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Contents

Digital Transformation: Challenges and Opportunities for the Irish Labour Market

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Abstract

AI and digital automation technologies have the potential to reshape labour markets and economies in difficult to predict ways. This *Article* examines the link between digital transformation and the Irish labour market, with four main findings. First, we find that at least 14 per cent of the current workforce may be employed in jobs with both high exposure to and low potential for augmentation by digitally transformed employment. Second, to date demand for AI-related skills is concentrated in ICT, Finance, and Professional Services, which combined account for 20 per cent of the workforce. Third, labour demand for highly skilled workers is running ahead of new domestic supply in key fields such as ICT and engineering. Fourth, our analysis indicates that digital skills mismatch is a significant barrier to occupational mobility, with higher mismatch associated with a lower probability of transitioning between occupations. These findings reflect current labour market conditions but AI technologies are developing quickly, such that further ongoing analysis is warranted. Public policy has a role to play in targeting retraining supports towards the most exposed occupations and sectors to facilitate workforce adaptability.

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1. Introduction

Ireland's long-term growth and its citizens' living standards will be shaped by several structural forces: demographic change and ageing, climate transition, geoeconomic developments, and digital transformation – particularly AI and automation (Conefrey et al., 2024). Of these, digital transformation is pivotal: it can reorganise production, alter labour-capital efficiency, and thus influence Ireland's growth trajectory. Yet it also poses risks of labour-market disruption.

Historically, technological advances have driven productivity and living-standard gains even as they displaced some jobs and created others (Autor et al., 2024). Today, generative AI and related technologies promise another wave of technological change, boosting productivity and innovation while reshaping job content and skill requirements (Trammell and Korinek, 2023). Policymakers, employers and workers must therefore reassess workforce strategies to ensure labour markets are adaptable, inclusive and resilient.

This article addresses three key questions:

1. **What is the current level of employment exposure in Ireland to digital transformation?** We apply three indices—the C-AIOE exposure index (Pizzinelli et al., 2023), Autor and Thompson's Expertise index (2025) and Prytkova et al.'s patent-based measure (2024)—to gauge sector and occupational exposure to AI.

2. **How are skill requirements changing?** By analysing online job postings, task content and digital-competency demands, we identify shifts in required skills.

3. **How does skills mismatch affect occupational mobility?** Using a task-based framework, we assess how differences in required skills constrain movement between occupations, with a focus on digital skills.

Our key findings are:

- Exposure to AI is uneven across occupations: Clerical and customer-service roles feature in the High-Exposure, Low-Complementarity (HELC) group, while ICT, science, engineering, legal and managerial roles fall into the High-Exposure, High-Complementarity (HEHC) group. This pattern is consistent across exposure measures used to assess new technology exposure in the Irish labour market. Around 14 per cent of workers are HELC under all three measures, rising to 31 per cent under two measures, highlighting the size of the workforce potentially exposed to substitution risk.

- AI-skill demand is concentrated in ICT, professional services and finance, which together account for 20 per cent of the total employment. Professional and technical occupations show the highest AI-skill intensity.

- Graduates in ICT and engineering have grown faster than other fields (2019–2023), yet their employment shares within key sectors have fallen, suggesting demand outstrips domestic supply and is met partly by migration.

- Occupational mobility is often limited by skill mismatch. Many workers move within the same occupational group, hindering transitions to emerging roles. Digital-skill gaps are a significant barrier to mobility.

- Mobility frictions are asymmetric and can create bottlenecks. Some occupations – such as Cleaners and Helpers or Food Preparation Assistants – are relatively easy to enter but hard to exit, which can trap workers in low mobility roles, while digital intensive occupations tend to be hard to access but open up wider progression once entered.

- Nature of digital-skill barriers varies by complexity: transitions to occupations requiring developer-level advanced digital skills face substantial constraints due to skill mismatch, whilst transitions across occupations requiring user- and practitioner-level digital skills are less restricted. This suggests that for many workers – particularly in the HELC group – upskilling needs may focus on AI use rather than AI development, potentially lowering barriers to beneficial mobility.

- Labour market conditions amplify occupational mobility frictions. When unemployment is higher, workers find it even more difficult to transition into new roles that require new skills, suggesting that skill mismatch barriers impact more when opportunities are scarce.

These findings underline the heterogeneous impact of digital transformation: some technologies automate labour, others augment it or have neutral effects (Prytkova et al., 2024). Adoption is uneven—larger firms and certain sectors lead, while skill shortages, costs, digital readiness and regulatory uncertainty slow uptake (OECD/BCG/INSEAD, 2025; Acemoglu et al., 2022).

However, our analysis comes with some caveats. First, the exposure indices we use are static, reflecting assessments of conditions as understood up until recently. They should be interpreted with caution as they may not

capture firm-level heterogeneity, evolving adoption rates, or potentially more rapid technological change than generally foreseen to date. Second, the relationship we document between exposure, vacancies, and occupation mobility are descriptive and do not provide a causal assessment of the link between AI adoption and employment outcomes. Data limitations, particularly around occupation detail and emerging AI tasks, may lead us to understate skill mismatches. Finally, our focus is on short-to-medium-term labour-market effects; we do not address general-equilibrium impacts on wages, productivity or inequality. Consequently, the findings presented here should be viewed as a snapshot of labour market dynamics at a particular point in time. Given the accelerating pace of technology development in recent years, it is difficult to predict the potential impact on the labour market, underscoring the time-bound nature of our findings and the need for ongoing research as technology evolves.

Nonetheless, our findings suggest important policy implications. First, the need for targeted reskilling and upskilling initiatives to bridge digital-skill gaps. Second, institutional support and investment in lifelong learning systems. Third, monitoring of technology adoption and labour-market outcomes to inform adaptive policies, not only regarding occupational mobility and digital skills gaps in high AI exposure areas but also in areas of low AI exposure where labour demand may continue to grow. In this context, the occupational mobility framework employed in this study can be used as a one of the monitoring tools to identify adjustment to technology shocks. Additionally, this framework can also be adapted to analyse labour market adjustment to range of economic shocks beyond technological change.

Section 2 examines exposure and complementarity measures. Section 3 provides a supply-side assessment of Ireland's talent base and analyses occupational mobility barriers. Section 4 concludes.

2. Digital transformation: exposure and complementarity

Past technological revolutions—from the mechanisation fears of the 1930s to the automation anxieties of the 1960s—ultimately saw labour markets adjust, aided by policy and institutional support (Keynes, 1930; OECD, 2019). Today's wave, driven by AI and digital technologies, differs because it extends into non-routine, high-skill occupations, raising the prospect of more widespread disruption if workers and institutions do not adapt (IMF, 2024).

Skills based assessment

We use a task-based framework—essentially treating each occupation as a bundle of tasks—to assess AI's likely impact on Irish jobs. Our principal tool is the Complementarity-adjusted AI Occupational Exposure (C-AIOE) index (Felten et al., 2021; Pizzinelli et al., 2023), widely adopted by the IMF, OECD and the Department of Finance. C-AIOE combines both exposure metrics – that is, the susceptibility of specific occupational tasks to AI automation – and complementarity metrics – that is, the extent to which AI augments existing roles. Further details are provided in an Appendix A.

Occupations are classified by whether their exposure and complementarity scores lie above or below the median of exposure and complementarity, yielding four groups:

1. High-Exposure, High-Complementarity (HEHC)
2. High-Exposure, Low-Complementarity (HELC)
3. Low-Exposure, High-Complementarity (LEHC)
4. Low-Exposure, Low-Complementarity (LELC)

Figure 1 shows the mapping C-AIOE scores to the 2023 Irish Labour Force Survey. We estimate that 32 per cent of employment falls into HELC group — roles, like general clerks and customer-service clerks, highly vulnerable to automation with limited scope for AI collaboration. Another 31 per cent are in HEHC group — occupations, such as engineers and service managers, where AI may augment decision-making and creativity. The remaining 37 per cent occupy the left-hand quadrants (LEHC and LELC) — including agricultural workers, machine operators and trade workers — where AI's impact is more limited. This classification highlights which sectors and occupations face the greatest risk or opportunity from AI, guiding workforce planning and targeted training interventions.

Occupations in the HELC quadrant account for 32 per cent of employment in 2023

Figure 1 AI exposure and complementarity across occupations (ISCO-08 2 digit)
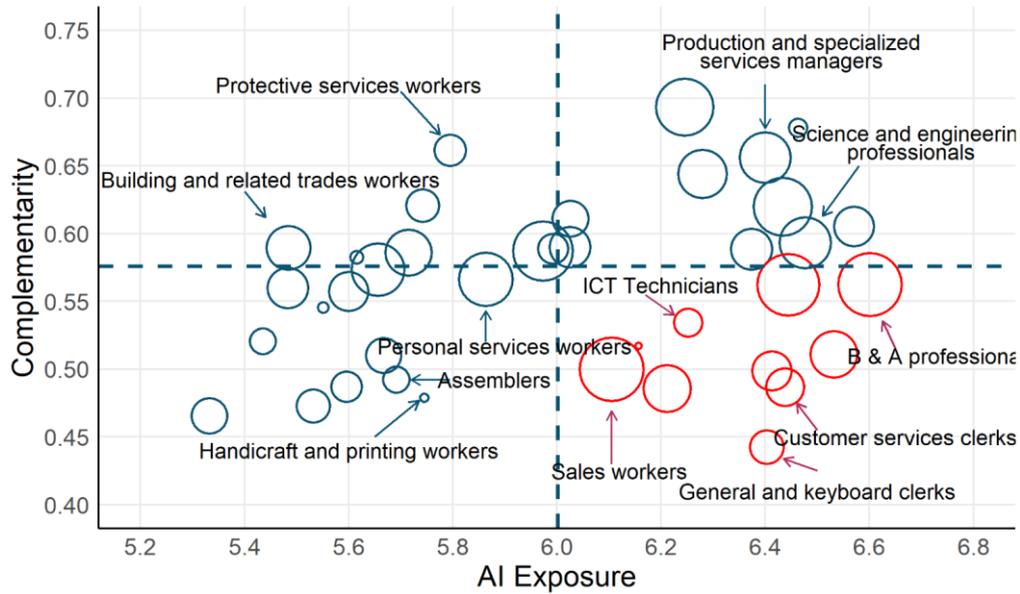
Source: CSO Irish LFS Q1-Q4 2023 and Authors' calculations.

Notes: The chart illustrates workforce exposure and complementarity to AI technologies across occupations in Ireland using the C-AIOE measure. The bubble size represents relative employment levels across ISCO-08 2-digit occupations, with larger bubble indicating higher employment. Occupation definitions: B & A professionals = Business and administration professionals; ICT Technicians = Information and Communication Technicians.

Expertise-based approach and *Patent*-based approach

A potential limitation of the C-AIOE is that it is a relative measure, relying on a set of just ten narrow AI applications (see Appendix A). We therefore consider two additional approaches: the Expertise based measure (Thompson and Autor, 2025) and a Patent-based measure (Prytkova et al., 2024). These rely on different assumptions about AI capabilities and occupational tasks, providing an alternative assessment of its potential impact.

Expertise-based approach

This measure draws on the Efficient Coding Hypothesis, which suggests that 'expert' vocabulary emerges when social groups – such as professional occupations – need to communicate technical ideas efficiently within their domain. These 'expert words' are generally infrequent in general language. Whereas commonplace words are those that are used more often when the idea is communicated to non-specialist audience across multiple domains. Autor and Thompson (2025) suggest that occupations involving a higher use of expert language are more resistant to AI substitution because they rely on tacit knowledge and specialised communication that current AI systems struggle to replicate. Using this approach, we analyse tasks descriptions and assign an

expertise score (details available in Appendix A). We combine the expertise-based exposure scores with the occupational complementarity index developed by Pizzinelli et al. (2023), which captures the extent to which AI is likely to complement or substitute for labour.[2]

Figure 2 plots Irish occupations across occupation expertise and AI complementarity dimensions. The Expertise-based exposure score is a relative measure, indicating how exposed an occupation is to new technology compared to other occupations. The size of each bubble represents an ISCO-08 2-digit occupation's share of total employment. Occupations in the bottom-left quadrant – low expertise and low complementarity – are most exposed to potential new technology disruption. These include occupations such as Sales workers and Personal Service workers, which involve relatively routine tasks and generalised communication, making them more amenable to automation. The expertise-based exposure measure identifies occupations accounting for 22 per cent of employment in 2023 as HELC. In contrast, occupations located in the top-right quadrant combine high levels of expertise with strong complementarity, indicating lower exposure and greater potential for AI to augment rather than replace human work. These include Science and Engineering professionals, Health professionals, Business and Administration professionals, Legal professionals, and Managers, whose roles often require domain-specific knowledge, critical thinking, and complex communication. Using the expertise-based measure, HEHC occupations account for 27 per cent of 2023 employment. The expertise-based measure offers an alternative lens that captures the linguistic and cognitive dimensions of work, complementing the technology-task overlap captured by the C-AIOE framework. As this measure is backward looking and based on AI capabilities at a point in time, this may limit its predictive insights.

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[2] The Pizzinelli et al. (2023) complementarity index was originally developed alongside the C-AIOE exposure measure, it is defined at the occupation level using job context and skill characteristics. Given it is constructed independently of any specific exposure metric and uses standard occupation classifications, it can be consistently paired with alternative occupation level AI exposure measures.

Occupations accounting for 22 per cent of 2023 employment considered HELC using the *expertise*-based measure

Figure 2 Expertise-based exposure measure and AI complementarity across occupations (ISCO-08 2 digit)
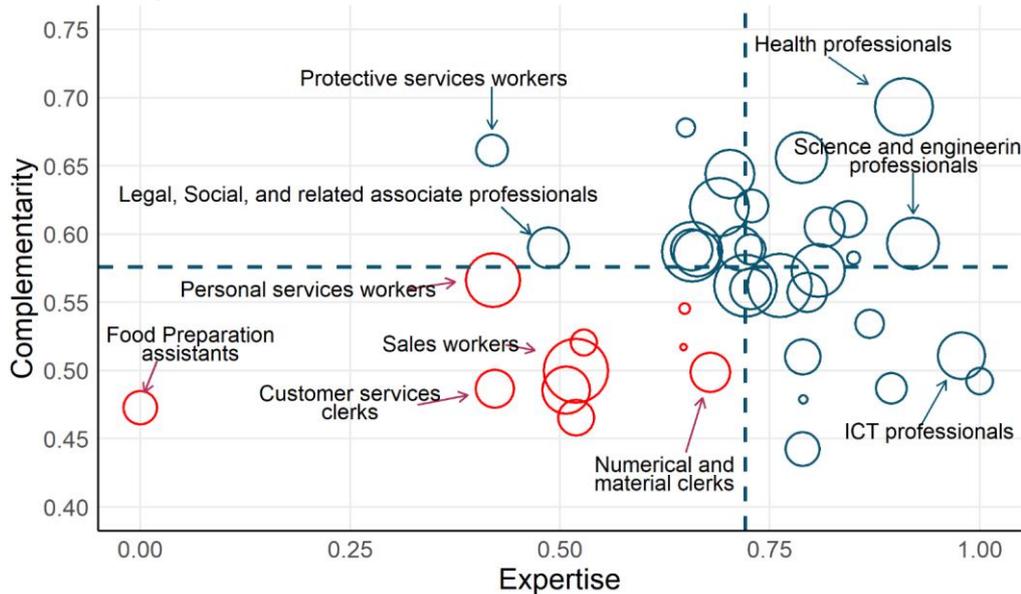
Source: CSO LFS Q1-Q4 2023 and Central Bank of Ireland

Notes: The chart illustrates workforce exposure and complementarity to AI technologies across occupations in Ireland using Expertise measure. The bubble size represents relative employment levels across ISCO-08 2-digit occupations, with larger bubble indicating higher employment. Occupation definitions: ICT Technicians = Information and Communication Technicians.

Patent-based approach

The patent-based exposure measure (proposed by Prytkova et al., 2024) uses natural language processing to assess how closely occupational tasks align with emerging digital technologies, based on semantic similarity between patent texts and occupation descriptions. The key intuition is that if the language used to describe an occupation is like that used in patents representing technologies, the occupation is more likely to be exposed to new technologies.

Unlike measures focused on AI alone, the patent-based approach captures a wider set of digital innovations and does not assume whether technologies act as complements or substitutes to labour. It reflects potential rather than realised exposure, offering a forward-looking metric of technological relevance based on real-time innovation trends. We use the occupation-level exposure scores published by the authors (details available in Appendix A) combined with Pizzinelli et al (2023) complementarity (Figure 3).

Occupations in the bottom-right quadrant – those with HELC – are most susceptible to displacement and account for 35 per cent of 2023 employment. Examples of these occupations includes Associate Professionals, Customer

Services Clerks and General Clerks, Personal Care Workers and Sales Workers. These jobs tend to involve routine or codifiable tasks that align closely with patented technologies but offer limited scope for AI to augment human work. Occupations in the top-right quadrant, which exhibit HEHC to new technologies, may benefit from development in new technologies through augmentation. These occupations include Science and Engineering professionals, ICT professionals, Managers and Legal professionals – roles that rely heavily on specialised knowledge and interpersonal skills. Remaining occupations fall into the lower exposure half of the distribution (left quadrants), reflecting relatively limited overlap.

Occupations accounting for 35 per cent of 2023 employment identified as HELC using the *patent*-based exposure approach

Figure 3 Patent-based exposure measure and AI complementarity across occupations (ISCO-08 2 digit)
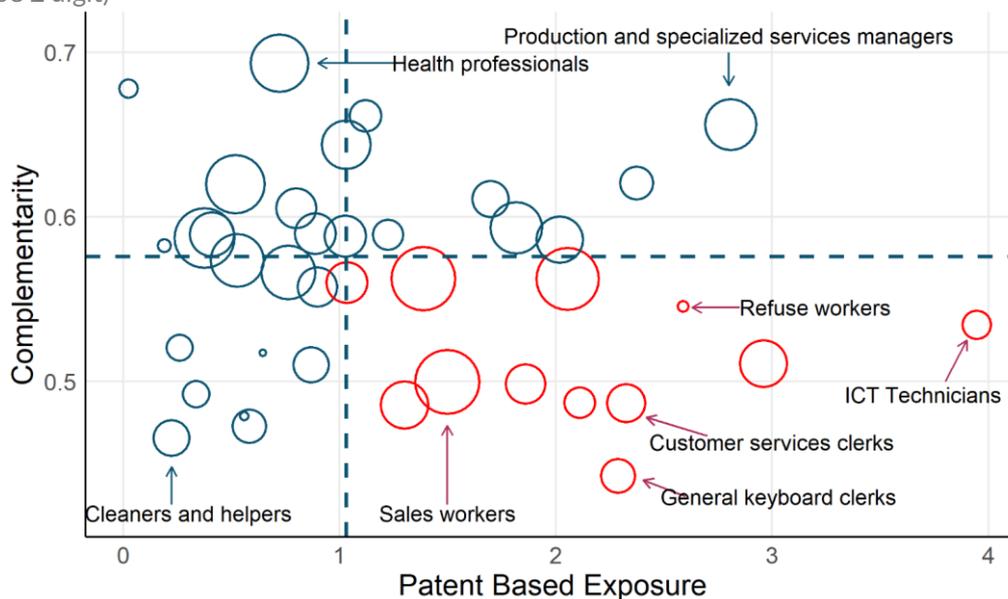
Source: CSO LFS Q1-Q4 2023 and Central Bank of Ireland

Notes: The chart illustrates workforce exposure and complementarity to AI technologies across occupations in Ireland using Patent-based measure. The bubble size represents relative employment levels across ISCO-08 2-digit occupations, with larger bubble indicating higher employment. Occupation definitions: ICT Technicians = Information and Communication Technicians. Source:

The three approaches presented offer complementary yet converging perspectives on the potential impact of new technologies on the Irish labour market. Whilst by definition the three measures are unanimous on the complementary of occupations to AI, they also consistently identify a common set of occupations as being most *exposed* to technological disruption. To illustrate this convergence, Table 1 reports the overlap of occupations classified as high-exposure, low-complementarity (HELC) across the three frameworks. Around 14 per cent of the workforce fall into occupations

identified as HELC across all three measures in 2023, while a further 17 percent are flagged in at least two. Another 12 percent appear in the HELC group under one measure only, whereas the remainder are not classified as HELC by any framework. Roles such as General Clerks, Customer Service Workers, Personal Care Workers, and Sales Assistants regularly emerge in the HELC quadrant across all three frameworks. Conversely, Science and Engineering Professionals, ICT specialists, Legal professionals, and Managers consistently appear in the HEHC category, suggesting these roles may evolve through augmentation rather than substitution.

The alignment across these independent measures (Table 1) strengthens confidence in the exposure assessments and highlights the need for targeted policy action, particularly in occupations where technological change may outpace workers' capacity to adapt. Using multiple measures offers a more nuanced, policy-relevant view of where interventions in training, education, and workforce planning will be most effective as the nature of work continues to evolve.

Table 1: Overlap of HELC Occupations across Exposure measures

HELC	Occupations
Overlap across 3 measures	Numerical and Material recording clerks; Customer service clerks; Sales workers; Other clerical support workers (14%)
Overlap across 2 measures	ICT Technicians; ICT Technology Professionals; Business and Administration Professionals; Business and Administration associate professionals; General and Keyboard clerks; Refuse workers and other elementary workers; Street and related sales and services workers (19%)
Exposed in (any) one measure	Labourers in Mining, Construction, Manufacturing and Transport; Stationary Plant and Machine operators; Agricultural, Forestry and Fishery labourers; Food preparation assistants; Personal Services workers; Cleaners and Helpers (12%)
Not in HELC	Production and Specialized Services managers; Science and Engineering Professionals; Health Associate Professionals; Personal Care workers; Teaching Professionals; Protective Services workers; Electrical and Electronics trades workers; Market-oriented skilled Forestry, Fishery and Hunting workers; Legal, Social and Cultural Professionals; Metal, Machinery and related trades workers; Market-oriented Skilled Agricultural workers; Food Processing, Woodworking, Garment and other craft and related trades workers; Assemblers; Handicraft and Printing workers; Hospitality, Retail and other services managers; Legal, Social, Cultural and related associate professionals; Health Professionals; Administrative and Commercial Managers; Science and Engineering Associate Professionals; Chief Executives, Senior officials and Legislators; Drivers and Mobile Plant operators; Building and related trades workers (excluding Electricians) (55%)

Source: Authors' calculations.

Table 2 further disaggregates the exposure measures by gender, age, and education level to highlight which groups are most represented in occupations classified as HELC. The results reveal distinct demographic patterns. Women account for a higher share of employment in occupations identified as HELC across all three measures (20 percent) compared with males (8 percent).

Workers under the age of 35 years also have a greater presence in HELC category (16 percent) than those aged 35 and over (11 percent). College educated workers comprise 19 percent of those in HELC occupations, compared with 14 percent among non-college educated workers. Overall, the findings reveal an uneven distribution of exposure across the Irish workforce. The groups most represented in HELC occupations may benefit from targeted opportunities for reskilling and workforce-transition policies.

Table 2: Overlap of HELC Occupations across Exposure measures – By Gender, Age, and Education level

HELC	Gender		Age group		Education level	
	Male	Female	Up to 35 years old	Over 35 years old	College Educated	Non-College Educated
Overlap across 3 measures	8	20	16	11	19	14
Overlap across 2 measures	19	19	19	19	11	19
Exposed in (any) one measure	12	12	15	10	20	12
Not in HELC	61	49	50	60	50	55
Total	100	100	100	100	100	100

Source: CSO and Authors' calculations.

3. Labour Supply and Occupation Mobility

Labour supply - workforce preparedness

The pace and scale of technology adoption depend not only on firm capabilities, but also on the availability of workers with the skills required to implement and use these technologies effectively. The availability of digitally skilled, adaptable, and AI-literate workers will be central to how effectively the economy can absorb the benefit from AI advancements. Understanding the supply of such talent involves looking not just at firm demand, but also at the talent supply coming from the education system and the broader workforce.

A useful indicator of workforce preparedness is the composition of higher education graduates across fields relevant to digital transformation. Table 3 reports the number of tertiary graduates in Ireland from 2019 to 2023 by broad field of study, alongside their share of total employment in related sectors. While the mapping between fields of study and NACE sectors is not exact, it offers a useful approximation of how graduate supply compares with labour market demand (Table D2 in the Appendix shows the mapping of field of study to NACE sectors).

Graduate numbers have expanded across most fields, with particularly strong growth in Business, Administration and Law, Education, and Health and

Welfare. In ICT and Engineering, Manufacturing and Construction, graduate supply also rose substantially between 2019 and 2023. However, despite this expansion, the employment share of graduates in key STEM fields such as ICT, Natural Sciences, and Health and Welfare all declined over the same period. This pattern can be interpreted as indicating that the number of graduates has increased while their employment share has declined. A potential explanation is that the supply of new graduates is not sufficient to meet the demand requirements in these sectors. This may reflect demand outpacing supply, where positions may be filled through alternative channels such as migration or upskilling of existing workforce. By contrast, fields such as Education and Business both registered an increase in graduate numbers and a higher share of graduates in employment, indicating a closer alignment between supply and demand. These patterns point to persistent pressures in technology fields, where workforce demand appears to be running ahead of graduate inflows, underscoring the importance of continued investment in talent pipelines for AI- and digital-intensive roles.

Table 3: Number of graduates by Field of Study in Ireland

Field of Study	Graduate Employment Share		Graduates	
	2023 share (%)	Change 2019-2023 (pp)	2023 level	Change 2019-2023 (%)
Arts and humanities	7.44	-0.27	9,155	-0.4
Education	4.36	0.62	9,735	41.4
Health and welfare	4.26	-0.34	15,355	13.9
Business, administration and law	3.81	0.26	22,185	18.4
Information and Communication Technologies (ICTs)	3.73	-0.22	6,495	32.1
Social sciences, journalism and information	2.40	0.20	6,065	23.0
Engineering, manufacturing and construction	1.98	0.12	9,715	19.7
Natural sciences, mathematics and statistics	1.42	-0.09	7,165	10.7
Agriculture, forestry, fisheries and veterinary	1.18	0.00	1,270	4.1
Services	0.44	-0.09	2,775	-11.6
Generic programmes and qualifications	0.26	-0.36	375	-47.2
Total	31.28		90,290	
Average		-0.02		9.5

Source: HEA, CSO and authors' calculations.

Workforce preparedness increasingly depends on the worker's ability to continuously update their skills in response to technological change. The growing availability of online learning platforms and industry-organised certifications has enabled many to acquire new competencies outside traditional academic pathways. The ongoing shift toward lifelong learning is well documented. The OECD reported that 37 per cent of adults participated in non-formal, job-related learning in the past year – significantly higher than the 8 per cent who took part in formal learning (OECD, 2025). This momentum

is reflected in the remarkable performance of Ireland, where 51 per cent of adults reported engaging in some form of adult learning — well above the OECD average of 40 per cent. Crucially, nearly 95 per cent of those who learned informally reported that the learning was useful, underlining its practical relevance across sectors.

While Ireland continues to expand its supply of domestic graduates and support upskilling among existing workers, there remains excess demand in some areas. For example, the SOLAS Difficult-to-Fill Vacancies Survey (2024) highlights widespread hiring challenges in ICT, engineering, life sciences, and financial services, with AI, machine learning, and cybersecurity skills frequently cited as difficult to source. In this context, attracting high-skilled migrants may be a critical lever for alleviating talent bottlenecks and supporting Ireland's digital and AI transition.

Migration

Ireland's labour market has seen significant growth since the pandemic, with significant employment generation and the unemployment rate around 5 per cent as of 2025. This tight market, particularly in high-skill sectors, has increased reliance on skilled migration to meet labour demand. According to Interface (2024), approximately 18 per cent of Ireland's AI workforce is foreign-born and concentrated in critical roles.[3] Further, employment permits issued to non-EEA nationals more than doubled between 2021 and 2024, with ICT and Health accounting for nearly 60 per cent of these permits, underscoring migration's role as a key mechanism for meeting labour demand across all sectors. The Irish employment permit system has become more responsive, expanding the Critical Skills Occupation List in 2023 to include many AI-related roles, although challenges remain in maintaining Ireland's attractiveness for global talent amidst increasing competition, infrastructure limitations, and the evolving relationship between migration and AI-related labour needs.

While the above provide insights on the supply side of labour market – through graduate pipelines and migration – it does not capture how rapidly employer demand for AI-related skills is evolving across the economy. To complement the supply side development, Box A examines the demand for AI-related skills using online job advertisements data, offering a view of where firms are seeking AI-related capabilities.

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[3] Where is Europe's workforce coming from?

Box A: AI Labour demand: what can we learn from job postings

Shifts in firm hiring behaviour and skill requirements provide early signals of how technological adoption is reshaping the labour market, even before large-scale effects on employment or productivity become visible. Against this backdrop, we analyse online job vacancy advertisements data – Eurostat's and Cedefop's Online Job Vacancy data Skills-OVATE (Online Vacancy Analysis Tool for Europe) (Cedefop and Eurostat, 2025)[4] – to track the evolving demand for AI-related skills in Ireland. A key advantage of OVATE is its consistent and harmonised classification of vacancies by NACE sector and ISCO occupational group across European union countries, together with ESCO skill coding, which enables highly disaggregated and comparable analysis across sectors, occupations, and countries. However, as it captures more digitally advertised roles, the data may skew towards certain sectors and occupations and should be interpreted with caution. Further details on data representativeness are provided in Appendix B.

Trends in job postings by HELC group

Figure 4 presents the distribution of online job postings across NACE economic sectors in Ireland for 2019 and 2023, where the sectors are disaggregated into HELC group and all other non-HELC group.[5] The aggregate level of postings in HELC sectors increased by 2 per cent between 2019 and 2023, compared with 10 per cent growth in non-HELC sectors. At the sectoral level, we find a negative relationship between sectoral HELC level and posting growth, with a correlation of -0.30. In other words, sectors in HELC group experienced weaker vacancy growth compared to non-HELC sector. Similarly, at the occupation level, the relationship is also negative, with a correlation of -0.20 between HELC occupations and total posting growth. The evidence is descriptive and should be interpreted as correlation.

Postings in HELC sectors have grown by less than those in non-HELC sectors 2019 to 2023

Figure 4 Total number of job postings by Sector (NACE 1-digit, '000s)

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4. This article uses experimental Online Job Advertisement data processed within the Eurostat Web Intelligence Hub (WIH). The outcomes derived from these indicators do not represent official statistics. The analysis and aggregated results were reviewed and approved for publication by the WIH operational group.

5 We derive a sector level C-AIOE measure by aggregating occupational exposure scores, weighted by the share of each occupation within each sector based on 2023 Irish LFS data (see appendix C for more detail).
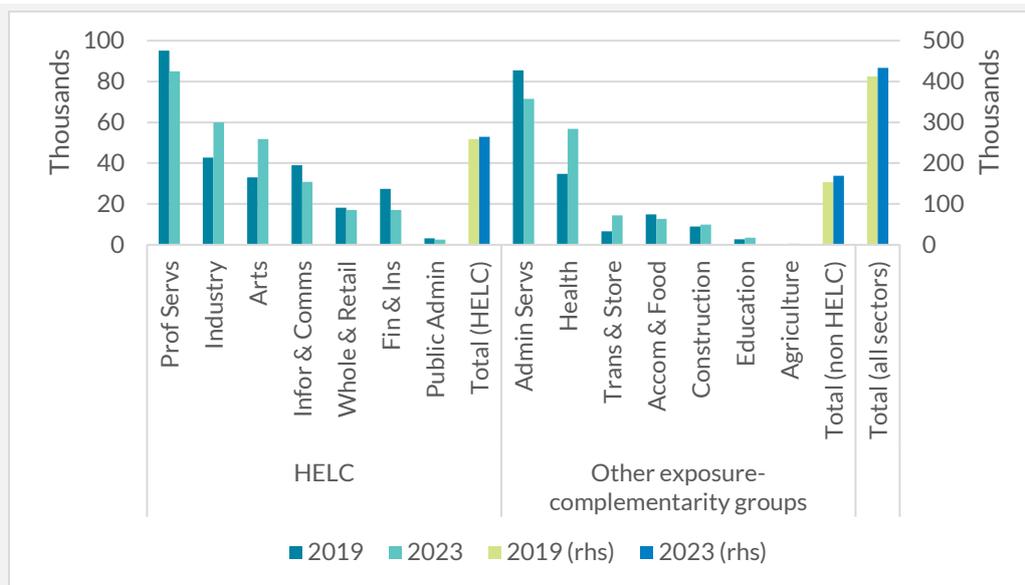
Source: Eurostat-Cedefop OVATE and Author's calculations.

Notes: HELC (High-Exposure, Low-Complementarity) and non-HELC calculated based on the C-AIOE approach.

AI-related job postings

To capture AI-related labour demand in job postings, we match the OECD's curated list of AI-related skills and technologies (Borgonovi et al. 2023) – which includes terms commonly associated with AI development and application, such as machine learning, natural language processing, neural networks, and robotics (for e.g. Autoencoders, Cognitive Robotics, Genetic Algorithm; see Table D1 in appendix for full list) – to the ESCO skills classification which underpins the skill taxonomy in the OVATE data. This taxonomy aligns closely with the technological domains underlying the C-AIOE exposure measure based on Feltan et al. (2021), ensuring consistency in how AI capabilities are defined across analyses in this Article. The OECD list, however, provides a more extensive list of skills, allowing a more detailed identification of emerging competencies in labour demand.

Using a keyword matching approach, we identify ESCO-defined skills where task descriptions include skills from the OECD AI list. These AI-related ESCO skills are then mapped to the Irish OVATE online job postings data, where each posting is assigned a set of ESCO defined skills based on its textual content. This enables us to identify whether a given posting requires AI-related skills and, by extension, to estimate the prevalence of AI-related labour demand in Ireland over time.

The sectoral distribution of AI-related labour demand in Ireland shows significant variation across industries and over time (Figure 5).[6] AI demand is concentrated in a few technologically intensive sectors. The ICT sector is the most AI-intensive, though the share of postings requiring AI-related skills fell from 59 percent in 2019 to 37 percent by 2023. Professional Services and Financial and Insurance also display persistently high AI-related demand, with around one-third of postings mentioning AI-skills by 2023. However, these three sectors together account for 20 per cent of employment, highlighting that the bulk of AI-related hiring up to 2023 occurred in relatively narrow segments of the labour market. Similarly, the Professionals occupation group consistently accounts for the largest share of AI-related postings (c. 44-47 per cent), broadly aligned with their sizeable and increasing share of overall employment (27 percent).

By contrast, the largest-employment sectors – Wholesale & Retail (13 per cent of total employment), Health & Social Work (13 per cent), and Industry (12 per cent) – exhibit low to moderate AI intensity, with fewer than 15 percent of postings requiring AI-related skills. Other sectors such as Education, Construction, and Public Administration also show relatively limited specific AI-skill demand. Smaller sectors such as Agriculture and Accommodation & Food remain at the lower end of both employment and AI exposure.

In Figure 6 we compare the share of AI-related job postings across selected European countries between 2019 and 2023. Ireland stands out as having the highest proportion of AI-related postings in both years, indicating a comparatively strong demand for AI-skills. However, the share of AI-related postings in Ireland declined slightly between 2019 and 2023, which may partly reflect slower hiring levels as labour demand stabilised. Other countries also show a modest decline over time. The figure also reports the share of postings in high AI-exposure occupations, which varies across countries but remain relatively stable over time. Notably, Ireland, the UK and Luxembourg display similarly high shares of postings in high exposure occupations, however Ireland consistently records a higher share of AI-related skill requirements. This pattern points to a greater intensity in AI-skill demand within jobs in Ireland. At the same time, without additional granular, cross-country data, it is difficult to disentangle whether these

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[6] The share of AI-related postings in Ireland follows a modest hump shaped pattern between 2019 and 2023, with 2023 levels slightly below those in 2019. The same qualitative pattern is observed using publicly available Indeed data. Further details are available from the authors upon request.

patterns reflect higher AI adoption, a more technology-intensive employment structure or both, highlighting an important avenue for future research.[7]

Limited demand for AI-skills in most employment intensive sectors in 2023

Figure 5 Percentage of online vacancies advertising positions requiring AI-related skills, by NACE 1-digit
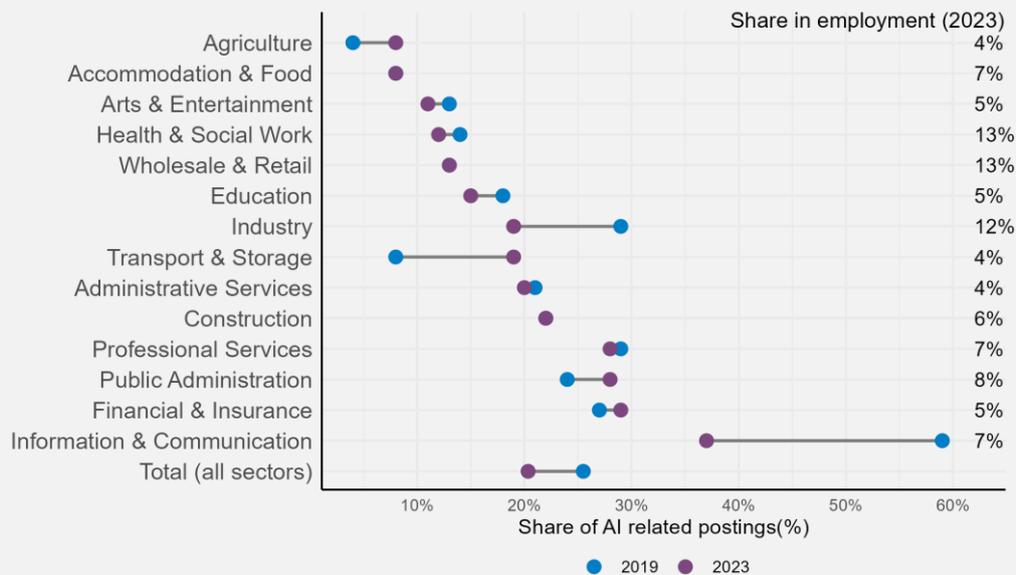
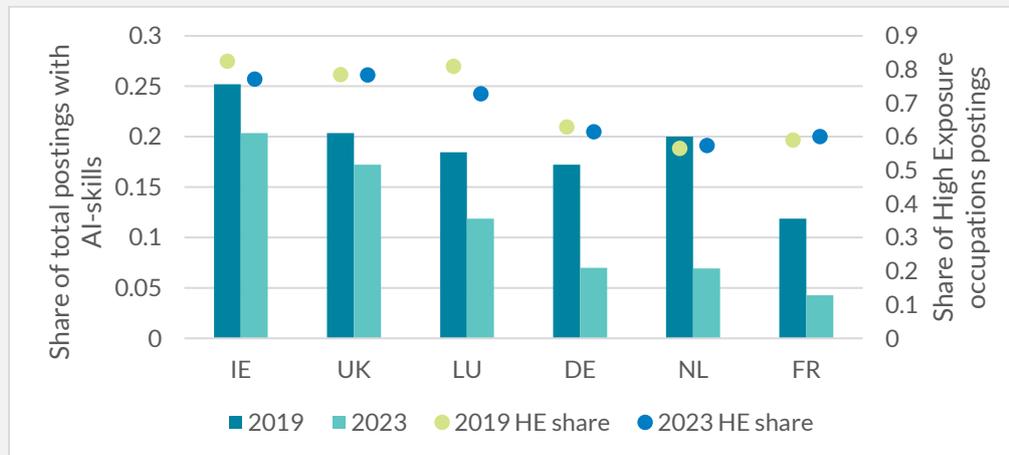Source: Eurostat-Cedefop OVATE, CSO and Author's calculations.

The descriptive evidence points to several notable patterns. Overall labour demand growth in Ireland was similar in 2023 to the pre-pandemic growth seen in 2019, with growth concentrated in non-HELC sectors and occupations, while postings in high-exposure groups have stagnated. When focusing on AI-related demand, a clear concentration emerges in ICT, Financial & Insurance, and Professional Services, and in high-skill occupations such as Professional and Technician roles (which together account for nearly 40 percent of total employment). This underscores both the opportunities and risks of digital transformation, since some of the most AI-intensive roles are also those most exposed to substitution pressures. Comparatively, Ireland has consistently exhibited a higher share of AI-related postings than other European countries. An important caveat is that the period studied, 2019–2023, has been volatile and relatively short, meaning that some of the observed trends may reflect cyclical fluctuations as much as structural change. While the evidence provides an overview of AI

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[7] Similar AI-related demand patterns are observed in Indeed job postings data. See appendix Table B1, which reports the share of AI-related postings based on Indeed data for 2019 and 2023. While the overall trends are comparable, level differences remain, likely reflecting variation in the underlying taxonomies used across datasets.

demand as reflected in job postings, firm-level capacity will be a key determinant of AI adoption – an important avenue for future research.

Demand for AI-skills flat or falling over 2019 to 2023

Figure 6 Share of total postings requiring AI-related skills by country

Source: Eurostat-Cedefop OVATE, CSO and Author's calculations.

Notes: IE = Ireland; UK = United Kingdom; LU = Luxembourg; DE = Germany; NL = Netherlands; FR = France. High exposure occupations include ISCO-08 1-digit groups 1-4 (Managers, Professionals, Technicians and Associate Professionals, and Clerical support workers). The figure reports the share of these occupations as the share of High Exposure occupations postings.

Occupational mobility

Building on evidence on AI exposure and demand of the Irish labour market, we now focus on workers' adjustment, as current and future employees may increasingly need to acquire new skills as the labour market evolves. As we have shown, workers in certain High-Exposure, Low-Complementarity (HELC) roles may face challenges as these new technologies become mainstream. The impact on workers will depend not only on which occupations are affected, but also on workers' ability to transition into new roles – an ability we label 'occupational mobility'. To better understand occupational mobility, we first provide an overview of occupational transitions in Ireland, followed by an analysis of the role mismatch between occupations' skill requirements plays in shaping occupational mobility.

Workers' occupation mobility patterns

Figure 7 shows patterns of yearly occupational transitions in Ireland in 2023, according to AI exposure and complementarity. The results indicate that over 95 per cent of workers remain within the same exposure-complementarity group over the year, while only a small share transition across groups. This high concentration of mobility within the same groups suggests that, without targeted interventions, the scope to transition between groups is limited.

These patterns are almost identical within gender and education groups, that is, limited mobility between AI-exposure-complementarity groups.

Over 95 per cent of all occupation transitions occur within exposure-complementarity quadrants

Figure 7 Occupational transition across exposure and complementarity groups in Ireland, 2023

From \ To	HEHC	HELC	LEHC	LELC
HEHC	97.5	1.42	0.49	0.6
HELC	1.47	97.7	0.24	0.59
LEHC	1.16	0.5	97.28	1.05
LELC	1.6	1.1	0.81	96.5

Source: CSO and Authors' calculations

Notes: HELC, HCHC, LEHC and LELC calculated based on the C-AIOE approach.

A potential barrier to mobility is skill mismatch – where the skills workers *currently* possess do not align with the requirements of new or emerging roles. In this section, we evaluate the role of skill mismatch in shaping occupational mobility in Ireland. This analytical approach complements the preceding descriptive analysis by quantifying how differences in skill requirements between occupations affect workers' ability to transition in response to technological change – particularly in the context of rising demand for digital skills.

As new technologies reshape the task content of jobs, workers are increasingly required to acquire new skills to remain employable. However, not all skills are easily transferable, and mismatches between the skill profiles of occupations can create significant barriers to mobility. These mismatches may hinder worker reallocation, prolong unemployment spells, and exacerbate labour market inequality. While prior work acknowledges the importance of these frictions, there remains limited quantitative evidence on their magnitude – especially with respect to digital skills. To address this, we estimate a model of occupational choice using worker transition data, detailed in Yadav et al. (2025), which allows us to assess the extent to which skill mismatches,

particularly in digital tasks,[8] constrain mobility across occupations. The estimation framework draws from both the matching and gravity literatures and conceptualises occupational mobility as a process influenced by transition costs, primarily determined by the degree of skill mismatch between the origin and destination occupations, in line with recent work on task-specific human capital (Cortes and Gallipoli, 2018; Gathmann and Schonberg, 2010). The model conceptualises occupational mobility as a function of both supply-side worker characteristics and destination-specific frictions, with a particular focus on the role of skill mismatch as a barrier to job switching (see appendix E for detail).

To our knowledge, this represents one of the first application of an occupational mobility network framework to Irish labour market data. While the analysis focuses on digital skill mismatch, the framework provides a general tool for assessing how different shocks that reallocate labour demand across occupations translate into mobility frictions and retraining needs.

Figure 8 presents digital skill mismatch across ISCO-08 1-digit occupation groups. One unit of skill mismatch is defined as one additional skill that is required in the destination occupation but is not required in the worker's current occupation. The figure reveals distinct patterns in digital skill mismatch across major ISCO-08 occupation groups. Occupations in groups 1–3 (Managers, Professionals, and Technicians) generally exhibit low mismatch with all other groups, suggesting greater digital skill overlap. In contrast, occupations in groups 4, 5, 7, and 8 (Clerical Support, Service, Craft, and Plant operators) tend to have higher mismatch when transitioning into groups 1–5, but relatively lower mismatch when transitioning among each other or into groups 6–9. Finally, occupations in groups 6 and 9 (skilled Agricultural and Elementary occupations) show the highest mismatch when moving into any of the higher-skilled groups (1–5), and even among lower-skilled occupations, their mismatch levels remain elevated – suggesting substantial skill mismatch to other occupations. Overall the digital skill mismatch index has an average of 7.45 with a standard deviation of 6.96.

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[8] In this analysis, digital skills are those skills that relate to any competencies and activities required to use, develop, manage, or integrate digital technologies across various domains. These digital skills range from basic digital literacy (e.g., using Excel) to advanced technical competencies (e.g., programming, AI, 3D-printing), where many of these skills support or enable automation (e.g., Robotics, Machine Learning).

Digital Skill mismatches between occupation is heterogeneous

Figure 8 Asymmetric skill mismatch between source and destination occupation

Source: CSO and Central Bank of Ireland

Notes:. The figure shows skill mismatches between occupations at the ISCO-08 1-digit level, while the analysis is based on the ISCO-08 2-digit level. See ISCO-08 classification for 1- and 2-digit level occupations.

The econometric model is estimated using worker flow data from the Irish Labour Force Survey (LFS) covering 2007 to 2023. By linking this with the ESCO based skill vectors, we calculate transition probabilities across occupation pairs at ISCO-08 2-digit level and directly assess how the degree of skill mismatch shapes observed mobility patterns. Crucially, the framework captures not only the average effect of mismatch but also the heterogeneity in frictions across different occupation pairs.

Figure 9 shows the results for the effect of skill mismatch on the occupation transition probability. One unit of skill mismatch is defined as one additional skill that is required in the destination occupation but is not required in the worker's current occupation.

The left-hand side panel (Skills) shows that higher overall skill mismatch is associated with a significant reduction in occupational mobility. Specifically, a one unit increase in skill mismatch corresponds to a 3.4 per cent decrease in the likelihood of transitioning between occupations. The red lines indicate the effect on occupation transitions when separating mismatch into digital and non-digital components. The results reveal that digital skill mismatch has a considerably larger negative effect on mobility. A one unit increase in digital mismatch lowers the probability of transition by about 12.4 per cent where the average digital skill distance between occupations corresponds to 7.4 skills.

The effect of non-digital mismatch is smaller at 2.6 per cent. This highlights the particular importance of digital skills mismatch in enabling occupational transitions. This finding is consistent with existing research showing that workers with more transferable or adaptive skills sets face lower mobility frictions (Cortes and Gallipoli, 2018; Artuc and McLaren, 2015).

The right-hand side panel of Figure 9 incorporate the unemployment rate in the source occupation in the regression. Unemployed workers may have more time to search and to make up any skill deficiencies required for the new occupation; on the other hand, it might be easier to acquire certain new skills when currently employed and to signal productivity to a prospective employer. The unemployment rate in the source occupation is positively associated with transitions, suggesting that higher unemployment is linked to increased outflows from occupations. However, interaction terms indicate that the effect of skill mismatch varies depending on labour market conditions. In particular, the negative effect of digital mismatch becomes stronger when unemployment is higher, while non-digital mismatch is less binding under slack labour markets.

We implement additional specifications incorporating vacancy rates and average wages in the destination occupation, using data available from 2019 onwards. The results are consistent with the baseline estimates. Vacancy rates are positively associated with occupational mobility, suggesting that workers are more likely to transition when job opportunities are more abundant. By contrast, higher wages in destination occupations are generally associated with lower mobility. This likely reflects stronger entry requirements or higher skill thresholds in better paying roles, which limit access despite the potential wage gain.

To assess whether the effect of digital mismatch depends on the complexity of skills involved, we disaggregate occupations into three digital-skill categories – **user**, **practitioner** and **developer** levels – following the ESCO classification. These categories capture increasing degrees of digital intensity, with user-level skills involving basic digital literacy, practitioner-level reflecting applied technical use, and developer-level requiring advanced, specialised competencies. We incorporate these categories into the gravity specification through dummy variables that indicate whether a transition occurs between occupations associated with different digital skill levels. The results show that transitions into occupations that require **developer-level skills** from non-developer skill occupations are significantly lower, with a 43-55 per cent reduction in the likelihood of making such transitions, whereas movements across **user-** and **practitioner-level** occupations display smaller and statistically insignificant effects. This pattern suggests that while basic and

intermediate digital skills are relatively transferable, transitions into advanced digital roles remain constrained by higher learning and adaptation costs.

Digital skills mismatch is a strong predictor of reduced occupation mobility

Figure 9 Effect of skill mismatch on the occupation transition probability
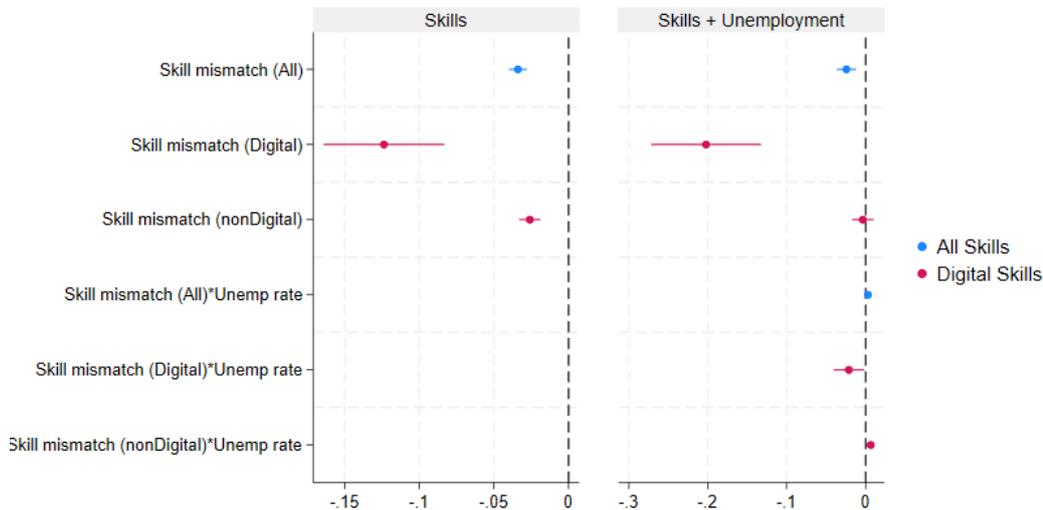
Source: CSO and Authors' calculations.

Occupation entry and exit costs

To better understand the role of specific occupations in the mobility network, we collapse the transition costs by source and destination occupations, yielding average entry and exits costs due to digital skill mismatch for each occupation. Figure 10 shows the average cost estimates for each occupation, both as a source and destination, due to digital skill mismatch. Higher costs for source occupations suggest workers in those occupations face greater difficulty transitioning to other occupations due to digital skill mismatch i.e. higher exit costs. Conversely, higher costs for destination occupations implies they are less accessible from other occupations in digital mismatch terms i.e. higher entry costs.

A strong negative correlation emerges between entry and exit costs: occupations that are easier to enter tend to be harder to exit, and vice versa. For example, occupations such as Cleaners and Helpers or Food Preparation Assistants have low entry but high exit costs, meaning they draw workers from many roles but offer more limited pathways out. Conversely, digital-intensive occupations often exhibit high entry but low exit costs, functioning as gateways that are hard to access but simultaneously allow broad mobility. This asymmetry in digital mobility frictions highlights a potential bottleneck: roles that are relatively more accessible may trap workers in low-mobility states. Meanwhile, overcoming initial digital barriers opens opportunities elsewhere.

These patterns underscore how digital skill gaps shape not only the direction of worker flows but also the persistence of occupational stratification in the labour market.

When viewed through the exposure–complementarity framework, occupations classified as High-Exposure, Low-Complementarity (HELC) tend to occupy the middle range of both entry and exit costs. This positioning suggests that these roles are not the most digitally restrictive. Workers can transition into these occupations with moderate difficulty, yet limited complementarities with AI imply few opportunities to develop transferable digital skills, constraining movement to more advanced roles. As such, HELC occupations represent transitional positions within the digital labour market, that are relatively accessible yet potentially offering limited scope for outward mobility. From a policy perspective, this suggests that whilst workers in these occupations will struggle to transition to new occupations if demand falls or automation accelerates, those in HELC occupations are not the only occupations that require access to digital upskilling. Policy interventions targeted at skills to equip workers looking to move to high entry-cost occupations, across HELC and non-HELC groups, may be useful to support and facilitate workforce adaptability.

HELC occupations occupy the middle range of both entry and exit cost

Figure 10 Average occupation mobility entry and exit costs – Digital skill mismatches
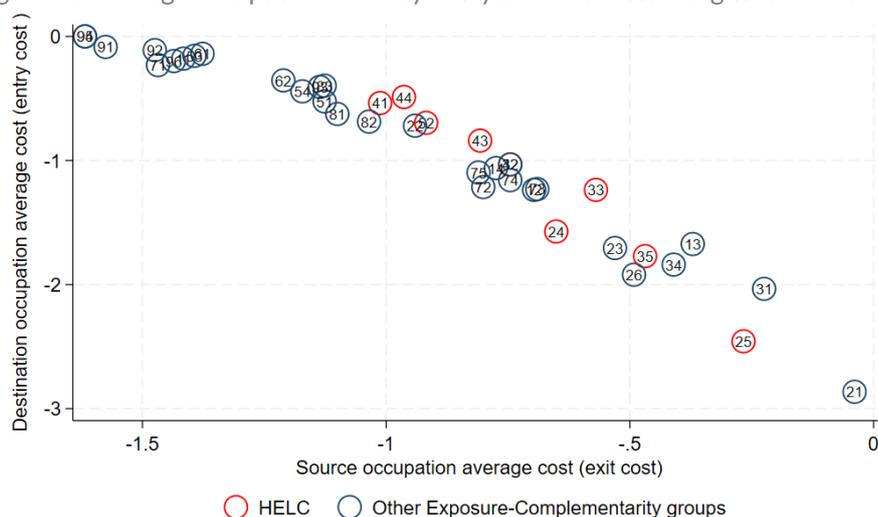
Source: CSO and Authors' calculations.

Notes:. Refer to Table E1 for occupation title for each occupation 2-Digit code. Additionally, the bubble colours represent HELC group or Other Exposure-Complementarity group according to C-AIOE measure.

Heterogeneity by group

The effects of skill mismatch may differ across demographic groups due to variation in adaptability, experience, and access to opportunities. Prior

research highlights how occupational mobility varies by gender, education, and age (Guvenen et al., 2020; Deming, 2023). To assess whether sensitivity to skill mismatch differs across groups, we extend our empirical model by interacting the mismatch measures with the demographic composition of the source occupation. Specifically, we test whether there is heterogeneity across different groups based on gender, age, and education level (Figure 11). Each group is divided into two categories: gender – male and female; education – college educated (bachelor's degree or higher) and non-college educated (high school or lower); and age – above 35 years and below 35 years.

As expected, the results suggest limited heterogeneity by gender or age, but clearer differences by education level. Occupations with larger proportions of male workers – such as Electrical and Electronic trade workers, Drivers and Mobile plant operators – appear to exhibit lower overall occupational mobility, potentially due to higher degrees of task specialisation or fewer adjacent occupations with similar skill requirements. However, the interaction between gender composition and skill mismatch is statistically insignificant, suggesting that the sensitivity of mobility to mismatch does not differ systematically between male- and female-dominated occupations. This indicates that while men and women may sort into different roles, the extent to which skill mismatch constrains their ability to transition is broadly similar. For age-based groups, we find no statistically significant differences in either baseline mobility or mismatch sensitivity between younger and older cohorts. This finding may reflect a balance of offsetting mechanisms where younger workers have greater flexibility and learning capacity, while older workers bring accumulated experience and established career paths. As such, while age composition may influence occupational preferences or transition behaviour more generally, it does not appear to systematically affect how skill mismatch shapes mobility patterns in our data.

Conversely, education related results reveal clearer distinctions. Workers in occupations that require tertiary education are generally less mobile, perhaps due to job desirability or specialisation. When mismatch is disaggregated by skill type, the interaction coefficient between tertiary education and type of skill mismatch is positive for digital skill mismatch and negative for non-digital skill mismatch. This implies that educated workers are better able to overcome skill mismatches due to digital skills, potentially due to broader and more transferable skill sets, greater adaptability to new roles, and better access to a professional network that reflects productivity ability.

Digital skills mismatch is heterogeneous in education

Figure 11 Effect of skill mismatch on the occupation transition probability by worker characteristics
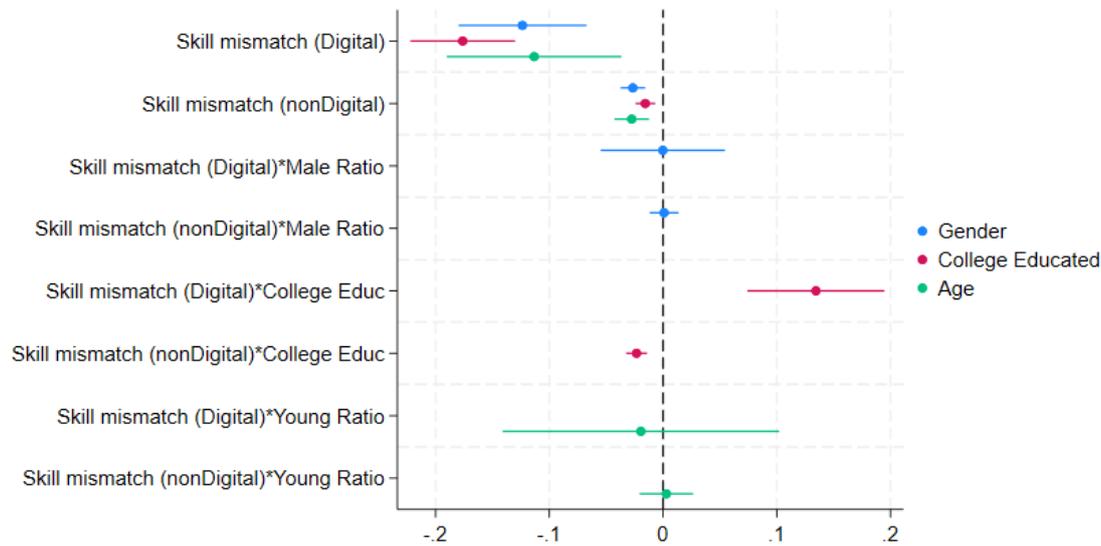
Source: CSO and Authors' calculations.

4. Conclusion

We combine exposure indices, vacancy and survey data, and empirical analysis to show how AI is influencing Ireland's labour market. The picture is mixed, with substantial opportunities for productivity and growth, as well as potential risks of disruption that warrant careful policy consideration.

Our key findings include:

- Uneven exposure: Clerical and routine cognitive roles face the highest substitution risk; Engineers and other knowledge-intensive, interpersonal professions are more likely to be augmented by AI.

- Vacancy signals: Demand for AI-related skills is strong—especially in ICT, Finance & Insurance, and Professional services—with Health, Professional and Administrative sectors also seeking a broad range of digital skills.

- Skills bottlenecks: Adoption barriers—costs, skills shortages and organisational readiness—are constraining firms from fully realising productivity gains.

- Limited mobility: Most workers move within the same exposure/complementarity group; digital skill mismatch hinders transitions into emerging roles.

- Occupational mobility bottlenecks: 'Sticky' jobs such as Cleaners and Helpers or Food Preparation Assistants pull workers in but offer few routes out as they offer limited development opportunities for transferable skills, creating barriers to transitions into more advanced roles. In general, HELC occupations present moderate entry-exit barriers, yet limited complementarities with AI imply few opportunities to develop transferable digital skills.

- Polarisation risk: The combined effect of demand shifts and mobility frictions risks labour market segmentation, with some groups gaining and others left behind.

Taken together, these findings imply that by pairing technology diffusion with active policies on skills, firm support and worker transition will be important in ensuring the effective adjustment of the labour market to the challenges and opportunities of AI. Priority policy actions to mitigate disruption and polarisation are likely to include scaling lifelong learning, helping SMEs to adopt technology, smooth re-skilling and mobility pathways, and maintaining targeted routes for high-skilled migration while strengthening domestic talent pipelines. Strategic policy action that combines upskilling to reduce displacement with reskilling to facilitate worker transitions into new roles will be essential to avoid disruption and may even facilitate inclusive, durable growth.

Our findings are descriptive and associational in nature and do not imply causal relationship between AI and labour market outcomes. Moreover, the analyses focus on short- to medium-term labour market patterns and does not address broader general equilibrium effects related to AI adoption, representing avenues for future research. Finally, this analysis is based on labour market developments to date. Given the rapid pace of technological development, the relationships documented here should be interpreted as reflecting current labour market dynamics, with the understanding that future AI trajectories may alter these patterns in ways that warrant ongoing reassessment.

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Appendix

Appendix A: Labour market exposure using alternate approaches

Expertise-based approach

The expertise-based exposure measure (proposed by Autor and Thompson, 2025) offers a language based approach to identify how susceptible occupations are to AI. This measure draws on Efficient Coding Hypothesis, a concept originated in sensory neuroscience. The Efficient Coding Hypothesis suggests that 'expert' vocabulary emerges when social groups – such as professional occupations – need to communicate technical ideas efficiently within their domain. The expert words are generally infrequent in general language. Whereas commonplace words are those that are used more often when the idea is communicated to non-specialist audience across multiple domain. For example, an economist will use 'arbitrage' when talking to other economist, on the contrary will use 'profit' when communicating with non-technical audience.

Autor and Thompson (2025) suggest that occupations involving a higher use of expert language are more resistant to AI substitution because they rely on tacit knowledge and specialised communication that current AI systems struggle to

replicate. To quantify this following Autor and Thompson, we analyse tasks descriptions from ESCO database and compute an expertise score based on the words used these descriptions. Each word is scored using data from SUBTLEX, a corpus of English word frequencies, where lower frequency, lower entropy words are considered more expert. This captures how specialised or domain-specific a task is, under the assumption that highly specialised tasks are more resistant to automation by current AI systems. To ensure robustness the measure is corrected for semantic outliers using the Dale-Chall readability index, which distinguishes words familiar to general population from specialised jargon. The expertise score for each task is computed by averaging the score of each word in the task description, after lemmatisation and removal of stop words. Then, task scores are aggregated at the occupation level. Finally, the scores are normalised to have a mean of zero and standard deviation of one, providing a relative measure of occupational expertise across the labour market. Higher expertise scores indicate that the occupation involves more specialised knowledge. These occupations are hypothesised to be less substitutable by AI.

The expertise-based measure provides information on exposure level of an occupation to new technologies, but it does not indicate whether the expertise involved is likely to complement or be substituted by new technology. To address this, we combine the expertise-based exposure scores with the occupational complementarity index developed by Pizzinelli et al. (2023), which captures the extent to which AI is likely to complement or substitute for labour. Although originally developed for the C-AIOE measure, this complementarity index is occupation-specific and independent of the exposure metric, making it suitable for use alongside alternative exposure measures. This approach allows us to assess occupation along both exposure and complementarity dimensions.

Patent-based approach

The patent-based exposure measure (proposed by Prytkova et al., 2024) uses natural language processing to assess how closely occupational tasks align with emerging digital technologies, based on semantic similarity between patent texts and occupation descriptions. The key intuition is that if the language used to describe an occupation is similar to that used in patents representing technologies, the occupation is more likely to be exposed to new technologies

The measure is constructed using a large corpus of over 190,714 patents filed between 2012 and 2021, sourced from the Derwent Innovation Index. Each patent title is pre-processed to extract two components: the essence of the

technology and its functional application. Similarly, each ISCO-08 occupation is represented by its title and a set of task descriptions. Using the sentence transformer model, both patents and occupations are embedded in a shared semantic space. K-means clustering is applied to these embeddings to create 40 distinct clusters representing core emerging digital technologies, including software, automation, Internet of Things, AI, and robotics.[9] Then, similarly, each occupation's titles and associated task descriptions are converted into embeddings (numbers). The semantic similarity between each patent and occupation is calculated using cosine similarity, capturing how closely the two descriptions align in meaning. Only highly relevant patent-occupation pairs are retained through a filtering process to improve accuracy. Similarity scores are then aggregated from the patent level to the technology level, weighted by patent citations to reflect their technological importance. The final exposure score for each technology in each occupation is normalised using an inverse hyperbolic sine transformation to account for skewness and then aggregated at the occupation level. This produces a relative measure of how exposed each occupation is to a broad range of emerging technologies.

Unlike measures focused on AI alone, the patent-based approach captures a wider set of digital innovations and does not assume whether technologies act as complements or substitutes to labour. It reflects potential rather than realised exposure, offering a forward-looking metric of technological relevance based on real-time innovation trends. In this analysis, we use the occupation-level exposure scores made available by the authors. Similar to expertise-based measure, the patent-based measure captures only the exposure dimension. Therefore, we combine it with the complementarity index provided by Pizzinelli et al (2023), allowing us to position occupations along the exposure and complementarity dimension.

Appendix B: Representativeness of Online Posting Data

Online job postings datasets – such as Skills-OVATE, Indeed, Lightcast, LinkedIn – may overrepresent higher skilled professional and technical occupations and underrepresent roles in sectors where recruitment occurs more informally (Hershbein and Kahn, 2018; Adrjan, 2024; Vermeulen and Amaros, 2024; Galetti and Yadav, 2024; Napierała et al., 2022). We find that in the OVATE Ireland data sectors such as Professional Services and occupations such as Technicians, Managers, and Professionals are overrepresented, while Accommodation and Food and Education sectors and Agriculture workers and Elementary occupations are underrepresented. At the EU level, Cedefop has

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[9] Embedding refers to the process of representing text (words, sentences, etc) as numerical vectors.

examined the methodological strengths and weaknesses of Skills-OVATE data and assessed its representativeness relative to traditional surveys (Napierała et al., 2022; Barnes et al., 2023; Astarita et al., 2024; Grigorescu et al., 2022; Pouliakas and Branka, 2020; Cedefop, 2025). The studies show Skills-OVATE data is broadly comparable in quality to other major online vacancy datasets, while offering complementary advantages through harmonised EU-wide coverage. Additionally, unlike most commercial sources, Skills-OVATE data is publicly accessible, updated regularly and coded to international standards (such as ISCO, NACE, NUTS-region, and ESCO).

In Ireland, SOLAS has incorporated Skills-OVATE data into its National Skills Bulletin in recent years to track labour market development across different skill categories (McNaboe et al., 2025; Condon et al., 2024; McNaboe et al., 2023). These papers highlight that Skills-OVATE is fairly representative and serves as a timely and complementary source of data to conventional surveys and administrative datasets. These applications demonstrate that, despite some biases, the dataset has become a key source of evidence for analysing emerging skill needs across Europe, including in Ireland. To further validate the use of this dataset for Ireland, we compare trends in Skills-OVATE data with Indeed data and official job vacancy statistics from the CSO's EHECS survey. The high correlation across these sources (see Appendix Figure A2) suggests that the main patterns remain consistent across alternative datasets, especially during 2019 and 2023 which are particularly relevant for examining emerging demand for AI-skills.

This Appendix evaluates the representativeness and validity of the Skills-OVATE dataset for Ireland. The validation draws on two complementary exercises: a comparison of sectoral composition with CSO's EHECS survey vacancies data and an analysis of aggregate vacancy trends related to Indeed data and the EHECS survey data.

B1. Representativeness by Sector

Figure A1 compares the sectoral distribution of vacancies in Skills-OVATE dataset with the vacancy distribution reported in CSO's EHECS survey data for 2019 and 2023. The two sources display broadly similar overall patterns, but with some differences at sectoral coverage. OVATE data has a higher share of vacancies in Professional and Technical Services, Administrative Services, and Information and Communication. Conversely, sectors such as Public Administration, Education, and Accommodation and Food account for a smaller proportion of postings in Skills-OVATE that in EHECS data. These discrepancies mirror prior findings on online job advertisements (Acemoglu et

al., 2022; Hershbein and Kahn, 2018). OVATE data primarily capture formal and digitally advertised recruitment, which is more prevalent among large private firms and high-skilled occupations. Overall, OVATE data offer a robust view of high-skilled and digitally advertised labour demand.

Figure A1 Comparison of sectoral distribution of vacancies in Skills-OVATE and EHECS data, percentage
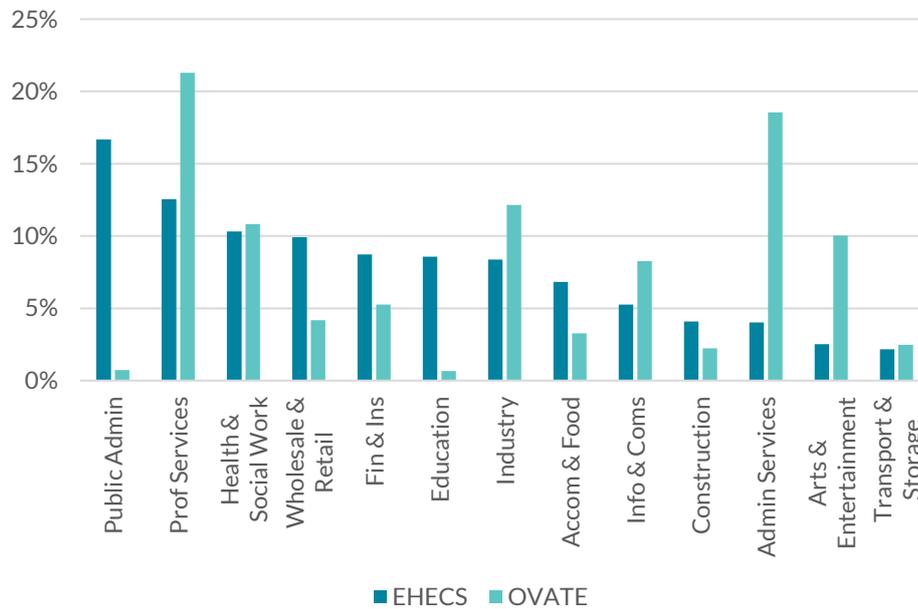
Source: CSO, Eurostat and Authors' calculations.

Notes: figures represent the average 2019 and 2023 levels.

B2. Validation of aggregate trends across data sources

To assess the robustness of Skills-OVATE dataset as a measure of labour demand in Ireland, we compare it with two independent sources – EHECS survey data and Indeed's job posting data. These sources differ in terms of coverage, data collection methods and definition of vacancies, however, benchmarking OVATE with other sources provides useful check on whether patterns observed in Skills-OVATE reflect similar developments in the market (Adrjan and Lydon, 2024). Figure A2 presents indexed vacancy series from the three datasets, standardised to a common reference point (2019 = 100) to allow for comparison. All three series show similar overall movements in job vacancies over the period. The high correlation among the three sources supports the validity of Skills-OVATE as an indicator of underlying labour demand conditions. Although, differences in coverage remain, the consistency in direction across datasets suggests that Skills-OVATE provides a credible proxy for monitoring job posting activity and labour market dynamics in Ireland.

OVATE compares favourably to EHECS and Indeed

Figure A2 Comparison of Skills-OVATE, Indeed, and EHECS over time
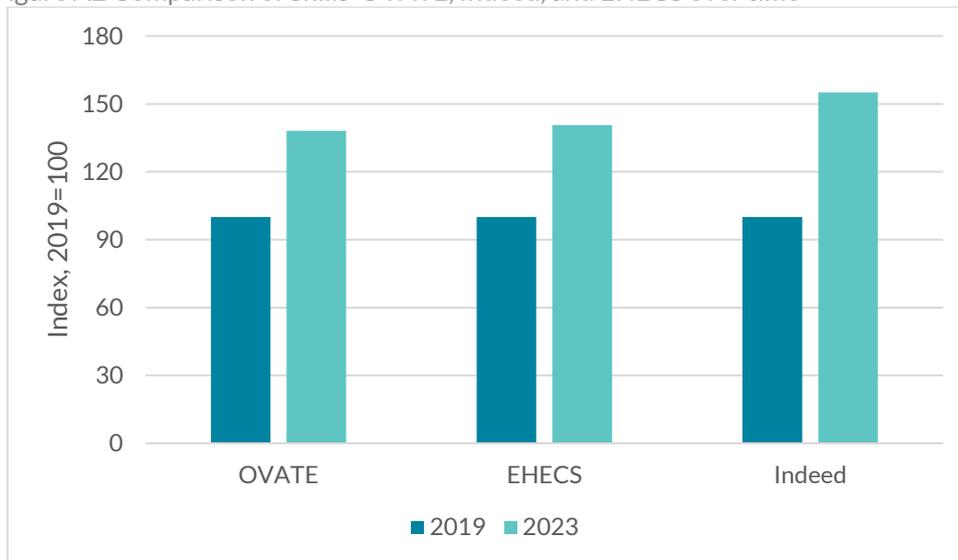
Source: CSO, Eurostat, Indeed and Authors' calculations.

Share of AI-related skill requirements in Indeed data

Table B1: Share of AI-related skill requirements in Indeed data

	2019	2023
Ireland	4	3.6
France	2	1.9
Germany	2	2.0
Netherlands	2	2.0
United Kingdom	2	1.9

Source: Indeed and Authors' calculations.

Appendix C: Computation of NACE sectoral C-AIOE scores

To NACE sector's C-AIOE scores are derived from occupational level exposure and complementarity scores obtained from the C-AIOE measure. Particularly, we use employment weights derived from the Irish-LFS 2023, which provides the share of each occupation within its corresponding NACE sector. For each NACE sector s, the sectoral exposure and complementarity indices are calculated as weighted average of the occupational scores:

$$Exposure_s = \sum_{o \in s} w_{os} \times Exposure_o$$

$$Complementarity_s = \sum_{o \in s} w_{os} \times Complementarity_o$$

where w_{os} denotes the share of employment of occupation o within NACE sector s. This approach ensures that sectors with a higher concentration of occupations exposed to AI receive higher aggregate exposure scores, while those with more complementarity occupation score higher on complementarity index. Following this

aggregation, each sector, as presented in Figure 4, is assigned to HELC group and Other exposure-complementarity group.

In Table C1, we present the share of employment within each NACE sector accounted for by occupations in each of the four exposure-complementarity groups, along with each NACE sector's share in total employment. Overall, the exposure-complementarity classification captures substantial heterogeneity in the potential impact of AI technologies across sectors. However, these results are based on the 2023 workforce composition and may evolve over time as the pattern of occupation structures change.

Table C1: Distribution of C-AIOE groups within NACE sector (2023)

	Exposure-Complementarity group					Share in total employment
	HEHC	HELC	LEHC	LELC	Total	
Agriculture	6	2	6	86	100	4
Industry	28	21	9	42	100	12
Construction	18	7	56	19	100	6
Wholesale & Retail	17	66	5	12	100	13
Transport & Storage	14	15	43	28	100	4
Accommodation & Food	31	8	2	59	100	7
Information & Communication	23	73	2	2	100	7
Finance & Insurance	23	75	1	1	100	5
Professional Services	45	44	5	6	100	7
Administrative Services	12	31	16	41	100	4
Public Administration	15	67	15	3	100	5
Education	69	11	14	6	100	8
Health & Social work	47	13	35	5	100	13
Arts & Entertainment	36	19	7	38	100	5

Source: Central Banks, various countries.

Appendix D: AI-skills and Mapping to NACE Sectors

Table D1: OECD (2023) list of AI-skills

Skills	Skills
AIOps (Artificial Intelligence For IT Operations)	Supervised Learning
Applications Of Artificial Intelligence	Support Vector Machine
Artificial General Intelligence	Test Datasets
Artificial Intelligence	Torch (Machine Learning)
Artificial Intelligence Development	Training Datasets

Artificial Intelligence Markup Language (AIML)	Transfer Learning
Artificial Intelligence Systems	Unsupervised Learning
Azure Cognitive Services	Vowpal Wabbit
Baidu	Xgboost
Cognitive Automation	Amazon Textract
Cognitive Computing	ANTLR
Computational Intelligence	BERT (NLP Model)
Cortana	Chatbot
Expert Systems	Computational Linguistics
Intelligent Control	DeepSpeech
Intelligent Systems	Dialog Systems
Interactive Kiosk	fastText
IPSoft Amelia	Fuzzy Logic
Knowledge-Based Configuration	Handwriting Recognition
Knowledge-Based Systems	Hugging Face (NLP Framework)
Multi-Agent Systems	Hugging Face Transformers
Open Neural Network Exchange (ONNX)	Intelligent Agent
OpenAI Gym	Intelligent Software Assistant
Reasoning Systems	Intelligent Virtual Assistant
Soft Computing	Kaldi
Syman	Latent Dirichlet Allocation
Watson Conversation	Lexalytics
Watson Studio	Machine Translation
Weka	Microsoft LUIS
Advanced Driver Assistance Systems	Natural Language Generation
Autonomous Cruise Control Systems	Natural Language Processing
Autonomous System	Natural Language Processing Systems
Autonomous Vehicles	Natural Language Programming
Guidance Navigation And Control Systems	Natural Language Toolkits
Light Detection And Ranging (LiDAR)	Natural Language Understanding
OpenCV	Natural Language User Interface
Path Analysis	Nearest Neighbour Algorithm
Path Finding	OpenNLP
Remote Sensing	Optical Character Recognition (OCR)
Unmanned Aerial Systems (UAS)	Screen Reader
AdaBoost (Adaptive Boosting)	Semantic Analysis
Apache MADlib	Semantic Interpretation For Speech Recognition
Apache Mahout	Semantic Parsing
Apache SINGA	Semantic Search
Apache Spark	Sentiment Analysis
Association Rule Learning	Seq2Seq

Automated Machine Learning	Speech Recognition
Autonomic Computing	Speech Recognition Software
AWS SageMaker	Statistical Language Acquisition
Azure Machine Learning	Text Mining
Boosting	Tokenization
CHi-Squared Automatic Interaction Detection (CHAID)	Voice Interaction
Classification And Regression Tree (CART)	Voice User Interface
Cluster Analysis	Word Embedding
Collaborative Filtering	Word2Vec Models
Confusion Matrix	Apache MXNet
Cyber-Physical Systems	Artificial Neural Networks
Dask (Software)	Autoencoders
Data Classification	Caffe
Dbscan	Caffe2
Decision Models	Chainer (Deep Learning Framework)
Decision Tree Learning	Convolutional Neural Networks
Dimensionality Reduction	Cudnn
Dlib (C++ Library)	Deep Learning
Ensemble Methods	Deeplearning4j
Evolutionary Programming	Keras (Neural Network Library)
Expectation Maximization Algorithm	Long Short-Term Memory (LSTM)
Feature Engineering	OpenVINO
Feature Extraction	PaddlePaddle
Feature Learning	Pybrain
Feature Selection	Recurrent Neural Network (RNN)
Gaussian Process	TensorFlow
Genetic Algorithm	Advanced Robotics
Google AutoML	Cognitive Robotics
Google Cloud ML Engine	Motion Planning
Gradient Boosting	Nvidia Jetson
H2O.ai	Robot Framework
Hidden Markov Model	Robot Operating Systems
Hyperparameter Optimization	Robotic Automation Software
Inference Engine	Robotic Liquid Handling Systems
K-Means Clustering	Robotic Programming
Kernel Methods	Robotic Systems
Kubeflow	Servomotor
LIBSVM	SLAM Algorithms (Simultaneous Localization And Mapping)
Machine Learning	3D Reconstruction Visual Image
Machine Learning Algorithms	Activity Recognition Visual Image
Markov Chain	Computer Vision Visual Image

Matrix Factorization	Contextual Image Classification Visual Image
Meta Learning	Digital Image Processing Visual Image
Microsoft Cognitive Toolkit (CNTK)	Eye Tracking Visual Image
MLflow	Face Detection Visual Image
MLOps (Machine Learning Operations)	Facial Recognition Visual Image
mlpack (C++ Library)	Image Analysis Visual Image
Naive Bayes	Image Matching Visual Image
Perceptron	Image Processing Visual Image
Predictionio	Image Recognition Visual Image
PyTorch (Machine Learning Library)	Image Segmentation Visual Image
Random Forest Algorithm	Image Sensor Visual Image
Recommendation Engine	Imagenet Visual Image
Recommender Systems	Machine Vision Visual Image
Reinforcement Learning	Motion Analysis Visual Image
Scikit-learn (Machine Learning Library)	Object Recognition Visual Image
Semi-Supervised Learning	OmniPage Visual Image
Soft Computing	Pose Estimation Visual Image
Sorting Algorithm	Realsense Visual Image
Software development	

Source: Borgonovi et al., 2023.

Table D2: Mapping of Field of Study to NACE sectors

Field of Study	NACE Sectors
Agriculture, forestry, fisheries and veterinary	Agriculture
Arts and humanities	Arts & Entertainment
Business, administration and law	Finance & Insurance; Wholesale & Retail; Administrati
Education	Education
Engineering, manufacturing and construction	Industry; Construction
Generic programmes and qualifications	Public Administration
Health and welfare	Health & Social Work
Information and Communication Technologies (ICT	Information & Communication
Natural sciences, mathematics and statistics	Professional Services
Services	Accommodation & Food; Transport & Storage; Wholes Retail
Social sciences, journalism and information	Public Administration; Administrative Services

Source: Central Banks, various countries.

Appendix E: Distance between occupations based on skills

In each period, workers face a decision of whether to remain in their current occupation or to transition to a new one, weighing the associated costs and

benefits. Central to this framework is the idea that occupational transitions are influenced by the degree of overlap in required skills – where lower overlap implies higher transition costs. The empirical specification is as follows:

$$m_{\overrightarrow{ij}t} = \exp\left(\alpha - \beta D_{\overrightarrow{ij}} + \gamma Z + \tau_{it} + \tau_{jt}\right) e^{\varepsilon_{ijt}}$$

where $m_{\overrightarrow{ij}t}$ denotes the transition probability from occupation i to occupation j at time t. $D_{\overrightarrow{ij}}$ is represents the directional (asymmetric) skill dissimilarity between occupations, Z includes the vacancy rate and wages in destination occupation as controls, τ_{it} and τ_{jt} are source-occupation-time and destination-occupation-time fixed effects.

To construct the mismatch measure, $D_{\overrightarrow{ij}}$, we rely on the European Skills, Competences, Qualifications and Occupations (ESCO) database, which provides granular task-level skill information for ISCO-08 occupations. Each occupation is represented as a vector of skills required to perform relevant tasks. We calculate an asymmetric mismatch score for each origin–destination pair by identifying the proportion of skills required in the destination occupation that are not present in the origin occupation. This directional structure captures the idea that acquiring new skills is generally more costly than shedding unused ones, and that moving into more complex or digitally intensive roles entails greater frictions.

For the baseline analysis, we construct occupation level skill profiles using ESCO's 3-digit classification, which yields a skill vector $O_i = (s_1, \ldots, s_n)$ for each occupation i, where n = 404 denotes the number of unique skills identified at this level of granularity. We then isolate the subset of digital skills, identified based on ESCO classification of skill as digital, and compute digital mismatch scores between all origin and destination occupation pairs.

Table E1: ISCO-08 1- and 2- digit level occupations

ISCO-08 1 Digit level	Occupation label	ISCO-08 2 Digit level	Occupation label
1	Managers	11	Chief executives, senior officials and legislators
1	Managers	12	Administrative and commercial managers
1	Managers	13	Production and specialized services managers
1	Managers	14	Hospitality, retail and other services managers
2	Professionals	21	Science and engineering professionals

2	Professionals	22	Health professionals
2	Professionals	23	Teaching professionals
2	Professionals	24	Business and administration professionals
2	Professionals	25	Information and communications technology professionals
2	Professionals	26	Legal, social and cultural professionals
3	Technicians and Associate Professionals	31	Science and engineering associate professionals
3	Technicians and Associate Professionals	32	Health associate professionals
3	Technicians and Associate Professionals	33	Business and administration associate professionals
3	Technicians and Associate Professionals	34	Legal, social, cultural and related associate professionals
3	Technicians and Associate Professionals	35	Information and communications technicians
4	Clerical Support Workers	41	General and keyboard clerks
4	Clerical Support Workers	42	Customer services clerks
4	Clerical Support Workers	43	Numerical and material recording clerks
4	Clerical Support Workers	44	Other clerical support workers
5	Service and Sales Workers	51	Personal services workers
5	Service and Sales Workers	52	Sales workers
5	Service and Sales Workers	53	Personal care workers
5	Service and Sales Workers	54	Protective services workers
6	Skilled Agricultural, Forestry and Fishery Workers	61	Market-oriented skilled agricultural workers
6	Skilled Agricultural, Forestry and Fishery Workers	62	Market-oriented skilled forestry, fishery and hunting workers
6	Skilled Agricultural, Forestry and Fishery Workers	63	Subsistence farmers, fishers, hunters and gatherers
7	Craft and Related Trades Workers	71	Building and related trades workers (excluding electricians)
7	Craft and Related Trades Workers	72	Metal, machinery and related trades workers

7	Craft and Related Trades Workers	73	Handicraft and printing workers
7	Craft and Related Trades Workers	74	Electrical and electronics trades workers
7	Craft and Related Trades Workers	75	Food processing, woodworking, garment and other craft and related trades workers
8	Plant and Machine Operators, and Assemblers	81	Stationary plant and machine operators
8	Plant and Machine Operators, and Assemblers	82	Assemblers
8	Plant and Machine Operators, and Assemblers	83	Drivers and mobile plant operators
8	Plant and Machine Operators, and Assemblers	91	Cleaners and helpers
9	Elementary Occupations	92	Agricultural, forestry and fishery labourers
9	Elementary Occupations	93	Labourers in mining, construction, manufacturing and transport
9	Elementary Occupations	94	Food preparation assistants
9	Elementary Occupations	95	Street and related sales and services workers
9	Elementary Occupations	96	Refuse workers and other elementary workers

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