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## Article

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ORIGINAL ARTICLE

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# Occupational exposures, complementarity and the potential consequences of A.I. for the labour market: some evidence from Ireland

Harry Williamson<sup>1</sup>, Dermot Coates<sup>2\*</sup>, Kevin Daly<sup>1</sup>, Keith FitzGerald<sup>2</sup> and Neil Gannon<sup>1</sup>

## Abstract

The adoption of AI technology by industry could significantly disrupt our current understanding of “typical” economic activity. As AI comes to pervade more sectors and occupations over time, it is likely that this technology will give rise to challenges and risks but also opportunities and benefits. There is, however, a significant degree of uncertainty regarding how future waves of technological change will impact the economy, including the labour market. Recent research has found that 40% of employment globally is exposed to AI and that this rises to 60% of employment in advanced economies. We analyse exposure and complementarity in tandem in order to better understand the potential impact across occupation types in Ireland. We find that Ireland is relatively more exposed to AI than is the case for other advanced economies. We also find that female workers in Ireland are more likely to work in highly exposed roles compared to males, that younger Irish workers are more exposed to AI than are older workers, and that both exposure complementarity to AI increase in line with educational attainment. Finally, we contend that the extent to which AI augments, or replaces, human labour in the medium to long-run will depend on a variety of economic, social and policy factors, including levels of AI regulation.

**JEL classification:** J21, J24, O31.

**Keywords** Artificial intelligence, Technological change, Labour markets, Ireland

## 1 Introduction

The emergence of advanced digital systems, including advanced robotics and artificial intelligence (AI) technology, is often characterised as the advent of a fourth industrial revolution. Schwab (2016) has outlined three previous industrial revolutions, roughly each one a hundred years apart. Each of these had a transformative impact on the production process, income levels and

standards of living. The first industrial revolution (c. 1784) came with the use of steam power to mechanise production. This preceded a second industrial revolution (c. 1870) that saw electricity powering mass production, while a third industrial revolution (c. 1969) was marked by the use of electronics and information technology to drive automation. Building on the groundwork laid during the latter period, the fourth industrial revolution is developing at an unprecedented pace. Within these distinct periods of innovation, development and change, new industries, occupations and tasks have emerged while others have diminished or disappeared entirely. For example, advancements made in the extraction of petroleum during the late-1800s enabled the production of kerosene and led to a decline in the whale oil industry.

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Kerosene, in turn, was supplanted by the use of electricity to light homes and industry. Indeed, it has been estimated that 60% of current jobs in the US did not exist in the 1940's (Autor et al. 2022).

The adoption of AI technology by industry could significantly disrupt our current understanding of “typical” economic activity. AI systems have the potential to bring about extraordinary benefits for society but also to sow disruption across many sectors of the economy, including labour markets globally. Each previous industrial revolution had a transformative impact but also created winners and losers in the labour market: eliminating some jobs but generating and augmenting others. As AI comes to pervade more sectors and occupations over time, it is likely that this technology will give rise to challenges and risks but also opportunities and benefits. Whilst prior technological developments are generally considered to have been a global net ‘good’, we must always remind ourselves that past performance is no guarantee of future results. Indeed, the key difference here is the nature of tasks that will be transformed. AI has the potential to perform complex cognitive tasks, setting it apart from previous general-purpose technologies which primarily affected physical tasks at the time of their invention. Certain tasks within occupations will become susceptible to automation, while others will benefit from AI assistance, enhancing productivity and augmenting human capabilities. The extent to which jobs are enhanced, rather than replaced, will depend on how well the strengths of AI and humans can complement each other within each job. There will also be a role for public policy and regulation in shaping the balance between technology, capital and labour.

The paper assesses Ireland’s overall labour market exposure (and complementarity) to AI, placing these results in a comparative international context. Our primary aim is to consider the potential consequences of AI for the labour market (and with a specific focus on the Republic of Ireland). We do so by examining methodological approaches developed by the IMF – amongst others – and applying these to granular datasets for Ireland. Specifically, we use Irish Census data, and a cross-walk from the ISCO occupational classificational system to UK SOC (the classification system used in Ireland), to map AI occupational exposure and complementarity scores as calculated by the IMF to an Irish context.

We find that – amongst other themes – that Ireland is relatively more exposed to AI than is the case for other advanced economies. We also find evidence of heterogeneity in exposure across demographic groups: female workers in Ireland, for example, are more likely to work in highly exposed roles compared to males, while and younger workers are typically more exposed to AI than are older workers. In addition, the analysis indicates that

exposure to AI increases in line with educational attainment but that the same applies for complementarity.

In undertaking this work, the authors have sought to contribute to the emergent discourse on how AI is reshaping labour markets. From a policy perspective, anticipating which occupations will be most exposed to AI can help inform targeted investments in up-skilling and re-skilling initiatives, as well as investments in labour-augmenting technologies. However, it is important to recognise that the process of AI adoption is still at a relatively early stage, with these technologies still developing at an exponential pace. At the time of writing, there are many projections – and investments – that in the future will likely come to be regarded as misplaced. This limits the availability of real-world empirical data and we recognise that further analyses will be necessary as the technology develops. The remainder of this paper is structured as follows: our methodological and theoretical approaches are summarised in the next Section. This is followed by a discussion based on our results in Sect. 3, including a set of cross-country comparisons. Section 4 concludes.

## 2 Methodological approach

The authors begin by drawing on the international literature. In so doing, we have endeavoured to ground our approach in these methodologies and to use this to assess the impact of AI on the Irish labour market. We build upon methodologies developed by Felten et al. (2021) and Pizzinelli et al. (2023) to create a complementarity-adjusted AI occupational exposure (C-AIOE) index for Ireland. The index is used to identify the occupations in Ireland that are most exposed to AI, and to assess the extent to which AI is a substitute or complement for labour in those occupations. We do so by providing an indicator of relative exposure and complementarity across occupations in Ireland.

### 2.1 International literature

Research by the International Monetary Fund (Cazzaniga et al. 2024) has found that 40% of employment globally is exposed to A.I. This rises to 60% of employment in advanced economies with approximately half of these considered to be negatively affected. A survey of AI experts by the Organisation of Economic Co-operation and Development (Lane et al. 2023) concluded that certain skills required in high-skilled roles are susceptible to automation due to recent advances in AI. What is evident from both pieces of analysis is that while many jobs may be exposed to AI, relatively few are at risk of disappearing completely. There is a high level of complementarity between AI and human capabilities for many ‘highly exposed’ roles. Indeed, the OECD states that being highly exposed to AI may be beneficial for workers, provided

they have the skills to use AI technologies effectively. Other studies, such as the World Economic Forum's Future of Jobs Survey 2023, have found that the number of companies expecting AI to be a net creator of jobs is far greater than those expecting AI to be a net displacer. Focusing specifically on ChatGPT, Zarifhonarvar (2023) estimates that 32.8% of occupations could be fully impacted by this technology, while 36.5% might experience partial impacts and 30.7% are likely to remain unaffected. This is based on a text-mining approach, that is used to analyse the ISCO and identify the occupations most susceptible to disruption by ChatGPT.

There is, however, a significant degree of uncertainty with regard to how future waves of technological change will impact the economy and through which channels these impacts will be transmitted. From a labour market perspective, the current international literature typically only provides an indication of impacts based on recent understandings of AI applications and does not attempt to predict how AI technologies will evolve in future, nor the rate of adoption across the enterprise base. There are those with a pessimistic viewpoint that suggest that AI will have a detrimental effect on employment through the substitution of capital for labour. By contrast, AI optimists expect that there will be significant efficiency gains associated with the use of AI that will result in the creation of new job and task opportunities. For instance, Frank et al. (2019) have found that AI will likely impact on specific skills rather than on whole occupations, albeit that there are barriers preventing deeper analysis of the potential impacts of AI at present. There are also those – for example, Felten et al. (2021, 2023) – that have posited an AI Occupational Exposure (AIOE) method which suggests that the most exposed industries will likely be those “white-collar” industries requiring high levels of education. Nonetheless, the extent to which AI augments – or replaces – human labour then into the future will depend on a variety of economic, social and policy factors (including levels of AI regulation). The future impact of AI on the labour market is therefore uncertain and will require ongoing analysis to understand its potential effects.

This analysis was undertaken as an early contribution to the public discourse in this field but there are, however, some important caveats to this work. Firstly, the measure of AI exposure used in this study – drawing on the work of Felten et al. (2021) – focuses on ten specific AI applications<sup>1</sup>, all of which can be considered to be “narrow” AI. Given that Felten's work was published in 2021, it does not capture the latest advancements in AI technology,

such as document summarisation or LLM-based searching. At the time of writing, these are AI applications that are now widely used through software such as ChatGPT, Gemini, Copilot and others. The approach used here also does not capture exposure to advanced robotics – which will also have profound impacts on the labour market – and/or how this might ultimately interact with AI deployment. As with any new technology or innovation, research on the impact of AI will always lag behind the rapid pace of development in the field. Research by the International Labour Organisation (ILO) suggests that the inclusion of more recent developments, such as LLM-based searching, would not significantly alter the results, however. The ILO (Gmyrek et al., 2023) assess occupational exposure specifically to Generative AI (such as GPT-4), finding that “knowledge workers” are the most highly exposed group to increased AI adoption (broadly in-line with existing research).

## 2.2 Constructing a measure of exposure and complementarity

The AIOE (exposure index) measure is derived by breaking down occupations into their constituent tasks and analysing the degree of overlap between these tasks and various AI technologies. Using data on the relatedness between given AI applications and a set of occupational abilities, Felten et al. (2021) had previously constructed a “relatedness” score (bound between 0 and 1) between each occupational ability and each AI application<sup>2</sup>. An occupational ability's AI exposure ( $A_{ij}$ ) measures the extent to which each ability is exposed to AI. For example, the occupational ability “oral comprehension” has a relatedness score of 0.89 with the AI application “Translation”, and 0.37 with the AI application “Image Recognition”. These two scores are summed along with the eight other AI applications to obtain an Ability Level Exposure Score ( $A_{ij}$ ) (bound between 0 and 10). This is then weighted by the prevalence ( $L_{jk}$ ) and importance ( $I_{jk}$ ) of that ability within each occupation and scaled by the weighted sum of all abilities used within an occupation (the denominator) to create an AIOE score. For example, the occupational ability “oral comprehension” has a prevalence score of 4.88 and an importance score of 4.50 for the occupation “Chief Executive Officer”. The maximum importance or prevalence score is 5. Abilities that are essential to an occupation have high prevalence and importance scores, while the opposite is true for abilities that are used less often. This ensures that AIOE provides a relative measure of AI exposure.

<sup>1</sup> The 10 AI applications used in the analysis are: Abstract Video Games; Real Time Video Games; Image Recognition; Visual Question Answering; Image Generation; Reading Comprehension; Language Modelling; Translation; Speech Recognition; and Image Track Recognition.

<sup>2</sup> The AI applications were based on categories defined by the Electronic Frontier Foundation's (EFF) AI Progress Measurement project, while occupational abilities were extracted from the Occupational Information Network (O\*NET) database developed by the United States Department of Labour.

$$AIOE_k = \frac{\sum_{j=1}^{52} A_{ij} \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}} \quad (1)$$

An AIOE score, however, only assesses occupational exposure and is agnostic as to whether an occupation is likely to be substituted or complimented by AI. To resolve this issue, Pizzinelli et al. constructed a complementarity measure,  $\theta$ , to augment the AIOE score. This measure adjusted specifically for two dynamics: job contexts and job zones. The former refers to those factors that shape the nature of work and the latter refers to factors such as occupations characterised by similar levels of education, on-the-job training, and professional experience required to perform the work<sup>3</sup>.  $\theta$  is computed as the arithmetic mean of the scores of the selected job zone/work context components and divided by 100 to be bound between 0 and 1.  $\theta_{\min}$  is the minimum value of  $\theta$  across all occupations<sup>4</sup>. This adjustment is to allow the complementarity measure to have a relative interpretation. Once a given occupation is assigned a measure of potential complementarity to AI, the baseline AIOE exposure level is then adjusted. For the purposes of this paper, we utilise this complementarity adjusted AI occupational exposure (C-AIOE) index to identify the occupations in Ireland that are most exposed to AI and to measure the extent to which AI is a substitute (or complement) for labour in those occupations.

This index provides a quantitative measure of the exposure of different occupations to AI technologies. The main advantage of this methodology compared to others is that it controls for complementarity to better measure occupational exposure to AI. Other studies focus on occupations that could be automated, without adjusting for complementarity (e.g., Briggs and Kodnani 2023; Webb 2019), or focus on specific AI applications. The World Economic Forum (2023), for example, assessed potential occupational AI exposure and complementarity to large language models only. The AIOE (exposure index) measure, originally constructed by Felten et al. (2021), is derived by breaking down occupations into their constituent tasks and analysing the degree of overlap between these tasks and various AI technologies.

$$C - AIOE_i = AIOE_i * (1 - (\theta_i - \theta_{\min})) \quad (2)$$

<sup>3</sup> As with the AIOE measure, this complementarity measure was created by using aspects of the O\*NET repository, specifically work contexts and job zones. O\*NET defines work contexts as the “physical and social factors that influence the nature of work”. These include contexts such as “public speaking” and “frequency of decision making”. For the work context “public speaking”, for example, the occupation ‘flight attendants’ have a score of 99/100, whereas ‘plumbers’ score 9/100.

<sup>4</sup> This value is 0.31 and corresponds to the US SOC code Hand Cutters and Trimmers.

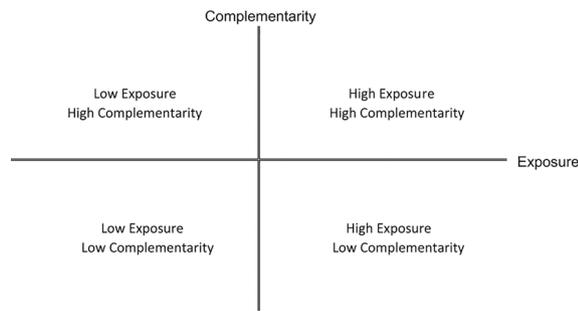
Analysing these two criteria in tandem (exposure and complementarity) is critical to understanding the potential labour market shifts each occupation might encounter over time. Occupations heavily exposed to AI, where tasks can be performed autonomously, may witness a decline in demand for human labour, with implications for labour income and income inequality. Conversely, heavily-exposed occupations with a high degree of complementarity to AI could see productivity enhancements, leading to an increased demand for labour. Complementarity can only be leveraged, however, if workers develop the skills required to take advantage of AI as a supporting technology. The median values for AIOE and  $\theta$ <sup>5</sup> used here are taken from Felten et al. (2021) and Pizzinelli et al., respectively, to allow for cross-country comparisons<sup>6</sup>. When interpreting the findings presented below, it is important to bear in mind that the measures of exposure and complementarity used in this study are both relative measures. They describe which occupations are more or less exposed/complementary than others. A high C-AIOE score does not mean that an occupation, or tasks within that occupation, will be replaced, but rather signifies its comparatively higher exposure to AI than other occupations.

It should be noted that this analysis provides a static view of AI exposure and complementarity. The analysis does not consider workers’ ability to re-locate across sectors or to develop new skills to realise the benefits of AI, even when their occupation has relatively low complementarity with AI applications. The analysis only provides an indication of *relative exposure* based on recent understandings of AI applications<sup>7</sup> and does not attempt to predict how AI technologies will evolve in the future, nor the rate of adoption across the enterprise base. The extent to which AI augments or replaces human labour will depend on a variety of economic, social and policy factors, including levels of AI regulation.

<sup>5</sup> These are used here: the median values for AIOE and  $\theta$  across all US SOC-2010 occupations are 6.002 and 0.576, respectively. The median values in Ireland using UK-SOC-2010, by contrast, are 6.081 and 0.581 respectively. Using these figures would result in 55% of occupations in Ireland being ‘highly-exposed’, as opposed to 63% using the SOC-2010 measure as calculated by the IMF.

<sup>6</sup> Pizzinelli et al. later converted the US-based SOC occupations into broader ISCO-08 occupations for their analysis. ISCO is the International Standard Classification of Occupations. For the purposes of this paper, it was possible to map ISCO-08 occupations to UK SOC codes, which is the occupational classification system used in Ireland, using a crosswalk from ISCO-08 to UK SOC-2010.

<sup>7</sup> These exposure/complementarity levels are relative across occupations. In a scenario where an equal number of people were employed in each occupation, approximately 25% of employment would fall into each of the respective exposure/complementarity categories.



**Fig. 1** Conceptual Framework for AI Exposure and Complementarity

**2.3 Our theoretical framework**

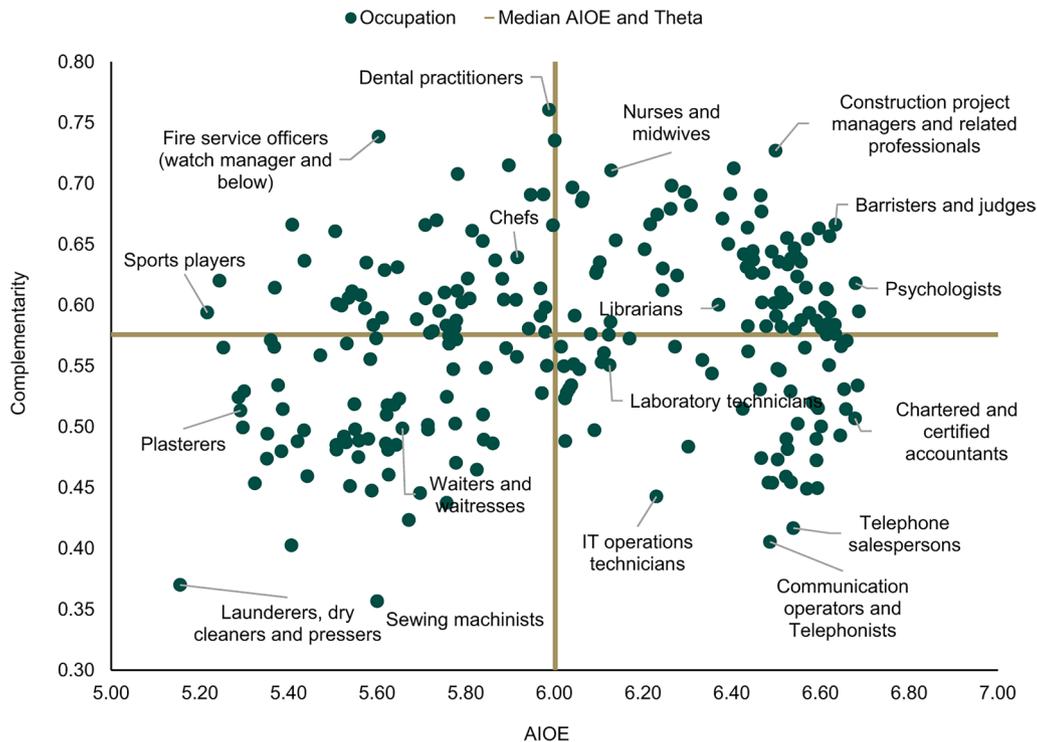
Each occupation can be thought of as belonging to one of four categories: (i) High Exposure, High Complementarity; (ii) High Exposure, Low Complementarity; (iii) Low Exposure, High Complementarity; and (iv) Low Exposure, Low Complementarity. These categories are presented graphically in Fig. 1 below. Quadrants are segmented using the median values of both AIOE and  $\theta$ . In other words, an occupation is considered to be ‘highly exposed’ if its AIOE value is greater than the median AIOE across all occupations. Similarly, if an occupation’s complementarity value  $\theta$  is greater than the median  $\theta$  across all occupations, then it is considered to be ‘highly

complementary’. As the median is the middle value in a dataset when all values are arranged in order, it represents the point where half the values are higher and half are lower. This means that, in this case, 25% of occupations fall into each quadrant, regardless of their absolute AIOE or  $\theta$  scores. Results should be interpreted with this in mind.

**3 Results and discussion**

**3.1 Overall results**

The results of our analyses indicate that 63% of employment in Ireland is relatively highly exposed to AI, with 30% of employment falling into the ‘at-risk’ category (or high-exposure, low-complementarity). Approximately 37% of persons work in occupations that are considered to have low exposure to AI. To give some indication as to the type of roles that fall into each category, four occupations per quadrant are labelled in Fig. 2. The role of ‘Nurses and Midwives’, for example, is highly exposed to AI but also displays a high level of complementarity. In comparison, ‘Telephone Salespersons’ are also highly exposed to AI, but have relatively low levels of complementarity. For ‘Telephone Salespersons’, the extent to which AI replaces human labour will depend on a number of factors, including societal



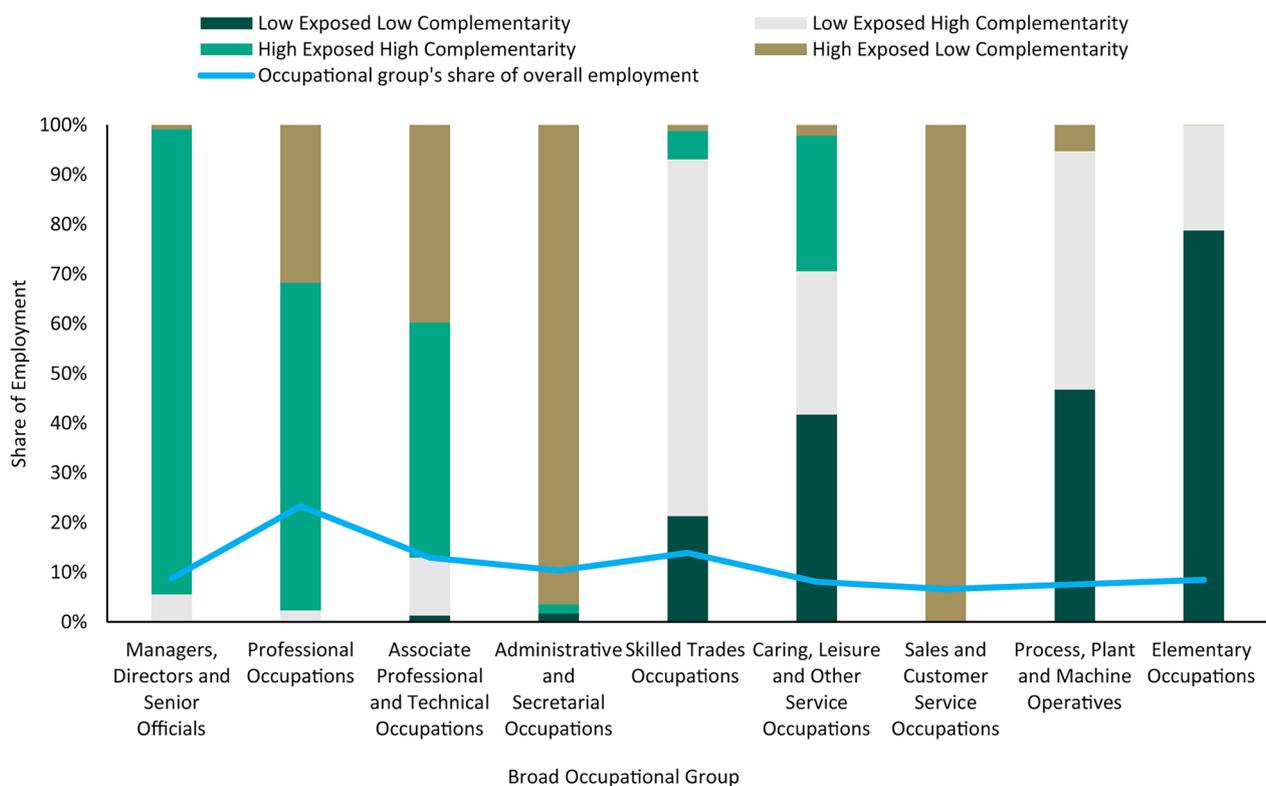
**Fig. 2** AI Exposure (AIOE) and Potential Complementarity ( $\theta$ ) in an Irish Context. Source: Author’s calculations Note: In the chart above, AIOE denotes the exposure to AI at the individual occupation level. Complementarity ( $\theta$ ) is derived from O\*NET work context variables and a single skill-level indicator (job zone). The diagram features reference lines that are based on the medians of AIOE and  $\theta$ , which divide occupations into four quadrants. Each quadrant represents a distinct combination of AI exposure and complementarity. Certain occupations are specifically highlighted for illustrative purposes. Occupations are classified using the US SOC 2010 system

preferences and the value consumers place on human-to-human interaction. For instance, AI may be adept at handling routine telephone queries but non-standard conversations are likely to require human intervention. In other words, AI may struggle to build meaningful long-term relationships with clients and these can be critical for creating customer loyalty. This example underlines the fact that there remains a great deal of uncertainty of AI’s potential impact on various occupations, and results should be interpreted with this in mind.

The bottom right quadrant can be viewed as reflecting an ‘at risk’ area, where occupations are relatively more exposed and substitutable to AI applications. The closer an occupation is to the bottom right-hand corner, the greater its relative risk to AI. It is again important to highlight that occupations falling into this category will not necessarily be substituted (or transformed) by AI. Rather, our current understanding of AI applications indicates that these are the occupations which would be most at risk, relative to other occupations. There are 72 occupations in Ireland which fall into this category. These occupations account for 30% of total employment in Ireland. When we consider the position of different occupations, Fig. 3 illustrates the share of employment in Ireland within each exposure/complementarity category across broad occupational groups.

For instance, highly skilled occupations such as Managers, Directors and Senior Officials, alongside Professional Occupations, are highly exposed to AI. These, however, are also likely to benefit from high levels of complementarity. For those working in Professional Occupations, two-thirds of same work in high-exposure, high-complementarity roles. Persons in these occupations potentially have the most to gain from AI, provided they are equipped with the skills to use AI as a supporting technology. On the other hand, Administrative and Secretarial Occupations and Sales and Customer Service Occupations are considered to be most ‘at risk’ from AI, relative to other occupations. Almost all occupations falling into these two broader occupational groups are in the ‘at risk’ category. These workers may need to be targeted for re-skilling and up-skilling interventions to ensure smooth transitions to more viable occupations. Other occupational groups, such as Elementary Occupations, Process Plant and Machine Operatives, and Skilled Trades Occupations, are considered to be relatively low risk in terms of their exposure to AI. These groups may have greater exposure to other digital technologies such as robotics, however, which isn’t captured in this measure of AI exposure.

Alternatively, we can examine these analyses through the prism of those NACE sectors in which persons are employed. The ‘Financial and Insurance’ and ‘Information



**Fig. 3** AI exposure and complementarity across broad occupational groups. Source: Author’s calculations

and Communication' sectors are most exposed to AI, with 97% and 94% of persons in these sectors working in highly exposed occupations, respectively (Fig. 4). The majority of these workers are in relatively 'low complementarity' roles, potentially posing a risk to employment as occupations within these sectors are relatively substitutable to AI. However, increased AI adoption within these sectors will give rise to new firms and new jobs, especially those involved in the designing and building of AI systems. There will therefore not necessarily be job losses in these sectors, but rather a redeployment of labour from low complementarity to high complementarity roles. Ireland's skills architecture will need to be adaptable enough to ensure that education and training provision is aligned with rapidly changing skills needs.

At the other end of the spectrum, the Agricultural, Forestry and Fishing sector is least 'at risk' from increased AI adoption, with the majority of persons working in this sector being employed in low exposure roles. Worth noting is the extremely high share of persons in high exposure, high complementarity roles within the Education sector. AI has the potential to enhance various teaching and administrative processes within the education sector. In particular, AI has the potential to automate marking for certain types of tests (e.g. multiple choice) and provide real-time feedback on students' work. In addition,

AI may also be able to assist with curriculum design and creating new teaching materials, freeing up teachers to focus on tasks that require human interaction and creativity. This sector therefore potentially has the most to gain in terms of productivity improvements, provided workers are equipped with the skills to use AI as a supporting technology.

From a Gross Value Added (GVA) perspective, sectors with the highest GVA – with the exception of manufacturing (although this will be highly exposed to robotics) – appear to be the most exposed to AI applications. In simple terms, GVA is the value that producers have added to the goods and services they have bought. It is a measure of the individual contributions of different sectors to the economy. Sectors highly exposed to AI could potentially benefit most from increased productivity, investment and competitiveness. This would serve to boost GVA further but these sectors most likely to face the greatest labour market disruptions. In the text that follows, we consider how AI exposure and complementarity varies with workers' demographic characteristics. It is possible to build a picture of the type of workers that are most vulnerable to AI, and those that are most likely to benefit from AI adoption.

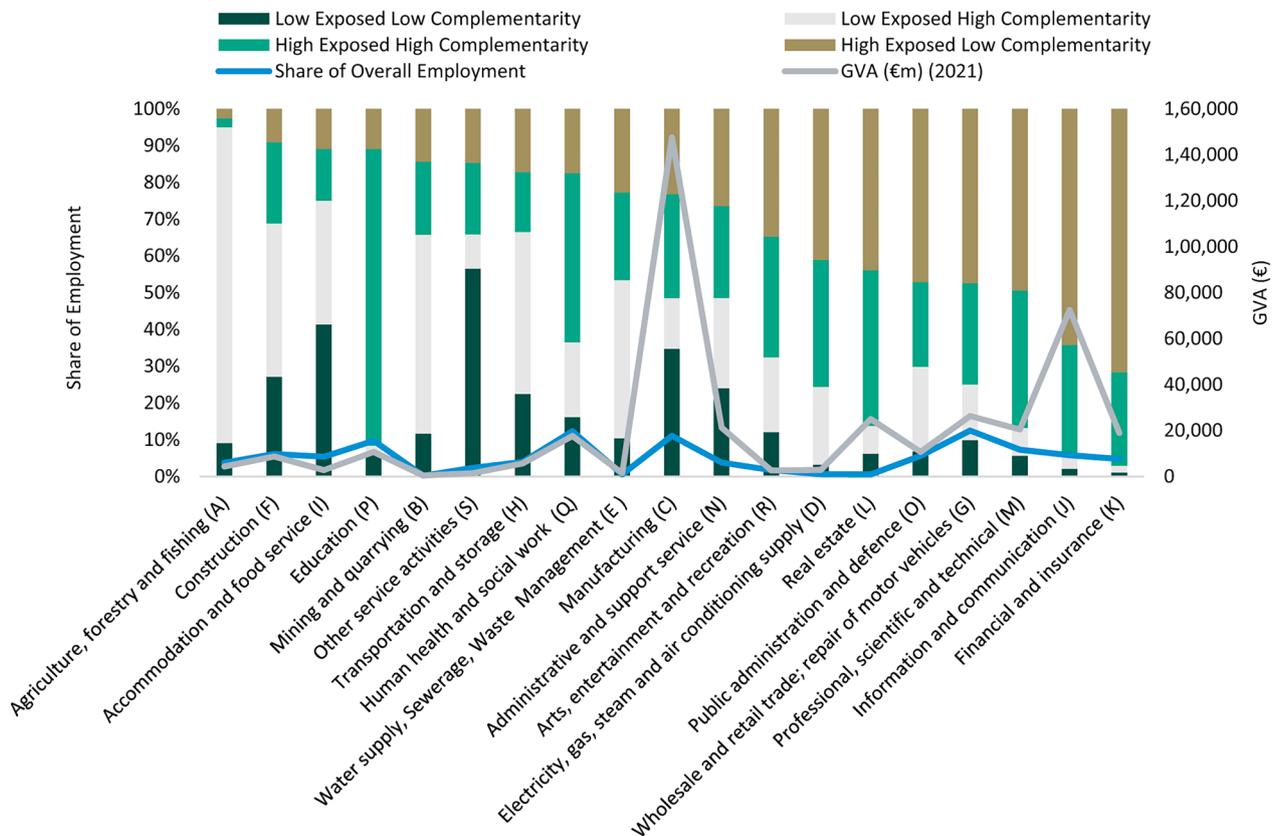


Fig. 4 AI exposure and complementarity across economic sectors.

### 3.2 Gender and age

When looking at exposure and complementarity, the relative employment shares differ significantly for males and females. Females are far more likely to work in highly exposed roles compared to males, with 76% of females working in occupations in these categories (Fig. 5). This is compared to 51% of males. Furthermore, approximately 38% of females are employed in roles which are considered to be most ‘at risk’ of AI disruption, far higher than the share of males in this high-exposure, low-complementarity category (23%). For example, approximately 5.8% of females are employed as ‘Sales and Retail Assistants’, an occupation which is considered to be highly exposed with low complementarity. In comparison, only 2.5% of males are employed in these roles.

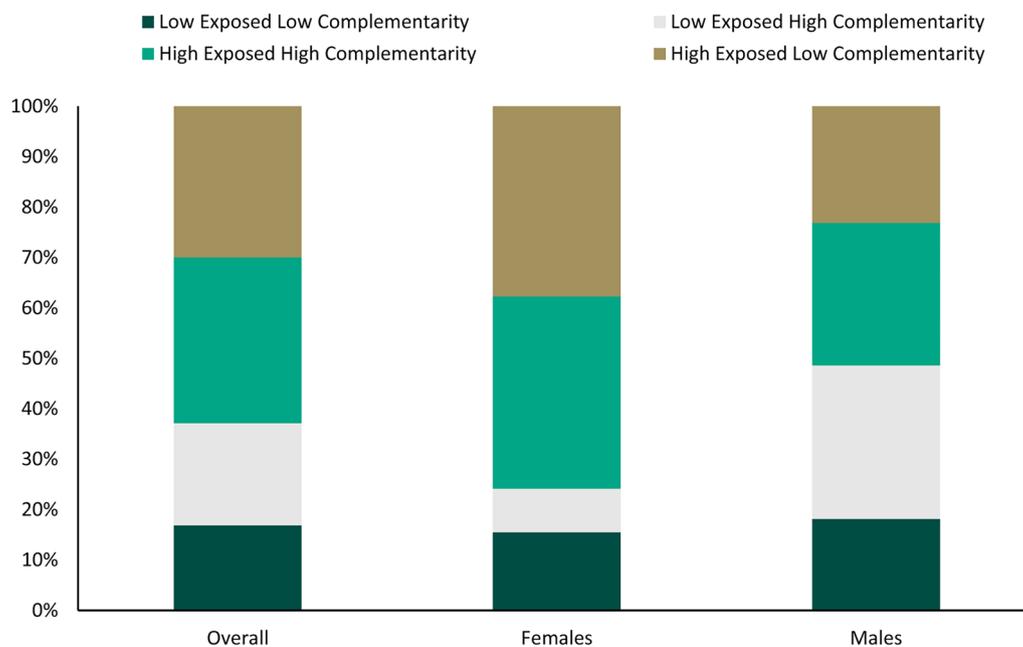
It is also common for females to be employed as ‘Nurses and Midwives’, with 5.6% of females in employment working in that role (compared to 0.5% of males). This occupation is also considered to be highly exposed to AI, albeit with high levels of complementarity. Males, on the other hand, are more likely to be employed as farmers (5% of men in employment are farmers, compared to 0.5% of women). This is an occupation which has low exposure to AI and is also highly complementary. Males are also far more likely to work in construction or transport-related roles which are also relatively less exposed to AI.

Younger workers (with the exception of those aged < 24 years) appear to be slightly more exposed to AI compared to older workers, with greater shares working in both ‘at risk’ and ‘high gain’ roles (Fig. 6). This is expected given

the educational attainment levels of the various cohorts. Older workers are much more likely to have left education with no/few formal qualifications and consequently, to be working in those Elementary or Skilled Trades roles which have relatively low exposure to AI. Despite their lower exposure, older workers are less likely to engage in lifelong learning and are typically less proficient at using digital technologies. It will be important to ensure that AI re-skilling/up-skilling interventions manage to reach groups that have previously had little engagement with the further education system.

### 3.3 Educational attainment and earnings

An individual’s educational attainment is a strong predictor of their likely exposure and complementarity to AI in their job. It is possible to assess the varying levels of educational attainment levels with regard to AI exposure and complementarity (Fig. 7). Exposure to AI increases as educational attainment increases. Approximately 95% of persons with a Doctorate work – or did work (for unemployed persons) – in occupations that are highly exposed to AI. This compares to just 26% of persons in the lowest educational attainment category (no formal education/primary education/lower secondary education). It is notable that exposure to AI not only increases with educational attainment, but complementarity does too. Persons with the lowest levels of educational attainment are more likely to work in low complementarity jobs (49% of persons in this category are in/were in high complementarity roles), compared to 80% of persons with a Doctorate.



**Fig. 5** Employment shares by gender by AI exposure and complementarity. Source: Author’s calculations

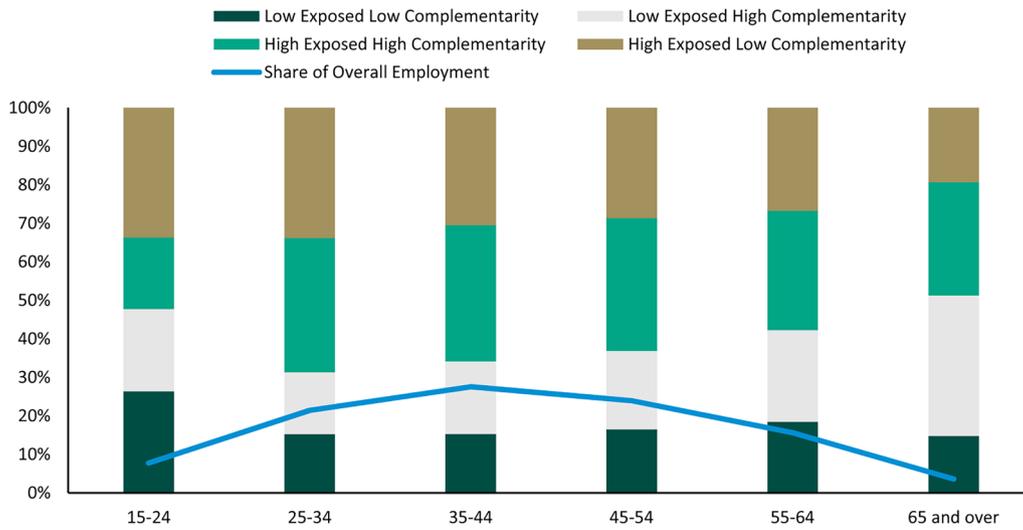


Fig. 6 AI exposure and complementarity by age cohort. Source: Author's calculations

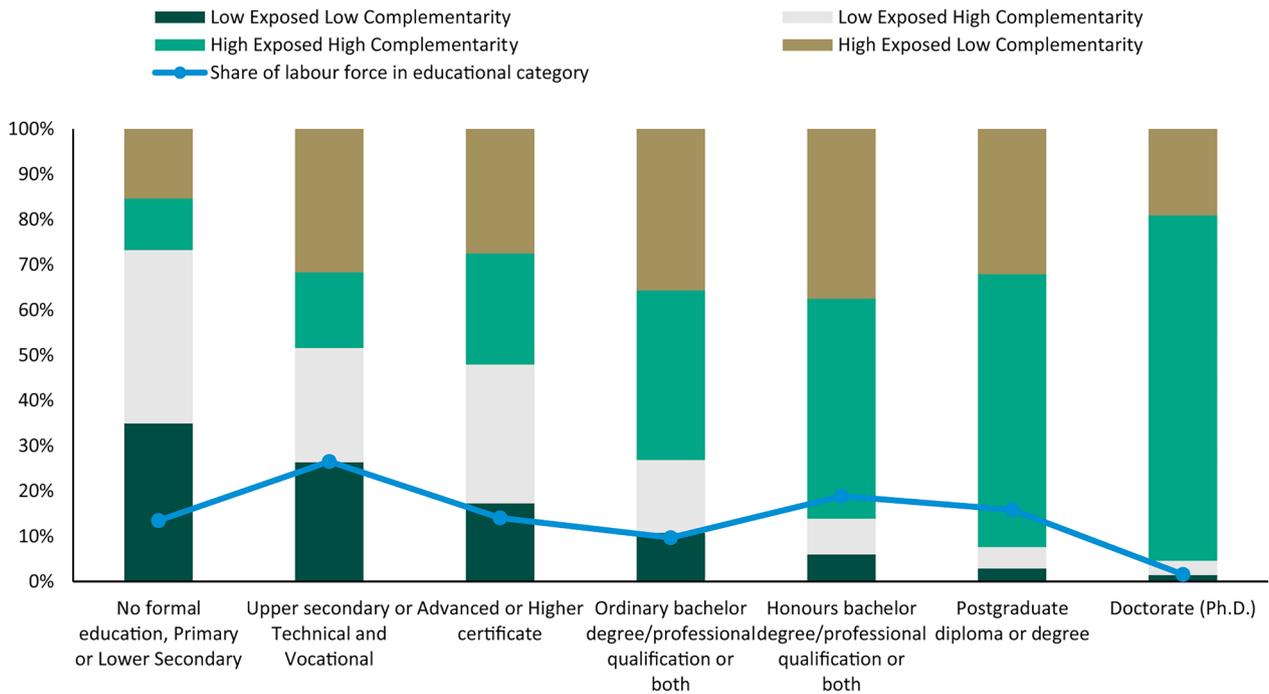


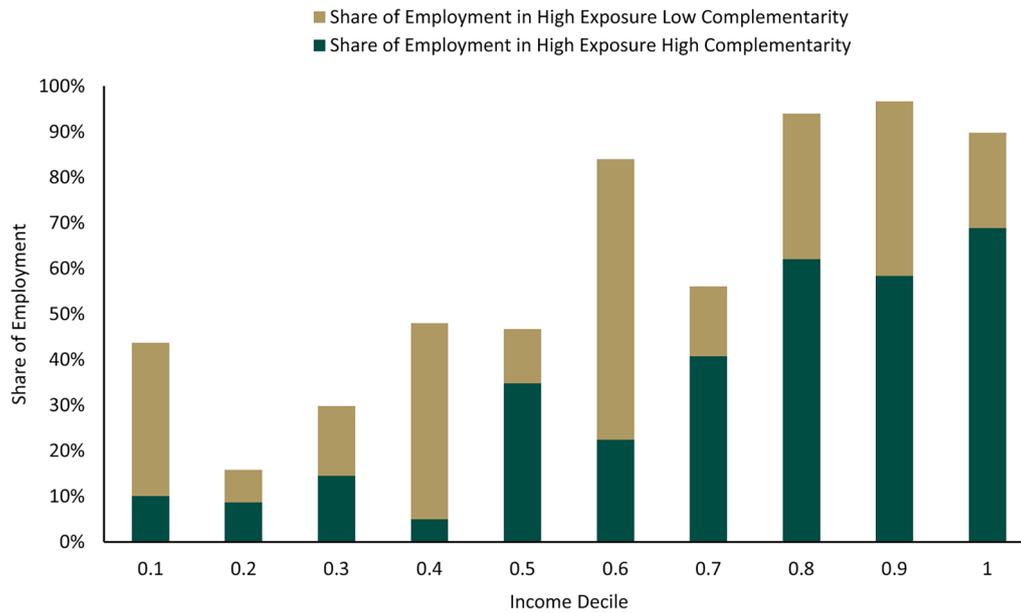
Fig. 7 AI exposure and complementarity by educational attainment. Source: Author's calculations

Although many potential ‘winners’ from AI adoption – say, those with high AI complementarity – are persons with Higher Education Awards<sup>8</sup>, some of the most vulnerable persons to increased AI adoption also have high educational attainment levels. For example, 38% of persons with an Honours (undergraduate or) Bachelor’s degree fall into the ‘at-risk’ high exposure, low complementarity category. This is the highest proportion of

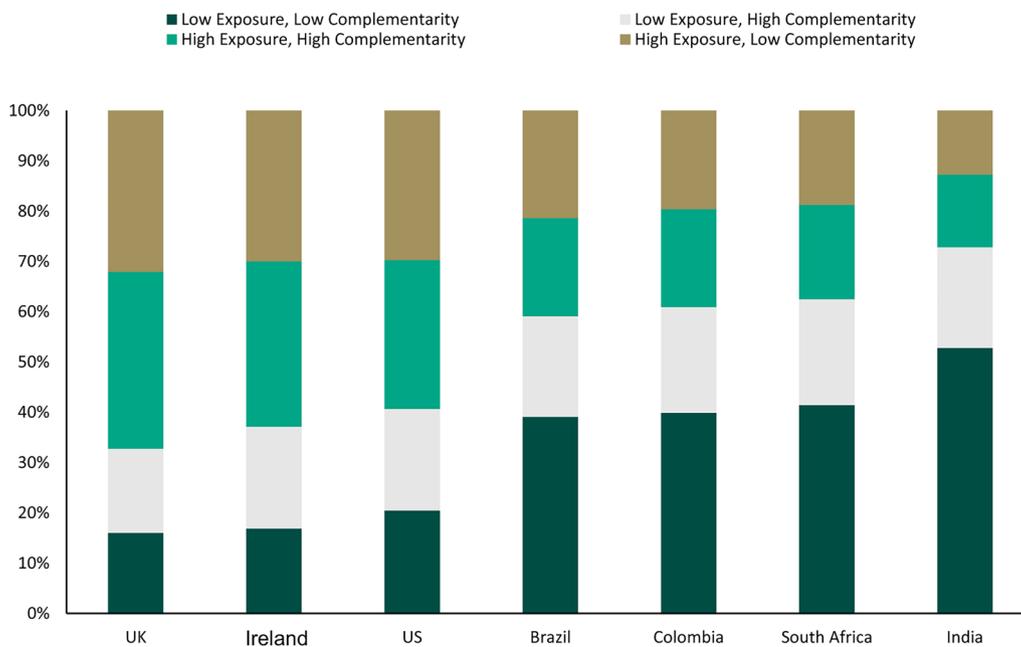
persons falling into this category across all educational attainment levels. The picture is therefore perhaps more complex than first appears, with the biggest winners and losers from increased AI adoption coming from highly educated backgrounds.

Finally, the distribution of incomes is of relevance when considering potential AI exposure (Fig. 8). This analysis suggests that there is a positive correlation between AI exposure and earnings. Approximately 44% of occupations in the first decile are ‘highly-exposed’ to AI, compared to 97% in the 9th decile and 90% in the top decile.

<sup>8</sup> Specifically, awards at levels 6 and/or 7 (or higher) on Ireland’s National Qualifications Framework (NQF) – levels 1 through 10.



**Fig. 8** AI exposure and complementarity by income decile. Source: Author’s calculations



**Fig. 9** Employment shares by country by AI exposure and complementarity. Source: Cazzaniga et al. (2024); Pizzinelli et al. (2023); and author’s calculations

Potential AI complementarity also increases with earnings, in a similar vein to educational attainment. This suggests that higher earners stand to benefit most from increased AI adoption, with potential implications for income inequality. This is consistent with findings by the IMF (Cazzaniga et al. 2024). Occupations in the ‘at risk’ high exposure, low complementarity category, are more evenly distributed across the earnings distribution, however, with the highest share of occupations in this category falling in the 6th income decile.

### 3.4 Cross-country comparisons

Research by the IMF (Cazzaniga et al. 2024) found that, on average, 60% of employment in advanced economies is highly exposed to AI. Ireland’s labour market is, therefore, marginally more exposed to AI than the advanced economy average, with 63% of persons in employment working in highly exposed occupations. In their analysis, Cazzaniga et al., focused on six countries at various levels of economic development: the UK, US, Brazil, Colombia, South Africa and India. Figure 9 presents a visual

representation of the employment shares in each exposure-complementarity category within each country. For comparison, Ireland's shares of employment have also been included.

Out of this cohort, only the UK has greater labour market exposure to AI than Ireland, with 67% of persons in employment working in highly-exposed roles. In the US, just under 60% of persons are employed in highly exposed roles, in line with the average across all advanced economies (Cazzaniga et al. 2024). While Ireland may have a higher-than-average share of persons in highly-exposed roles, Ireland also has a high share of persons working in high-complementarity roles. Approximately 53% of persons in Ireland work in roles which are highly complementary to AI, compared to 52% in the UK, and 50% in the US. In emerging market economies, such as India, the share of persons working in highly exposed roles is much lower, although a far lower proportion of persons work in roles that are highly complementary to AI. In five out of the six countries in the IMF sample, women face a higher exposure to AI than men albeit that none of these divergences are as large as in Ireland.

This is likely due to a range of factors, with one potentially being the high share of agricultural employment (for men) in Ireland, resulting in men disproportionately working in 'low exposure' roles compared to other advanced economies. There appears to be a high degree of polarisation in exposure to AI in the Irish labour market. On the one hand, a considerable share of workers are employed in high-exposure, low-complementarity roles, and are therefore at higher risk of labour displacement. On the other hand, there is a substantial share of workers employed in high-exposure, high-complementary occupations. According to the IMF, these are the workers that are most likely to gain from increased AI adoption, potentially experiencing productivity gains.

In part, this reflects the prevalence of certain types of work in these economies but it may also be a function of the global distribution of 'compute' resources. The term compute here refers to applications requiring resources for purposes such as computation and processing (i.e. cloud computing or big data) and it is a core input to the development and deployment of AI. For instance, Central Processing Units (CPUs), Accelerated Processing Units (APUs) and Graphics Processing Units (GPUs) are considered compute resources. Lehdonvirta et al. (2024) consider the global deployment of those chips necessary to underpin compute for AI development and deployment (i.e., to train AI models). They also consider the geographic dispersal of public cloud compute<sup>9</sup> (or 'public

cloud regions'), including market leaders such as AWS, Microsoft Azure and Google Cloud.

This analysis found that a small number of countries constitute 'Compute North' (or those countries which host the technology necessary for AI development). The rest of the globe is categorised as 'Compute South' (i.e. technology for AI deployment rather than development) and 'Compute Desert' (i.e., those countries which host no public cloud AI compute at all). The vast majority of countries across the globe have no public cloud regions. Despite its small size, Ireland is one of only 39 countries across the globe to host at least one public cloud region and is one of only 17 countries – Compute North – where the type(s) of high-end chips required to provide compute for AI are located. Indeed, close to 20% of the EU27's GPU-enabled regions are based in Ireland (rising to 25% for more advanced chip technology<sup>10</sup>).

#### 4 Concluding comments

The paper then assesses Ireland's overall labour market exposure to AI and places these results in a comparative international context. We do so by means of building upon methodologies developed by Felten et al. (2021) and Pizzinelli et al. (2023) in order to create a complementarity-adjusted AI occupational exposure (C-AIOE) index for Ireland. This approach allows us to consider both exposure and complementarity in parallel. This is critical to understanding the potential labour market shifts a given occupation might encounter over time. For instance, those occupations heavily exposed to AI – and where tasks can be performed autonomously – are likely to see a decline in demand for human labour. By contrast, heavily-exposed occupations with a high degree of complementarity to AI could see productivity enhancements, leading to an increased demand for labour. This paper suggests that the impacts of AI on the labour market are unlikely to be uniform. We find that 63% of employment in Ireland is relatively highly exposed to AI, with 30% of employment falling into the 'at-risk' category.

This finding suggest that Ireland is relatively more exposed to AI than is the case for other advanced economies. We also find distinct differences in the likely impact of AI adoption for workers across multiple dimensions. For instance, we find that female workers in Ireland are far more likely to work in highly exposed roles compared to males and that younger Irish workers are more exposed to AI than are older workers. We also find whilst exposure to AI increases in line with educational attainment, so too does complementarity. The extent to which AI augments, or replaces, human labour in the medium

<sup>9</sup> These large providers are sometimes referred to as 'hyperscalers' and the reference to 'public' does not imply any Government affiliation (but rather that these services are available on demand and shared by many customers).

<sup>10</sup> Ireland being home to two of the EU27's 11 GPU-enabled regions as well as two of the EU27's eight A110-enabled regions (the latter being the Nvidia A100 GPU developed in 2020).

to long-run will depend on a variety of economic, social and policy factors, including levels of AI regulation. Furthermore, the capacity to leverage the potential benefits afforded by AI requires that workers develop the skills necessary to take advantage of AI as a supporting technology.

This work suggests a number of possible avenues for future research. For instance, there is value in re-visiting how occupational classifications – complementarity and exposure – would differ when based on Irish or European median values (rather than US-derived data) and/or to determine whether there are any job/role-specific differences that arise between countries. There is also value in updating these findings to capture much more recent – at the time of writing – technological advances (i.e., LLM); the prospect for enhanced integration between AI, automation and robotics; and the role to be played by emergent regulatory architecture.

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#### Author contributions

HW – contributed to the design of this research; led on the analysis and interpretation of the data; has contributed to the drafting this paper; and has approved the submitted version.

DC – contributed to the design of this research; contributed to the analysis and interpretation of the data; has contributed to the drafting this paper; and has approved the submitted version.

KD – contributed to the design of this research; contributed to the analysis and interpretation of the data; and has contributed to the drafting this paper.

KF – contributed to the design of this research; contributed to the analysis and interpretation of the data; and has contributed to the drafting this paper.

NG – contributed to the design of this research; contributed to the analysis and interpretation of the data; and has contributed to the drafting this paper.

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#### Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

#### Declarations

#### Competing interests

The authors confirm that they have no competing interests (financial and/or non-financial).

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