1.14	Increasing
Feature Learning	1,336	1,494	1.12	Increasing
Diffusion model	11	12	1.09	Increasing
Cognitive computing	663	715	1.08	Increasing
Pedestrian detection	275	292	1.06	Increasing
Regression tree	18	19	1.06	Increasing
Obstacle avoidance	897	921	1.03	Increasing
Ambient intelligence	1	1	1.00	Decreasing
Blind signal separation	3	3	1.00	Decreasing
Intelligence augmentation	1	1	1.00	Decreasing
Intelligent Algorithm	9	9	1.00	Decreasing
Q learning	1	1	1.00	Decreasing
Rough set	2	2	1.00	Decreasing
Multi sensor fusion	163	160	0.98	Decreasing
Trajectory tracking	952	933	0.98	Decreasing
Recommender system	1,703	1,640	0.96	Decreasing
Autoencoder	2,818	2,706	0.96	Decreasing
Object detection	4,862	4,623	0.95	Decreasing
Object recognition	572	533	0.93	Decreasing
Transformer	323	293	0.91	Decreasing
Collision avoidance	1,153	1,038	0.90	Decreasing
Federated learning	348	310	0.89	Decreasing
Hierarchical clustering	47	41	0.87	Decreasing
Face recognition	1,158	992	0.86	Decreasing
Gaussian mixture model	111	94	0.85	Decreasing
Association rule	35	29	0.83	Decreasing
Cluster analysis	99	82	0.83	Decreasing
Graph Learning	6,621	5,411	0.82	Decreasing

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Topic Modelling	132	105	0.80	Decreasing
Decision Forest	307	241	0.79	Decreasing
Similarity Learning	4,477	3,325	0.74	Decreasing
Intelligent Agent	6,426	4,718	0.73	Decreasing
Dictionary learning	15	11	0.73	Decreasing
Human action recognition	202	141	0.70	Decreasing
String Kernel	1,365	924	0.68	Decreasing
Bayesian learning	441	290	0.66	Decreasing
Planning algorithm	251	155	0.62	Decreasing
Spectral clustering	13	8	0.62	Decreasing
Rule-based System	2,054	1,226	0.60	Decreasing
Genetic Programming	182	108	0.59	Decreasing
Inductive monitoring	291	166	0.57	Decreasing
Optical character recognition	917	516	0.56	Decreasing
Machine Intelligence	34	19	0.56	Decreasing
Image processing	28,866	16,063	0.56	Decreasing
Independent component analysis	267	137	0.51	Decreasing
Support Vector Machine	233	119	0.51	Decreasing
Speech processing	5,399	2,745	0.51	Decreasing
Expert System	199	100	0.50	Decreasing
Feed-Forward Network	2	1	0.50	Decreasing
Label Propagation	18	9	0.50	Decreasing
Neural Gas	2	1	0.50	Decreasing
Visual servoing	8	4	0.50	Decreasing
Swarm optimization	47	23	0.49	Decreasing
Gesture recognition	587	287	0.49	Decreasing
Collaborative filtering	111	54	0.49	Decreasing
Machine translation	4,127	1,926	0.47	Decreasing
Conditional Random Field	52	24	0.46	Decreasing
Human-AI interaction	44	20	0.45	Decreasing
Fuzzy system	554	245	0.44	Decreasing
Pattern recognition	1,093	471	0.43	Decreasing
Sparse representation	50	21	0.42	Decreasing

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
MapReduce	79	33	0.42	Decreasing
Learning To Rank	3	1	0.33	Decreasing
Evolutionary algorithm	57	18	0.32	Decreasing
Graphical model	183	56	0.31	Decreasing
Classifcation Algorithm	28	8	0.29	Decreasing
Hidden markov model	160	45	0.28	Decreasing
Adaptive Boosting	29	8	0.28	Decreasing
Boosting Algorithm	10	2	0.20	Decreasing
Rule induction	5	1	0.20	Decreasing
Radial Basis Function Network	11	2	0.18	Decreasing
Hebbian learning	6	1	0.17	Decreasing
Bootstrap aggregation	-	1	-	Emerging
Graph neural network	-	52	-	Emerging
Large Language Model	-	3	-	Emerging
Memetic algorithm	-	1	-	Emerging
Mixture Of Expert	-	5	-	Emerging
Multiclass Classifcation	-	5	-	Emerging
Multilabel Classifcation	-	1	-	Emerging
Multilabel Learning	-	2	-	Emerging
Nearest neighbour algorithm	-	3	-	Emerging
Neural turing	-	1	-	Emerging
Semi supervised learning	-	1	-	Emerging
Statistical Relation Learning	-	3	-	Emerging
Xgboost	-	5	-	Emerging
Committee Machine	1	-	-	Obsolescent
Firefly algorithm	1	-	-	Obsolescent
Grammatical Inference	7	-	-	Obsolescent
Gravitational search algorithm	1	-	-	Obsolescent
Hough transformer	4	-	-	Obsolescent
Inductive Logic Programming	1	-	-	Obsolescent
Instance based learning	1	-	-	Obsolescent
Liquid State Machine	1	-	-	Obsolescent
Multi Kernel Learning	1	-	-	Obsolescent

AI Technoloy	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Multi objective evolutionary algorithm	1	-	-	Obsolescent
Natural gradient	1	-	-	Obsolescent
Neurofuzzy	1	-	-	Obsolescent
Rankboost	3	-	-	Obsolescent
Relevance Vector Machine	2	-	-	Obsolescent

Appendix 3 – From Tech to Skills

Skill	AI Technology	Skill	AI Technology	Skill	AI Technology
Algorithms	Intelligent Algorithm	Evaluate translation technologies	Machine translation	Principles of artificial intelligence	Artificial Intelligence
Analyse images	Image processing	Forensic intelligence	Machine Intelligence	Produce scanned images	Image processing
Analyse text before translation	Machine translation	Grammar	Grammatical Inference	Prolog (computer programming)	Inductive Logic Programming
Artificial neural networks	Neural Network	Guidance, navigation and control	Obstacle avoidance	Pronunciation techniques	Speech processing
Augmented reality	Computer vision	Hadoop	MapReduce	Recommend books to customers	Recommender system
Automatic control system	Autonomous system	Hand gestures	Gesture recognition	Recommend product improvements	Recommender system
Biometrics	Face recognition	Human-computer interaction	Human-AI interaction	Revise translation works	Machine translation
Build recommender systems	Recommender system	Human-robot collaboration	Human-AI interaction	Robotics	Autonomous system
Characteristics of faces	Face recognition	Identify research topics	Topic Modelling	Semantics	Natural Language Understanding
Cognitive computing	Cognitive computing	Identify statistical patterns	Pattern recognition	Sensors	Sensor data fusion
Cognitive psychology	Cognitive computing	Image formation	Image processing	Signal processing	Image processing
Comprehend the material to be translated	Machine translation	Image recognition	Object recognition	Spatial planning	Motion planning
Computational biology	Genetic Programming	Imaging techniques	Image processing	Speech recognition	Speech processing
Computational linguistics	Large Language Model	Improve translated texts	Machine translation	Speech techniques	Speech processing

Computer graphics	Computer vision	Information extraction	Natural Language Processing	Study topics	Topic Modelling
Computer vision	Computer vision	Label components	Multilabel Classifcation	Test sensors	Inductive monitoring
Control systems	Autonomous system	Machine learning	Machine Learning	Track geometry	Trajectory tracking
Create digital images	Image processing	Machine translation	Machine translation	Tracking principles	Trajectory tracking
Data analytics	Machine Learning	Make decisions	Decision model	Train planning	Planning algorithm
Data mining	Machine Learning	Make price recommendations	Recommender system	Translate different types of texts	Machine translation
Data mining methods	Machine Learning	Manage obstacle control	Obstacle avoidance	Translate foreign language	Machine translation
Data models	Machine Learning	Memorise information	Long Short Term Memory	Translate language concepts	Machine translation
Decision support systems	Decision model	Memorise large amounts of information	Long Short Term Memory	Translate spoken language	Machine translation
Decode handwritten texts	Optical character recognition	Motion capture	Trajectory tracking	Translate texts	Machine translation
Deep learning	Deep Learning	Motion graphics	Trajectory tracking	Understand spoken English	Natural Language Understanding
Determine image composition	Image processing	Natural language processing	Natural Language Processing	Unified modelling language	Large Language Model
Determine imaging techniques to be performed	Image processing	Operate voice picking systems	Speech processing	Urban planning	Planning algorithm
Develop a translation strategy	Machine translation	Optical character recognition software	Optical character recognition	Use computer-aided translation	Machine translation
Develop classification systems	Machine Learning	Perform asset recognition	Object recognition	Use dictionaries	Dictionary learning
Develop computer vision system	Computer vision	Perform data mining	Machine Learning	Use logic programming	Inductive Logic Programming
Develop predictive models	Learning Model	Perform dimensionality reduction	Dimensionality reduction	Use mine planning software	Planning algorithm
Develop translation memory software	Machine translation	Perform image editing	Image processing	Use word processing software	Speech processing
Digital image processing	Image processing	Phonetics	Speech processing	Utilise decision support system	Decision model
Electroencephalography	Brain computer interface	Photographic processing techniques	Image processing	Utilise machine learning	Machine Learning
Employ translation techniques	Machine translation	Polygraphy	Computer vision	Virtual reality	Computer vision
Evaluate training	Training Algorithm	Post-processing of photographs	Image processing	Voice interpreting	Speech processing

Appendix 4 – Growth index for skills

Skill	Total No. of patents	No. of patents (2010-2019)	No. of patents (2020-2023)	Growth Index	Growth pattern
Deep learning	3,370	402	2,968	7.38	Increasing
Principles of artificial intelligence	5,030	628	4,402	7.01	Increasing
Artificial neural networks	9,786	1,798	7,988	4.44	Increasing
Spatial planning	132	29	103	3.55	Increasing
Memorise information	57	15	42	2.80	Increasing
Memorise large amounts of information	57	15	42	2.80	Increasing
Evaluate training	5,863	1,601	4,262	2.66	Increasing
Develop predictive models	5,639	1,888	3,751	1.99	Increasing
Automatic control system	7,830	2,704	5,126	1.90	Increasing
Control systems	7,830	2,704	5,126	1.90	Increasing
Robotics	7,830	2,704	5,126	1.90	Increasing
Data analytics	24,729	8,540	16,189	1.90	Increasing
Data mining	24,729	8,540	16,189	1.90	Increasing
Data mining methods	24,729	8,540	16,189	1.90	Increasing
Data models	24,729	8,540	16,189	1.90	Increasing
Develop classification systems	24,729	8,540	16,189	1.90	Increasing
Machine learning	24,729	8,540	16,189	1.90	Increasing
Perform data mining	24,729	8,540	16,189	1.90	Increasing
Utilise machine learning	24,729	8,540	16,189	1.90	Increasing
Information extraction	2,052	728	1,324	1.82	Increasing
Natural language processing	2,052	728	1,324	1.82	Increasing
Decision support systems	66	24	42	1.75	Increasing
Make decisions	66	24	42	1.75	Increasing
Utilise decision support system	66	24	42	1.75	Increasing
Perform dimensionality reduction	114	42	72	1.71	Increasing
Sensors	7,176	2,715	4,461	1.64	Increasing
Semantics	346	133	213	1.60	Increasing
Understand spoken english	346	133	213	1.60	Increasing
Electroencephalography	27	11	16	1.45	Increasing
Augmented reality	3,310	1,454	1,856	1.28	Increasing
Computer graphics	3,310	1,454	1,856	1.28	Increasing
Computer vision	3,310	1,454	1,856	1.28	Increasing
Develop computer vision system	3,310	1,454	1,856	1.28	Increasing
Polygraphy	3,310	1,454	1,856	1.28	Increasing
Virtual reality	3,310	1,454	1,856	1.28	Increasing

Cognitive computing	1,378	663	715	1.08	Increasing
Cognitive psychology	1,378	663	715	1.08	Increasing
Guidance, navigation and control	1,818	897	921	1.03	Increasing
Manage obstacle control	1,818	897	921	1.03	Increasing
Algorithms	18	9	9	1.00	Decreasing
Motion capture	1,885	952	933	0.98	Decreasing
Motion graphics	1,885	952	933	0.98	Decreasing
Track geometry	1,885	952	933	0.98	Decreasing
Tracking principles	1,885	952	933	0.98	Decreasing
Build recommender systems	3,343	1,703	1,640	0.96	Decreasing
Make price recommendations	3,343	1,703	1,640	0.96	Decreasing
Recommend books to customers	3,343	1,703	1,640	0.96	Decreasing
Recommend product improvements	3,343	1,703	1,640	0.96	Decreasing
Image recognition	1,105	572	533	0.93	Decreasing
Perform asset recognition	1,105	572	533	0.93	Decreasing
Biometrics	2,150	1,158	992	0.86	Decreasing
Characteristics of faces	2,150	1,158	992	0.86	Decreasing
Identify research topics	237	132	105	0.80	Decreasing
Study topics	237	132	105	0.80	Decreasing
Use dictionaries	26	15	11	0.73	Decreasing
Train planning	406	251	155	0.62	Decreasing
Urban planning	406	251	155	0.62	Decreasing
Use mine planning software	406	251	155	0.62	Decreasing
Computational biology	290	182	108	0.59	Decreasing
Test sensors	457	291	166	0.57	Decreasing
Decode handwritten texts	1,433	917	516	0.56	Decreasing
Optical character recognition software	1,433	917	516	0.56	Decreasing
Forensic intelligence	53	34	19	0.56	Decreasing
Analyse images	44,929	28,866	16,063	0.56	Decreasing
Create digital images	44,929	28,866	16,063	0.56	Decreasing
Determine image composition	44,929	28,866	16,063	0.56	Decreasing
Determine imaging techniques to be performed	44,929	28,866	16,063	0.56	Decreasing
Digital image processing	44,929	28,866	16,063	0.56	Decreasing
Image formation	44,929	28,866	16,063	0.56	Decreasing
Imaging techniques	44,929	28,866	16,063	0.56	Decreasing
Perform image editing	44,929	28,866	16,063	0.56	Decreasing
Photographic processing techniques	44,929	28,866	16,063	0.56	Decreasing
Post-processing of photographs	44,929	28,866	16,063	0.56	Decreasing

Produce scanned images	44,929	28,866	16,063	0.56	Decreasing
Signal processing	44,929	28,866	16,063	0.56	Decreasing
Operate voice picking systems	8,144	5,399	2,745	0.51	Decreasing
Phonetics	8,144	5,399	2,745	0.51	Decreasing
Pronunciation techniques	8,144	5,399	2,745	0.51	Decreasing
Speech recognition	8,144	5,399	2,745	0.51	Decreasing
Speech techniques	8,144	5,399	2,745	0.51	Decreasing
Use word processing software	8,144	5,399	2,745	0.51	Decreasing
Voice interpreting	8,144	5,399	2,745	0.51	Decreasing
Hand gestures	874	587	287	0.49	Decreasing
Analyse text before translation	6,053	4,127	1,926	0.47	Decreasing
Comprehend the material to be translated	6,053	4,127	1,926	0.47	Decreasing
Develop a translation strategy	6,053	4,127	1,926	0.47	Decreasing
Develop translation memory software	6,053	4,127	1,926	0.47	Decreasing
Employ translation techniques	6,053	4,127	1,926	0.47	Decreasing
Evaluate translation technologies	6,053	4,127	1,926	0.47	Decreasing
Improve translated texts	6,053	4,127	1,926	0.47	Decreasing
Machine translation	6,053	4,127	1,926	0.47	Decreasing
Revise translation works	6,053	4,127	1,926	0.47	Decreasing
Translate different types of texts	6,053	4,127	1,926	0.47	Decreasing
Translate foreign language	6,053	4,127	1,926	0.47	Decreasing
Translate language concepts	6,053	4,127	1,926	0.47	Decreasing
Translate spoken language	6,053	4,127	1,926	0.47	Decreasing
Translate texts	6,053	4,127	1,926	0.47	Decreasing
Use computer-aided translation	6,053	4,127	1,926	0.47	Decreasing
Human-computer interaction	64	44	20	0.45	Decreasing
Human-robot collaboration	64	44	20	0.45	Decreasing
Identify statistical patterns	1,564	1,093	471	0.43	Decreasing
Hadoop	112	79	33	0.42	Decreasing
Computational linguistics	3		3		Emerging
Label components	1		1		Emerging
Unified modelling language	3		3		Emerging
Prolog (computer programming)	1	1			Obsolescent
Grammar	7	7			Obsolescent
Use logic programming	1	1			Obsolescent