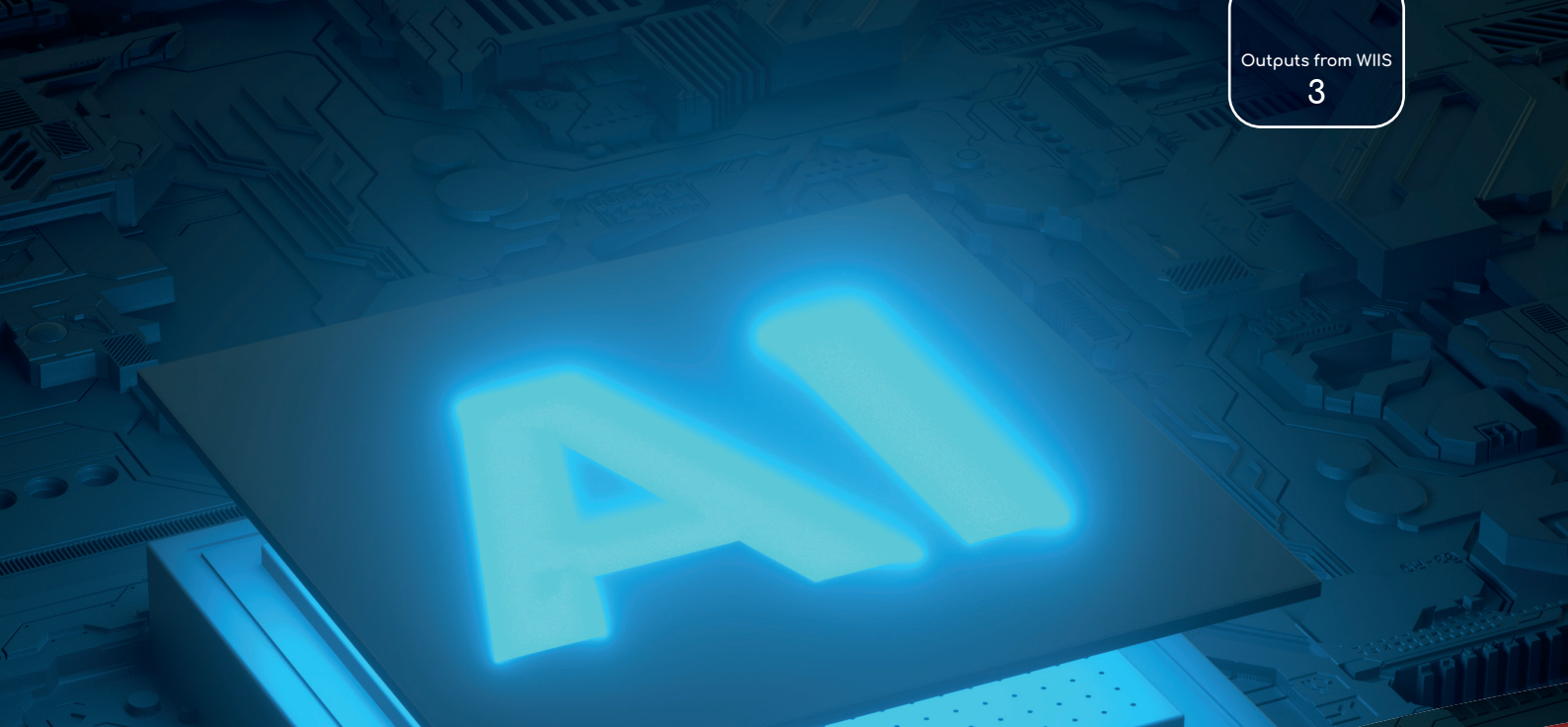
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GenAI Use in Work: its reach, effects, risks and limits

Findings from the Working in Ireland Survey, 2025

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The Working in Ireland Survey

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This report examines the adoption of generative AI (GenAI) in the workplace and its effects on workers across the island of Ireland. The data are drawn from the Working in Ireland Survey (WIIS), 2025. This is the second such WIIS survey; the first was conducted in 2021 and was confined to the Republic of Ireland. The 2025 survey covers both the Republic of Ireland (RoI) and Northern Ireland (NI) and draws on a nationally representative sample of 4,300 workers in paid employment, 3,040 in the RoI and 1,260 in NI. Here, we look specifically at the incidence of intentional GenAI use among workers, the tools they use and the tasks for which they use them, the intensity and depth of that use, the training they receive and the competence they acquire, the governance frameworks within which they operate, and the effects of GenAI use on their productivity, innovativeness, work quality and working conditions. A particular concern is whether AI is being used primarily to augment and complement workers' skills and capabilities, making them more productive, innovative and better able to do their jobs, or whether it is being used to automate and displace human effort. A further question is who captures the productivity gains that GenAI generates: the employer, the worker, or both. Our findings from the current survey are compared, where appropriate, with evidence from the international literature and are set against the public policy context, in particular the implications of GenAI adoption for training provision, workplace governance, and the fair distribution of AI's economic benefits across the workforce.

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Report Headlines

AI isn't coming, it is here and it is diffusing rapidly. Are we ready for it? Have we the governance systems in place? Are people trained to use it responsibly? Will it benefit us? If it is to, how can we ensure that the gains are not disproportionately acquired by one party but that they are distributed fairly so as to improve the conditions of employment and living standards of those who use it? These are among the pressing questions confronting policy makers, employers, employee representatives and workers. The answers, however, are not self-evident. One of the telling lessons of the history of the introduction of new technologies is that they have no automatic effect: progress is not preordained (Acemoglu and Johnson, 2023; Frey, 2025). Outcomes depend on the choices WE make. As such, the findings from the Working in Ireland Survey 2025 come at an important time for public policy formulation in respect of AI on this small island.

In brief, our report details the extensive use of this new technology across workplaces both in the Republic of Ireland and Northern Ireland. However, we find its adoption to be uneven and unequal. We further find that training provision is chronically insufficient and organisational governance is patchy and weak. The productivity gains from AI adoption are considerable but at this point they are flowing predominantly to employers and not to workers.

The points listed below detail in summary form our principal findings. The report itself provides extensive details on our findings and should be read in conjunction with these headline findings.

1. The adoption of GenAI among workers in the RoI and NI is substantial and is above European averages. In the Republic of Ireland, 29.3% of workers intentionally use GenAI in their work; in Northern Ireland, the figure is 26.1%, giving an all-island adoption rate of 28.4%. These figures place Ireland comfortably above European Union average estimations by Eurofound and Eurostat.[1]
2. GenAI adoption is deeply and consistently unequal. Adoption is strongly stratified by education, occupation, earnings and firm size. Workers with postgraduate qualifications are up to fifteen times more likely to use GenAI than those with primary education. In the RoI, adoption rates rise from 8.5% among workers earning under €15,000 to 73.8% among those earning €110,000 or more, a near-ninefold gradient that is one of the most striking findings in the survey. Professional and managerial occupations record adoption rates close to 50%, while process plant operatives, caring occupations and skilled trades record rates of 3–9%. Large firms are more than 1.6 times as likely as small firms to have GenAI-using workers.

3. Writing and communication tasks dominate GenAI use in both jurisdictions, but Northern Ireland workers deploy the technology for substantially more knowledge-intensive purposes. Writing communications is the most commonly reported task in the RoI (39.6%). NI workers report approximately double the RoI rate for structuring ideas and writing (51.4% vs 22.6%), coding software (25.4% vs 11.6%) and data analysis and visualisation (30.0% vs 18.4%). Whether these differences reflect the occupational and sectoral composition of NI's GenAI-using workforce, or represent deeper differences in how the technology is being adopted, merits further investigation.

4. Around 45% of users in both jurisdictions use GenAI every day or most days, but the majority use it for 30 minutes or less per day. Thus, while they use it frequently, they use it lightly. ChatGPT is used by approximately three-quarters of those who use standalone GenAI tools in both jurisdictions. About half of users (52% in the RoI and 47% in NI) use two or more GenAI tools, and these multi-tool users engage more intensively with the technology: in the RoI, 21% of these multi-tool users who used GenAI in the past week did so for an hour or more per day, compared with 11% of single-tool users. Multi-tool users are more likely to work in managerial and professional occupations, to hold postgraduate qualifications, to work full-time and to be employed in the private sector. They are not distinguished by gender, age, organisation size, or salary.

5. When we look at the headline figures, men are marginally more likely to be GenAI users than women: across the island, the proportions are 29% of men and 27.8% of women. However, when we drill deeper into our findings and take account of workers' education, occupation, sector, firm size, contract type and age, the gender gap is somewhat larger, but it remains relatively modest at about 4 percentage points. That said, the gap is more pronounced in the RoI than it is in NI. Comparable international surveys have tended to find more pronounced male dominance in AI adoption that we do for Ireland.

   When it comes to how intensively GenAI is used there is little difference between males and females. In the RoI, 53% of male and 51% of female users use multiple tools, and the differences in the frequency of use is also small (46% vs 43%) as it is also in the case of intensity of use (18% vs 15%). The data therefore do not suggest that the gender gap widens as one moves up the intensity distribution. This contrasts sharply with international evidence where men are considerably more likely to use multiple AI tools and with more intensity in their work than are women. In Ireland, we find that among those who use GenAI, differences in depth of engagement run along occupational and educational lines rather than gender. This is a finding which has important implications for debates about equitable access to AI-related skills and productivity gains in the workplace.

6. Employer training provision is insufficient, frequently very brief, and asymmetric in content. Only 42.8% of RoI employees and 37.7% of NI employees have received or are receiving employer training in GenAI. The majority of GenAI-using workers have taught themselves. Among those who have received training, the total duration is typically very limited: almost 60% of RoI workers report training of less than one full day. Training on the advantages and benefits of GenAI is rated significantly more positively than training on its disadvantages and risks, a gap of approximately 10 percentage points in the RoI, suggesting that workers may be better equipped to use GenAI productively than responsibly.

7. Self-assessed competence, not the volume of training, is associated with productivity gains from GenAI use. Workers who rate their GenAI competence more highly report significantly larger time savings and quality improvements. Training volume alone does not predict quality improvements in people's work. This implies that how organisations invest in GenAI training matters as much as whether they invest at all. A short induction or a single workshop is unlikely to move the needle on competence and, by extension, on productivity. The returns to GenAI adoption are not automatic, they depend on the depth of capability that workers bring to the technology, which in turn depends on the seriousness with which employers approach the task of building it.

8. Productivity gains from GenAI are real but are being captured primarily by organisations rather than by workers. The majority of users in both jurisdictions report some time savings from GenAI use. NI workers report more substantial savings, with 52.2% reporting large or very large time savings compared with 33.1% in the RoI. Critically, over 60% of workers who save time redirect it to more complex and creative job tasks rather than to rest or personal time. Fewer than 15% redirect GenAI-generated savings to non-work activities. This pattern, combined with the finding that work pace has intensified for a third of users while only a small minority report a shortening of their working day, suggests that the productivity dividend from GenAI is being captured predominantly by employers.

9. The impacts of GenAI on work quality outputs and innovativeness are positive but more pronounced in Northern Ireland than in the Republic of Ireland. In the RoI, 53.8% of GenAI users report large or moderate quality improvements; in NI, the equivalent is 70.7%, with 34.5% of NI users reporting large quality improvements in their work outputs compared with 16.7% in the RoI. On innovativeness, 54.7% of RoI users report meaningful gains compared with 71.0% in NI. These differences are consistent throughout the data but should be treated with appropriate caution given the smaller NI sample size.

10. Employer governance of GenAI use is underdeveloped in both jurisdictions, with NI particularly exposed. Only 52.2% of RoI employees and 36.5% of NI employees work in organisations with an official policy or set of guidelines for GenAI use.

AI output labelling is inconsistent: only 31.6% of RoI users and 21.7% of NI users always label AI-assisted outputs as such. Workers strongly endorse the need for human oversight, 88.5% in the RoI and 84.1% in NI, yet many operate in organisational contexts that provide no formal framework to support such oversight. Deeper employer engagement with workers' AI activities is positively associated with workers' self-assessed knowledge of GenAI's limitations and risks, suggesting that governance and risk literacy are mutually reinforcing.

11. Workers are considerably more positive about GenAI's employment consequences than much public commentary would suggest. Fear of job replacement is cited by fewer than 1% of workers as a reason for not increasing their GenAI use. Reduced job satisfaction is cited by 4.7% and employer discouragement by 1.6%. The dominant barriers to adoption among non-increasing users are pragmatic task unsuitability (35.7%) and self-sufficiency (29.5%) rather than anxiety, distrust or constraint. The near-universal endorsement of human oversight, combined with low trust in the unconditional completeness or reliability of AI outputs, describes a workforce that approaches GenAI with informed optimism rather than naïve enthusiasm or fearful resistance.

12. The great majority of current GenAI users expect to increase their use substantially over the next two years. In the RoI, 84.2% of GenAI users anticipate some increase in their use; in NI, the figure is 85.7%. Around a third in each jurisdiction expect to greatly increase their use. This implies that the governance, training and policy challenges identified in this report will become significantly more pressing in the near term, and that organisations and policy-makers which are currently unprepared will face a rapidly evolving challenge.

13. We conclude our report with an assessment of the legislative and policy landscape as it pertains to AI governance in the RoI and NI. We are forthright in our conclusions: there are considerable gaps between the regulatory aspirations of the state in both jurisdictions and the reality of AI adoption and use in the workplace. Closing that gap will require sustained and coordinated effort from policy-makers, employers, trade unions and civil society. It will require investment in training that builds genuine competence rather than nominal compliance; governance frameworks that protect workers as well as organisations; and deliberate choices about how the economic gains from AI are shared. The Working in Ireland Survey will continue to monitor these dimensions in future waves, and we hope the evidence it provides will inform and sharpen the policy response.

1. Introduction

Despite widespread claims about artificial intelligence's adoption and its effects on the future of work, we lack systematic empirical evidence about how this new technology is actually being used by workers and with what consequences for workers' skills, job security and job quality (Chatterji et al., 2025; Eloundou et al., 2023; Handa et al., 2025; Hartley et al. 2025). A central research conundrum for many is whether AI is being used (by employers) to augment and complement employees' skills, expertise and capabilities, or whether it is being used to automate complete tasks and eliminate job roles. Skill augmentation is often assumed to make workers more productive which in turn will generate new economic activity along with new employment (Daugherty and Wilson, 2024). Automation, it is feared, will displace workers and lead to job losses (Baldwin, 2019). Of course, both scenarios are possible at the same time along with a third one, where AI creates entirely new tasks and job roles. There is thus the possibility of both magnificent opportunities and portending risks (Brynjolfsson and McAfee, 2014; Schwab, 2016). Alongside this question is the one of whether the use of AI creates new opportunities for workers to enhance their skills and capabilities, to be more innovative in their work and to enjoy a better quality of work life, or not. And also whether any such outcomes are associated with particular occupations or industries over others. A further concern is whether AI is deployed responsibly and safely, and whether workers are provided with adequate training. This paper provides the first large-scale empirical measurement of the incidence and effects of AI use among workers in the Republic of Ireland and Northern Ireland. Our analysis is guided by the following questions:

- First, are the claims of GenAI's widespread adoption correct, and, if so, who is using it and for what purpose and within what policy parameters or ethical guidelines?
- Second, who pays for its adoption and use?
- Third, how well trained are workers to use AI?
- Fourth, what productivity effects does it generate? And if there are productivity effects, are they garnered by augmenting workers' skills or by displacing workers or impairing their working conditions?
- Fifth, who acquires the productivity gains, employers or employees?
- And finally, what effects does the use of GenAI have on workers' job quality?

2. The significance of AI

Artificial intelligence is widely seen as a powerful and potentially revolutionary technological innovation, on occasion referred to as being, with the internet and other information and communication technologies, the basis for a "Fourth Industrial Revolution" (Schwab, 2016). Other commentators speak of the arrival of "The Age of AI" (The Age of AI, 2019-20) which, although long in its development, is now advancing at breakneck speed (Bick et al., 2024). A statistic often cited is that in just five days after its launch in 2022, the monthly active users of OpenAI's ChatGPT exceeded 100 million, making it the fastest-growing consumer application in history. The equivalent for Netflix was 2.5 years and for Instagram 2.5 months. Since ChatGPT's launch other widely used AI technologies have been developed that include Anthropic's Claude, Google's Gemini, Microsoft's Copilot, and Meta's Llama. With this increased market competition, and the advent of so-called smaller models, such as China's DeepSeek, that are now capable of matching the performance of the aforementioned larger models, the costs of querying (i.e., using) an AI tool has become ever more affordable (AI Index Report 2025). In parallel, astronomical sums of money continue to be invested in the development of new AI applications both by private companies and, more recently, by national governments. The AI Index Report (2025) estimates that private investment in GenAI in 2024 reached $33.9 billion, over 8.5 times higher than 2022 levels. The GenAI sector now represents more than 20% of all AI-related private investment. With this speed of AI development and reputed adoption the task of understanding what AI is and how it might affect people's work and employment has become an enormously urgent and complex undertaking.

Understanding what AI is, what it tries to do and fails to do

Understanding what AI is, is probably best approached, at least initially, by understanding what it is not and foremost here is to understand that AI is not a form of intelligence. AI tools are not thinking machines. They do not engage in some sort of synthetic computer cognition that approximates to or surpasses human-level thinking (Surden, 2019).

Among GenAI's key attributes is that it is an instantaneously, universally-available, general purpose technology[2] which can be used by anyone with access to an electronic device and the internet. It may be used for a variety of work tasks that include: understanding, interpreting and generating new content, writing fluent lucid prose, creating videos or podcasts from text, converting spoken words into text, creating code, analysing and reducing data and text, language translation, and answering precise questions from large, multiple documents or data sets. It can undertake all such and other tasks with remarkable speed and in a manner that resembles human outputs.[3] It is often referred to as a

form of machine learning by which is meant, the more data it is trained on, the more accurate the output materials will be. It scrapes its (training) data from publicly available sources on the web. It then works by identifying patterns within the data from which it can then identify, analyse and create new content.

A great many of the tasks that can be given over to AI are those which traditionally would have been seen as routine, repetitive, and time-consuming, offering employees little job autonomy or satisfaction. Increasingly, however, as AI has developed further, it is able to handle more complex and varied tasks that also includes it being integrated into existing systems and work processes across various business functions, including, for example:

- In sales and marketing, AI might be deployed to create targeted advertisement content, to identify potential leads, and to upsell, cross-sell, and provide real time sales analytics.
- In HR, it can be used to simplify recruitment processes, generate job descriptions, and assist with induction and redundancy processes.
- With respect to production systems it can be adopted to help with analysing vast amounts of data, even if complex and unstructured, and with aggregating key metrics and analysing inventory flows.
- In finance, it may be utilised to generate forecasts, auto-generate and customise purchase orders, contracts and invoices.
- In legal practice, it may help with identifying and providing precises of relevant case law, drafting court submissions and preparing contracts.
- And in IT, it may be employed in writing code, detecting and mitigating security threats, and analysing communications for phishing attempts.[4]

Such are the advances made by AI in recent years that Standford University's AI Index Report pronounced, "As of 2024, there are very few task categories where human ability surpasses AI. Even in these areas, the performance gap between AI and humans is shrinking rapidly" (AI Index, 2025: 96). Still, despite this remarkable advancement in its capabilities, AI has limits and weaknesses. Five in particular warrant highlighting.

The first relates to its capabilities in respect of complex reasoning. While advances have been made in what is referred to as chain-of-thought reasoning, GenAI still cannot reliably solve problems for which provably correct solutions can be found using logical reasoning, such as arithmetic and planning, especially on instances larger than those they were trained on (AI Index Report 2025). As a consequence, their reliability, trustworthiness and suitability in high-risk applications may be called into question.

Second, AI can and does 'hallucinate'; that is, it may generate false or inaccurate information. This risk has attracted particular attention in the legal profession where court submissions have been found to contain citations fabricated by LLM systems (Dahl et al., 2024).

Third, despite efforts to reduce explicit (easy-to-see and relatively blatant) bias in AI models, many models continue to reveal implicit biases, which tend

to be less intentional, less controllable, and unconscious especially in respect of racial, religion, health and gender stereotyping (Bai et al., 2025). For example, AI models, including ChatGPT-4, Claude and Llama models, continue to associate negative terms with Black individuals, recommend White people to more senior positions, more often associate women with humanities and men with STEM subjects, and favour men for leadership roles. As such, if used uncritically and without adequate oversight, they risk further reinforcing rather than reducing bias and discrimination in decision-making.

A fourth identifiable risk relates the deployment of appropriate mechanisms to assess the effectiveness, accuracy and safety of AI models' decision-making (Magesh et al. 2025). The term used to describe this process is responsible AI (RAI). As the AI Index Report (2025, 170) states plainly: "(w)hile major model developers consistently test their flagship models on the same general capabilities benchmarks—covering math, coding, and language skills—no such standard exists for safety and responsible AI assessments". It is not that such benchmarks do not exist – they do – the problem is that there is no standardised agreed-upon international benchmarks by which users can compare and determine which AI models are safe and responsible.

Finally, there is what we term a capstone risk that relates to the provenance of data. As indicated above, AI models are (pre-)trained by scraping data that is available on the internet. This data might subsequently be curated in different ways, added to and repackaged often on multiple occasions with other data sources. As such, while AI tools are often misconceived as being monolithic data sources they more often constitute a combined lineage of a series of data extractions. Increasingly in the midst of this complexity there is a tendency, as Longpre et al. (2024) have emphasised, for improper or inadequate attribution of data sources and violation of the rights of original copyright holders. In this ambiguous and confusing AI landscape users of AI, be they employees or businesses, run the risk of using data that are inconsistently documented, misattributed, and that may not be licenced for commercial use. In sum, these various risks pose enormous challenges for organisations in respect of data use governance and staff training so as to ensure the outputs derived from AI models are reliable, safe, ethical and meet legal requirements.

3. Means of measuring AI adoption and its effects

Measuring AI adoption is a difficult exercise and no method is ideal or complete. The task is made more complex by the speed at which the technology is being developed, by employers' confusion or uncertainty as to which AI technologies and workforce skills they have or will adopt or require, and from a research viewpoint what mode of data collection is most appropriate. In the face of these challenges, a variety of forms of data collection and measurement have and may be used.

One way, and the one most often used, particularly by management consultancy firms and by professional membership organisations, is to ask management to report whether or not their organisations have adopted AI. The results of such studies generally find that the use of AI has climbed very significantly in recent years having stagnated for some years. For example, McKinsey find that from around 2018 to 2023 AI adoption by respondents' organizations, in at least one business function, was in and around 50%. However by 2025 it had jumped to 88% and this was spread across all global regions and the increase was particularly evident in professional services. In regard to the specific adoption of GenAI, 79% of respondents indicate their organizations are regularly using GenAI in at least one business function, up from one-third in 2023 (McKinsey & Company Survey, 2025).

A second way is to ask workers themselves. This approach is very rare indeed and where it is the sample sizes are often small or are of dubious provenance and representativity. There are some notable exceptions, however, that include Bick et al. (2024) who found that the number of respondents who reported using generative AI in at least one business function more than doubled, from 33% in 2023 to 71% in 2024 (AI Index Report 2025).

A third way is to examine demand in the labour market for workers who possess AI skills. There are a number of notable such surveys. One of the most detailed is that conducted by Nobel prize-winning economist Daron Acemoglu and colleagues which, over a ten-year period (2007 and 2010-18), looked at AI-related vacancies in the United States (Acemoglu et al., 2022). Their approach is to use job postings that cite AI skills as a proxy for firms' adoption of AI technologies. A similar approach is used by the OECD (2023) in its examination of the demand for AI skills. It uses data supplied by Lightcast, the US labour market consultancy firm. Since 2010, Lightcast has analysed hundreds of millions of job postings over tens of thousands of online job sites, identifying those that require AI skills. While these studies have merit in that they can be used to predict directional skills shifts in the labour market they have their limitations. Job advertisements may not be accurate representations of the skill requirements of a particular job either because an employer may not be

conversant with the future demands of a job or consider AI-related skills to be so ubiquitous they are not cited as being necessary for a given position, and, of course there is always the possibility that new posts are filled internally without any external recruitment. These existing incumbents may already be using AI in their jobs but it may be that it was never a part of their job description when hired. LinkedIn's data is invariably affected about how their users choose to use the site and how they seek to represent themselves and their skills. Thus, while these data cannot be considered reliable measures of AI use, they do, however, provide a useful measure of a direction of travel, in that they indicate the skill sets employers are now looking for.

Another approach seeks to assess the actual or potential exposure of jobs to GenAI. A variety of different indices have been used for this purpose (Acemoglu et al., 2022; Eloundou et al. 2023; Felten et al., 2021; Webb 2020; Brynjolfsson et al., 2019). However, in essence all such approaches provide a proxy measure of the exposure or suitability of job tasks to being undertaken by AI. This is achieved by looking at the profile of jobs, their task composition and their compatibility with the capabilities of new technologies. This research draws on a rich vein of work in economics over many years which has examined the effects of new automative technologies on the labour market. It is particularly associated with the work of Autor (2013; 2015), Autor et al. (2003), and others, including Acemoglu and Restrepo (2018) and Frey and Osborne (2017) who focus on the specific tasks associated with particular occupations and then enquire whether new technologies may augment and enhance people's skills and expertise, or automate tasks and displace workers, or lead to the creation of entirely new tasks and job roles. The emerging GenAI literature which adopts such an approach is best exemplified by Eloundou et al. (2023) who assign a predicted exposure score to each occupation based on the proportion of that occupation's tasks they believe will be substantially affected by GenAI. They define exposure as a measure of whether access to AI would reduce the time required for a human to perform a specific work activity or task. As such, this literature focuses on examining the potential exposure of jobs to GenAI. Such predictive studies have been found to be reasonably good predictors of actual AI adoption (Bick et al., 2024).

In a recent development of this work, more emphasis is placed on the concept of expertise and the manner in which it and the tasks associated with it are bundled within occupations (Autor and Thompson, 2025). Any given task may be performed across multiple occupations by workers with different levels of skills and expertise. In one occupation the performance of this given task may constitute a major role and represents a high level of expertise. However, in another occupation this same task and level of expertise may be marginal in the range of tasks performed. As a consequence, the effects of automation may be to simultaneously replace experts, while complementing expertise in other occupations. This development in the literature is important as the effects of new technologies are seen not only in terms of how many job's tasks, but also which tasks – routine or expert - may be lost to or augmented by automation.

Other studies examine people's use of specific AI tools, some of which measure self-reported adoption and effects of GenAI tools (Bick et al., 2024), while others examine user interactions on specific AI tools (Handa et al., 2025 and Chatterji et al., 2025). Chatterji et al.'s sample is a random selection of messages sent to ChatGPT on its various consumer plans (Free, Plus, Pro). It examines users' use of the tool across both work and non-work related queries. Handa et al. (2025) examine user interactions with Claude.ai and map these against specific work tasks and occupational categories in the U.S. By this means, they are able to distinguish those tasks and occupations wherewith AI tools are most frequently used from those that demonstrate modest or minimal use. This approach thus permits one to quantify the depth of AI use within occupations. It also provides a means of identifying which tasks and skills as currently performed by workers are complimentary to being assisted by AI tools. By examining the intensity of interaction between the user and the AI tool, the authors are also able to assess whether AI is associated with task augmentation or replacement/automation. While this approach has considerable merit, it has a number of weaknesses as the authors concede: first, usage data cannot reveal how AI outputs are actually used in practice; second, it cannot identify whether entirely new tasks or jobs might be created from AI use as their analysis involves shoehorning their data into existing, static occupational classifications; and finally, it only looks at one AI tool, albeit one that is widely used.

4. Who is using AI and how extensively

There is considerable emerging international evidence that GenAI is widely adopted by workers across developed economies (Bick et al. 2024; Hartley et al., 2025; Humlum and Vestergaard, 2024; Brynjolfsson et al. 2025b). In the main, AI usage at work is estimated to be between 20% and 35% of workers. It is slightly above this level in Handa et al.'s (2025) study of the use of one particular AI tool, Claude.ai, in the United States. They find that AI use has diffused quite widely, with roughly 36% of occupations using it for at least a quarter of their associated tasks. Far fewer, however, use AI to a greater extent: only 4% of occupations use AI for at least 75% of the tasks they perform. Where adopted, it is used primarily for software development and writing tasks, which together account for nearly half of all total usage. Use is highest in software engineering roles (e.g., software engineers, data scientists, bioinformatics technicians), professions requiring substantial writing capabilities (e.g., technical writers, copywriters, archivists), and analytical roles (e.g., data scientists). By contrast, tasks in occupations involving physical manipulation of the environment (e.g., anaesthesiologists, construction workers) demonstrate minimal use of AI.

Relatedly, use of Claude is more prominent in respect of work that demonstrates cognitive skills like reading comprehension, writing, and critical thinking and is considerably less evident in respect of physical skills and managerial skills. Handa et al. further find that the AI tool is used mainly – 57% of interactions - for augmenting human capabilities, such as iterating back-and-forth on a task, while 43% demonstrate automation-focused usage, that is fulfilling a request with minimal human involvement. Most occupations that were found to use AI did so in a manner which would suggest that it is used both to automate and augment people's work, and, as a consequence, that it is used both to increase efficiency and the quality of a person's work.

These findings parallel sectoral studies where demand for AI-related skills is identified to have grown rapidly in recent years in sectors such information, professional and business services, finance, and manufacturing sectors (Acemoglu et al., 2022). More recent research confirms these early findings and further points to its diffusion to software engineering, education, real estate, construction and marketing, with its use less evident in agriculture, mining and in public services (Brynjolfsson, et al., 2025b; Hartley et al., 2025; Peng et al., 2023).

Hartley et al.'s (2025) survey of US workers found, too, that there is considerable variation in the extent and intensity to which AI is used. For example, while 33% use GenAI five days per week at work, 12% use it only on one day per week and 17% and 18% use it two and three days per week respectively, and less than 10% use it over 4 days. The number of hours at work each week that GenAI is used is reported in most cases to

be less than 3 hours per day which might be read to suggest that it is used for specific purposes throughout the working day.

There is also evidence that AI adoption varies considerably across different segments of the workforce. For example, take up rates are often considerably lower among females, even among coworkers performing similar work tasks in the same workplace (Humlum and Vestergaard, 2024, 2025). This has been explained less by women's skills or access to AI tools, and more by systematic differences in how women and men perceive AI's societal risks (Stephany and Duszynski, 2026). AI adoption is also found to be considerably higher among comparatively younger, less experienced, and higher-earning workers, and among those in professional occupations (Bick et al., 2024; Hartley et al., 2025; Otis et al., 2025).

Since 2022 and the launch of ChatGPT, the growth in job postings mentioning GenAI skills has been extraordinary, up 800% alone for jobs outside IT and Computer Science (Lightcast, 2025). LinkedIn (2025), too, uses its users' data to measure the proportion of workers who possess AI skills. Ireland is ranked among those countries with the highest concentration of staff who possess AI skills. And while the proportion is a mere 1.11%, the figures for males are significantly higher than they are for women. LinkedIn also measure the ratio of staff recruitment with AI capabilities relative to the overall recruitment levels. The ratio varies considerably peaking at 33% in India and being close to 25% in the US and Ireland.

5. What is GenAI being used for?

Bick et al.'s (2024) survey of US workers found that GenAI was used across a broad range of tasks, the most useful being writing, administrative support, interpreting and summarizing information, and searching for facts and information.

What are its (likely) effects?

a. Productivity

As explained earlier, there is considerable debate and uncertainty as to the actual effects of GenAI. The recency and speed of AI adoption complicates matters considerably. Evidence remains relatively sparse particularly in respect of the frequency and intensity of GenAI adoption (Bick et al. 2024). On the one hand, there is considerable research evidence drawn from various forms of research design – much of which is undertaken by economists - which points towards GenAI increasing workers' productivity (Brynjolfsson et al., 2025b; Cui et al., 2024; Dell'Acqua et al., 2023; Noy and Zhang, 2023; Peng et al., 2023). Other economists project that GenAI will produce large aggregate economic effects (Chui et al., 2023; Filippucci, Gal, and Schief, 2024).

Advocates for the adoption of AI within the technology industry and the business community more broadly claim it has delivered and will continue to deliver major productivity growth, economic expansion, material advancement, and social development and progress (Baily et al., 2023; McKinsey, 2023). Adding weight to these claims is the recently produced report by the French Government's Artificial Intelligence Commission (2024) that claims that AI, if deployed correctly, could increase France's productivity by 1.35% in the medium term and increase its GDP from €250 billion to €420 billion within ten years. While the French Commission acknowledges that this productivity effect can be expected to be finite, it still foresees that AI could produce a longer-term effect by accelerating innovation, identifying new products and new forms of organization. As one its co-chairs, and recently Nobel prize for economics recipient, stated elsewhere: "AI should boost productivity growth as it automates not only the production of goods and services, but also the production of ideas" (Aghion et al., 2019).

On the other hand, other observers are more cautious and circumspect. Among those are Acemoglu (2024) whose experimental study predicts that the effects of GenAI on employment and productivity, as derived from task-based estimates of exposure to Genai, will be modest. This view is confirmed in recent evidence reported by the AI Index Report (2025). It found that, while many businesses report they use AI, the gains are limited. In respect of particular business functions, 49% of organizations use AI in service operations, followed by supply chain management (43%) and software engineering (41%) but the cost savings are generally less than 10%. Revenue gains, too, at less than 5%, were small

Again, these relatively modest productivity gains are repeated in important recent research by Bick et al. (2024), which draws from the first nationally representative U.S. survey of GenAI use at work and at home. In respect of the former, their data are

derived from workers' self-reported time savings. They estimate a mean time savings of 5.4% among all GenAI work users, which equates to time savings of 2.2 hours per week for an individual working 40 hours per week. When all workers (including non-users) are included a mean time savings of 1.4% is recorded. Time savings were found to be highly correlated with the intensity of GenAI use and varied widely across occupations and industries. Using a standard model of aggregate production, the authors estimate a potential aggregate productivity gain of 1.1% at current levels of worker GenAI usage. This figure is nonetheless higher than that reported by Acemoglu (2024), who estimates a potential productivity gain of 0.7% using estimates of task-based exposure to GenAI rather than actual adoption data. It bears emphasis, however, that Bick et al.'s estimates assume that time savings derived from AI use will be captured by the employer and not the employee who may otherwise use any time saved for non-work activities. This is an obvious limitation of deriving estimates of productivity gains that are based solely on reported time saving measures.

The 2024 AI Index report was among the first reports to highlight research showing AI's positive impact on productivity. Last year, additional studies reinforced those findings, confirming that AI boosts productivity and, in most cases, helps narrow the gap between low- and high-skilled workers (AI Index Report 2025).

b. Earnings

AI use has often been found to be associated with higher salaries (Stephany and Teutloff, 2024). Lightcast's research estimates that jobs that require AI skills can and do obtain a wage premium. For instance, job postings that mention at least one AI skill advertise salaries 28% higher than those which do not, and that premium rise to 43% where at least two AI skills are mentioned. Other research, too, that surveys workers points to significant gains in workers' earnings where there is a high use of AI, namely among already high-income earners and well-educated workers. (Hartley et al., 2025).

c. Job quality

Considerable benefits have also been recorded by workers in their use of AI, in terms of increased job satisfaction (Noy and Zhang, 2023). As AI helps to release workers from undertaking more tedious and repetitive tasks so they are thereby enabled to concentrate on core tasks of their role (Armour et al., 2022; Stade et al., 2024). It is also associated with increased employee retention (Brynjolfsson et al. 2025b), enhanced workers' learning and skill development. The latter is derived from workers exposure to novel knowledge and the attendant generative function of the technology that enables learning through dialogue and exploration of new combinations of ideas and perspectives that can persist beyond its immediate use (Krakowski, 2025). Whether such long-term skill benefits arise, however, will depend on whether a person's engages with the tool passively or with active engagement and reflection (van den Broek et al., 2021).

However, there are also costs particularly in respect of longer working hours, impaired work-life balance, heavier workloads and a more intense work regime arising from AI's capacity to measure and monitor employees' work across a diverse range of professions and industries (Jiang et

al., 2025; Surden, 2019). Drawing on individual-level time diary data from 2004–2023, Jiang et al. (2025) find that workers with higher exposure to GenAI experienced longer work hours and reduced leisure time. The increases were substantial, too, after controlling for a variety of individual characteristics and fixed effects, amounting to as much 2.25 additional hours per week. This effect, which the authors attribute to the launch of ChatGPT, was found to be primarily evident in occupations that are more complimentary to GenAI use. Thus while the new technology might in theory have been expected to aid workers to complete tasks more efficiently and thereby reduce their working time, this was found not to be the case. Further, working hours and wage rates were found to increase monotonically with the level of AI exposure which suggests that AI-augmented productivity incentivizes workers to extend their working hours. These negative effects were found to be accentuated where workers have limited bargaining power. In such circumstances, the benefits of productivity gains are instead captured by consumers or firms.

d. Who will be affected more?

One commonly-cited expectation is that, while most occupations exhibit some degree of exposure to GenAI, professional workers, those with higher earnings, and university educated, such as lawyers, accountants, architects and marketing professionals, are, as or more, exposed to its effects than are those without formal educational qualifications (Eloundou et al., 2023; Susskind and Susskind, 2018). This disruptive effect – most often seen to involve the decomposition of job tasks and staff redeployment - is thought to be one of the unique consequences of this particular technological revolution. That said, however, job roles that are heavily reliant on science and critical thinking skills are less likely to be affected by GenAI, while programming and writing skills are more susceptible to GenAI exposure (Eloundou et al., 2023). There will also be considerable variation in the adoption and the effects of AI across industries with some such as information processing exhibiting high exposure, while manufacturing, agriculture, and mining demonstrating lower exposure (Eloundou et al., 2023).

As to whether AI will compliment and augment people's work or lead to automation and displacement a great deal of evidence suggests that the effects will be varied and mixed. In law, for example, there is evidence that AI will substitute for lawyers in some tasks and that it will also change the work of those who remain (Armour et al., 2022). This latter category subdivides into two further groups: one, those who use AI-enabled services as inputs to their work (i.e., AI-augmentation), and two, those who occupy new roles as legal (i.e., AI product) experts in producing these AI-enabled services. In stock analysis, AI has been found to both outperform analysts in some tasks thus questioning whether humans are required for such tasks, but in other areas of stock analysis, however, when AI is combined with human expertise the benefits are found to be substantially greater than if either the person or AI endeavoured to complete the tasks on their own; thus suggesting that analysts' capabilities are augmented by AI (Cao et al., 2024). And in another context where an AI system was conceived initially to rid workers from the process of staff selection – that is to automate

the hiring process – the developers and experts instead settled on a new hybrid practice that relied on a combination of AI and domain expertise. AI thus came to augment workers' knowledge (van den Broek et al., 2021).

There is also considerable evidence that those workers who are relatively inexperienced in their jobs stand to gain most from using AI (Brynjolfsson et al., 2025b; Noy and Zhang, 2023; Peng et al, 2023). That there may be such an incentive for young, inexperienced workers to use GenAI seems to be borne out by the evidence. Humlum and Vestergaard (2024), for example, find that every additional year of age and experience is associated with a 1.0 and 0.7 percentage point lower likelihood of using ChatGPT. However, within this cohort of workers there is also considerable variation in that those who are already among the most able and more educated are more likely to adopt ChatGPT.

The effects of GenAI on young workers are not however without negative consequences. Recent large-scale research in the American labour market indicates that early-career workers, aged between 22 and 25, in occupations most exposed to AI, such as software development and customer service, experienced 16% relative employment declines. By contrast, older more experienced workers' employment security, including those working in the same occupation, remained relatively unaffected (Brynjolfsson et al., 2025a). These job losses were particularly apparent where AI is used to automate work, but not where it is used to augment it. Indeed, AI augmentation was found to be associated with employment growth. The authors speculate that the reasons why young workers are more likely be displaced lies with the likelihood that AI disproportionately substitutes for the skills and job tasks typically performed by young workers that include the use of codified knowledge, including both the "book-learning" that forms the core of formal education and the insights in digital company data that can be codified by AI. AI is less capable, however, of replacing tacit knowledge, the idiosyncratic tips and tricks that accumulate with experience but which are never digitized (Acemoglu and Autor, 2011). In other words, AI may be automating the codifiable, checkable tasks that historically justified entry-level headcount, while complementing the judgment-, client-, and process-intensive tasks performed by experienced workers (Brynjolfsson et al., 2025a). Of course, it is also easier and cheaper to fire (or not hire) young, inexperienced staff than it is to fire older more experienced staff.

In the midst of all this flux, workers exhibit considerable apprehension as to the likely effects of AI. However, these fears are more evident in respect of AI's capacity to reshape jobs than it is regard to the likelihood that it will replace workers. Globally, 60% of respondents agree that AI will change how individuals do their job in the next five years. However, a smaller subset of respondents, 36%, believe that AI will replace their jobs in the next five years (AI Index Report 2025).

6. AI use by workers in the Republic of Ireland and Northern Ireland

A great deal of our knowledge of the reach and effects of AI in the Republic of Ireland and Northern Ireland is derived in large part from two sources; first, evidence of firms use of AI (see Smyth (2026) for a useful review); and second, on studies that research the likely impact of AI on the labour market and the potential exposure of different occupations (Department of Finance, 2024; Donaldson et al., 2026). For the main part, significant numbers of firms, especially large-sized ones, but also small medium-sized ones, are seen to be adopting AI in the Republic of Ireland. The Republic is also identified as being among the leaders in the EU in its preparedness to adopt AI given the composition of its enterprises and the skills of its workforce. While policy makers in the Republic are mindful that more work needs to be undertaken to ensure that Ireland is well positioned to benefit from AI, there is elevated concern in Northern Ireland, given its relatively low skill base and productivity gap with other nations, that it is more exposed to the negative employment effects of AI. Apart from these aforementioned studies, however, there is little or no research on the use of AI by workers apart from that which can be gleaned from EU sources but this is only in respect of the Republic.

Eurostat (2025) found that 22% of Irish people between the ages of 16 and 74 years used GenAI for work purposes in 2025. This places Ireland in 8th position in Europe behind such countries as Denmark, Estonia, Finland and the Netherlands but ahead of Germany, France and Sweden. This reported incidence of AI use is considerably larger than that found by the European Working Conditions survey which was conducted a year earlier in 2024. Then, the EWCS found that 14% of Irish workers used GenAI which was slightly above the EU average of 12%, but considerably below countries like Luxembourg (25%) and Sweden (21%) (Eurofound, 2025).

The question put to respondents in the EWCS was, "And do you use the following equipment in your work? Artificial intelligence that simplifies complex mental tasks or makes recommendations on how you should be working? (ChatGPT, LLAMA, DALL-E, Midjourney, Jasper)'.

Other research also points to Irish workers being among the highest users of GenAI tools at work. At 40%, Hartley et al. (2025) find Ireland to be ahead of many EU countries and the US.

7. The Working in Ireland Survey 2025

The Working in Ireland Survey 2025 (WIIS 2025) surveys people's work and employment on the island of Ireland. It is the most significant and comprehensive survey of its kind, covering a wide range of topics including skills and training, employee involvement and autonomy, the use of artificial intelligence, remote working, trade union allegiance, health and wellbeing, job churn and intention to quit, low pay, and job quality.

The fieldwork for the survey was conducted between May 15th and August 28th, 2025. A total of 3,040 interviews were conducted in Republic of Ireland and 1,260 interviews in Northern Ireland. The survey fieldwork was undertaken by Ipsos B&A in both jurisdictions.

To ensure a nationally representative sample of working people aged 16 years and over, the data were weighted for age, gender, region and economic sector to agree with the then most recent population estimates as derived from the Republic of Ireland's Central Statistics Office's Labour Force Survey (LFS) Q1 2025, and in Northern Ireland, the Northern Ireland Statistics Research Agency's Labour Force Survey June-Aug 2025 and the Business Register and Employment Survey (BRES), Northern Ireland, September 2022. All the analyses in this report use the weighted sample.

The Working in Ireland Survey 2025 is the second survey in the WIIS series. The first survey, conducted between May and August in 2021, was confined to the Republic of Ireland. It had a sample size of 2,046. It also too drew from a representative sample of people of working age in paid employment and was conducted by the same means as WIIS 2025.

A mobile telephone only sample approach was used. In the Republic of Ireland, the approach used was Random Digit Dial (RDD) whereby a sample was randomly generated using known mobile stems as provided by the Commission for Communications Regulation. RDD is not an appropriate methodology for NI, as the use of mobile stems could result in calls being made to individuals across the United Kingdom. Instead, a sample comprising only NI mobile numbers was acquired for the research.

Respondents underwent a series of screening questions to confirm their eligibility for inclusion in the study, including inquiries about their age and employment status. The research was confined to working people, employed and self-employed, of over 16 years of age who were at work for at least one hour in producing goods and providing services for pay or for profit in the week prior to the survey.

All interviewers attended a training/briefing webinar convened by an Ipsos B&A project manager and which was attended by all call centre supervisors and the WIIS's principal investigator, John Geary. Interviewers had the opportunity to ask questions to all team members. Directly after the webinar, all interviewers logged on to the test script to familiarise themselves with the questionnaire and the routing of

questions, and to address any queries they might have had before administering the survey in the field.

A pilot survey was also conducted to ensure that respondents understood the questions asked and were able to provide clear answers, as well as to ensure that the routing of questions was appropriate and that the questionnaire was not too long as to make unreasonable demands on respondents. New questions in the questionnaire were cognitively tested, first by members of the research team and second by the survey agency. Lessons were then shared and the questions adapted as required. The reformatted questions were then tested again during the pilot survey.

Several methods were employed to monitor the quality of interviewing, including a proportion of all interviews being monitored by supervisory staff from the start to the end of an interview. For the WIIS 2025, 13.4% of the Republic of Ireland interviews and 15.9% of interviews in Northern Ireland were fully monitored. Call centre managers were responsible for the scheduling of resources, monitoring of interviewers and sample management, and were in close contact with the project management team, including the PI, to ensure fieldwork was progressing well and to respond to queries from the interviewers. Interviewing was conducted between 2pm to 9pm Monday to Friday, 10am to 6pm on Saturday and 11am to 7pm on Sunday.

Interviewees were dialled a minimum of three times, over various time periods such as afternoons, evenings and weekends.

8. Findings

The incidence of worker adoption of AI

Measuring worker adoption of AI and intensity of its use is not an easy task. First, we asked respondents whether or not they "use artificial intelligence technologies or tools in (their) work". We elaborated further by indicating that 'These [technologies or tools] are often referred to as GenAI' and that "examples include ChatGPT, Claude AI, Gemini, Microsoft Copilot or your employer may provide a particular in-house GenAI tool." This approach is broadly similar to that used recently by others, notably Bick et al. (2024). In addition, however, we further stipulated to the respondent that they should only answer yes where they "intentionally or knowingly use" GenAI tools in their work.

In the Republic of Ireland (RoI), 29.3% (887 of 3,040) of workers indicated they use AI intentionally in their work. In Northern Ireland (NI), the equivalent figure is 26.1% (329 of 1,260), giving a combined total adoption rate of 28.4% (1,216 of 4,300) across the island of Ireland. RoI is thus modestly ahead of NI in GenAI adoption, though both jurisdictions are broadly aligned and sit comfortably above European averages. Respondents who indicated they use AI (intentionally/knowingly) in their work were then invited to answer a series of more detailed questions about their use. In the RoI 747 respondents and 71 in NI indicated they were prepared to do so. The data analysed in the sections below relate to these workers' responses.

Which workers use GenAI?

Table 1 presents the rates of intentional GenAI adoption across a range of demographic, occupational, and organisational characteristics for workers in the RoI and NI, and on a combined all-island basis.

The gender difference in GenAI adoption is small. Across the island as a whole, 29.0% of men and 27.8% of women use GenAI at work (Table 1), a gap of about one percentage point that is not statistically significant. When we adjust for education, occupation, sector, firm size, contract type and age, women are about 4 percentage points less likely than men to use GenAI at work (−3.6 points, $p \approx 0.05$).[1] In the Republic of Ireland the adjusted gap is somewhat larger (−4.6 points, $p < 0.05$) but remains relatively small. In Northern Ireland the adjusted estimate is imprecise and not statistically significant, so no conclusion can be drawn about a gender gap there given the smaller sample.

We also examined whether men and women differ in multi-tool use, that is, the use of two or more GenAI tools. In the Republic of Ireland we found no gender difference: 53% of male and 51% of female GenAI users use multiple tools, and this holds once controls are included. The Northern Ireland numbers are too small for any robust interpretation. It warrants emphasis that the small size of the gender gap contrasts with that recorded in many comparable international surveys, which have tended to find more pronounced male dominance in AI adoption. The WIIS 2025 data suggest that, at least in terms of reported use, women in Ireland are not substantially less likely

than men to incorporate GenAI tools, be that one, two or more, into their working lives.

Workers on permanent contracts and those on non-permanent or fixed-term contracts exhibit broadly similar adoption rates in the RoI: 29.6% and 27.2% respectively. In NI, however, the divergence is more pronounced: 26.6% of permanent workers use GenAI compared with only 19.0% of those on non-permanent contracts. This pattern may reflect the sectoral and occupational composition of non-permanent employment, which tends to be concentrated in lower-skill, lower-autonomy roles, rather than any direct effect of contract type on AI access or use.

Age is among the most powerful predictors of GenAI adoption in both jurisdictions. In the RoI, the highest adoption rate is recorded among workers aged 25–34, at 42.0%; the equivalent figure for NI is 33.5%. Rates decline progressively with age in both jurisdictions: among those aged 55–64, adoption stands at 19.9% in the RoI and 20.6% in NI, falling further to approximately 10% among those aged 65–74. The comparatively low adoption rate among the youngest workers, 16.8% in the RoI and 18.2% in NI for those aged 16–24, is initially counter-intuitive. It likely reflects the fact that younger workers are more concentrated in lower-skill, lower-autonomy occupations in hospitality, retail and other service industries, where the use of GenAI tools is less prevalent. The 25–34 cohort, by contrast, is the most highly educated age group in the workforce and is disproportionately represented in ICT, professional and financial services.

When we turn to education we observe the strongest individual-level factor associated with GenAI adoption in both jurisdictions. At the lowest levels of educational attainment, adoption rates are very low: 3.4% in the RoI and 3.9% among lower secondary graduates. The gradient is steep and consistent: adoption rises through post-secondary and short-cycle tertiary education (around 15–20%), to Bachelor's level (35.0% in the RoI; 37.3% in NI), and reaches its peak among workers with postgraduate qualifications. In the RoI, almost half of workers with a Master's degree (49.8%) or a doctoral qualification (48.7%) report using GenAI, a rate that is more than fifteen times that recorded among primary-educated workers. In NI, the gradient is similarly steep, though postgraduate adoption is somewhat lower than in the RoI: 41.2% for Master's graduates and 33.3% for doctoral graduates, though the latter figure is based on only twelve respondents and should be treated with caution.

In relation to occupational differences in GenAI adoption, as one would expect, professional occupations record the highest adoption rate in the RoI at 49.2%, closely followed by managers, directors and senior officials at 49.0%, and associate professional occupations at 40.9%. In NI, associate professional and professional occupations are similarly prominent, at 42.3% and 44.2% respectively, though managers show a notably lower adoption rate than in the RoI (34.2% versus 49.0%), a difference that merits further investigation.

At the other end of the occupational spectrum, process, plant and machine operatives record the lowest adoption rate of any occupational group in both jurisdictions: 2.9% in the RoI and 4.7% in NI. Caring, leisure and other service

occupations (6.6% RoI; 8.0% NI), skilled trades (8.7% RoI; 12.0% NI) and elementary occupations (7.1% RoI; 16.2% NI) also show low rates of adoption. The NI figure for elementary occupations is notably higher than the RoI equivalent. Administrative and secretarial workers occupy an intermediate position: 21.8% in the RoI and 17.5% in NI, broadly consistent with the mixed nature of that occupational category, which encompasses both highly routine and more knowledge-intensive roles.

When respondents are classified by the type of organisation they work for, the private sector records the highest adoption rate in both jurisdictions: 34.0% in the RoI and 30.2% in NI. The public sector trails behind at 25.6% in the RoI and 21.0% in NI. Not-for-profit and NGO workers show adoption rates of 28.9% in the RoI and 37.8% in NI, though the NI figure is based on only 37 respondents. The state-owned company category shows a striking difference across the two jurisdictions: 20.0% in the RoI compared with 45.5% in NI, a figure that should be treated with considerable caution given an NI base of only 11 respondents.

The industry-level analysis reveals the clearest and most consistent picture of sectoral concentration in GenAI adoption. ICT, professional, scientific and technical services, the broadest of the ten sectors, records the highest adoption rate on an all-island basis at 45.6% (47.4% RoI; 40.7% NI). Financial services and real estate is the second most intensive sector: 44.2% in the RoI and 46.7% in NI. The education sector is also notable: 46.6% in the RoI, though adoption is substantially lower in NI at 34.4%, a gap that stands out within the sector-level comparisons. Manufacturing records above-average adoption in the RoI at 38.1%, a figure considerably higher than in NI (25.3%), possibly reflecting differences in firm size and the types of manufacturing activity concentrated in each jurisdiction.

At the lower end of the distribution, agriculture, forestry, fishing and mining records the lowest adoption rate at 4.8% in the RoI (the NI base is n=1 and has been suppressed). Transport and hospitality follows at 13.3% in the RoI and 17.1% in NI. Human health records modest but not negligible rates, 16.2% in the RoI and 18.5% in NI, while wholesale and retail stands at 18.6% and 17.8% respectively. Public administration and defence is relatively low in both jurisdictions: 20.0% in the RoI and 17.5% in NI, consistent with the more conservative pace of digital transformation typically observed in this sector.

Finally, Table 1 also presents the distribution of GenAI adoption by organisation size in both jurisdictions. The data are based on a three-category classification: small (1–49 employees), medium (50–249 employees) and large (250 or more employees). They show a clear and consistent size gradient in RoI, a more complex pattern in NI, and an overall all-island picture that is shaped heavily by the larger RoI sample.

On an all-island basis, adoption rises from 24.2% in small firms to 30.5% in medium-sized firms and 34.2% in large firms. This gradient is broadly consistent with what would be expected given the greater resources, more developed digital infrastructures and higher concentrations of knowledge-intensive roles typically found in larger organisations.

In the RoI, the size effect is pronounced and monotonic: adoption

Table 1: GenAI use by demographics in the RoI and NI

	RoI	NI	Total
Total sample			
Total	29.3% (3,026)	26.1% (1,254)	28.4% (4,280)
Gender			
Men	29.9% (1,587)	26.8% (665)	29.0% (2,252)
Women	28.8% (1,419)	25.2% (584)	27.8% (2,003)
Employment contract			
Permanent	29.6% (2,723)	26.6% (1,176)	28.7% (3,899)
Non-permanent	27.2% (301)	19.0% (79)	25.5% (380)
Age group			
16–24	16.8% (340)	18.2% (137)	17.2% (477)
25–34	42.0% (610)	33.5% (275)	39.3% (885)
35–44	33.3% (763)	29.8% (305)	32.3% (1,068)
45–54	30.8% (666)	25.3% (285)	29.1% (951)
55–64	19.9% (517)	20.6% (194)	20.1% (711)
65–74	10.0% (110)	13.5% (52)	11.1% (162)
75+	10.0% (20)	0.0%† (6)	7.7% (26)
Education			
Primary education	3.4% (29)	0.0%† (5)	2.9% (34)
Lower secondary education	3.9% (129)	16.0% (106)	9.4% (235)
Upper secondary education	8.8% (475)	15.9% (220)	11.1% (695)
Post-secondary non-tertiary	15.8% (146)	10.9% (101)	13.8% (247)
Short-cycle tertiary	20.0% (486)	19.2% (208)	19.7% (694)
Bachelor's or equivalent	35.0% (977)	37.3% (391)	35.7% (1,368)
Master's or equivalent	49.8% (669)	41.2% (160)	48.1% (829)
Doctoral or equivalent	48.7% (76)	33.3%† (12)	46.6% (88)
Occupation			
Elementary occupations	7.1% (198)	16.2% (74)	9.6% (272)
Professional occupations	49.2% (762)	44.2% (294)	47.8% (1,056)
Associate professional occupations	40.9% (337)	42.3% (123)	41.3% (460)
Administrative and secretarial	21.8% (298)	17.5% (120)	20.6% (418)
Skilled trades occupations	8.7% (344)	12.0% (158)	9.8% (502)
Caring, leisure and other services	6.6% (197)	8.0% (112)	7.1% (309)
Sales and customer service	11.7% (213)	7.9% (101)	10.5% (314)
Process, plant and machine operatives	2.9% (138)	4.7% (64)	3.5% (202)
Managers, directors and senior officials	49.0% (245)	34.2% (120)	44.1% (365)

Sector of employment			
Private sector	34.0% (1,695)	30.2% (597)	33.0% (2,292)
Public sector	25.6% (818)	21.0% (419)	24.0% (1,237)
State-owned company	20.0% (75)	45.5%† (11)	23.3% (86)
Not-for-profit / NGO	28.9% (90)	37.8% (37)	31.5% (127)
Sector			
Agriculture, forestry, fishing & mining	4.8% (125)	—	4.8% (126)
Energy & Construction	22.7% (277)	24.1% (108)	23.1% (385)
Wholesale & retail	18.6% (370)	17.8% (202)	18.4% (572)
Transport & hospitality	13.3% (316)	17.1% (129)	14.4% (445)
ICT, prof., scientific, tech., admin & support, arts & other services	47.4% (647)	40.7% (236)	45.6% (883)
Financial services & real estate	44.2% (138)	46.7% (45)	44.8% (183)
Public administration & defence	20.0% (170)	17.5% (80)	19.2% (250)
Education	46.6% (279)	34.4% (122)	42.9% (401)
Human health	16.2% (382)	18.5% (211)	17.0% (593)
Manufacturing	38.1% (291)	25.3% (95)	35.0% (386)
Organisation size			
Small (1–49 employees)	22.8% (157)	28.5% (78)	24.2% (235)
Medium (50–249 employees)	30.9% (145)	29.7% (57)	30.5% (202)
Large (250+ employees)	37.4% (495)	25.7% (135)	34.2% (630)

† Sub-sample n<20 — interpret with caution.

stands at 22.8% in small firms, 30.9% in medium firms, and 37.4% in large firms. Large RoI firms are thus 1.6 times more to have workers using GenAI as small firms. This is a substantial differential that points to organisation size being a meaningful structural driver of GenAI adoption in the Republic.

The NI pattern departs notably from this trajectory. Adoption in small NI firms (28.5%) is already higher than in their RoI counterparts and is close to the NI medium firm rate (29.7%), while large NI firms record the lowest adoption of the three size bands at 25.7%. Rather than the expected positive gradient, the NI data suggest an essentially flat, and at the upper end, slightly inverted, relationship between firm size and GenAI use. This may reflect the particular occupational and sectoral composition of large public sector and manufacturing employers in NI, where knowledge-intensive roles are less concentrated than in comparable large RoI firms. The relatively small NI sub-samples, particularly at the medium and large firm level, also introduce greater variability into these estimates and warrant caution in interpretation.

Salary level is among the most powerful predictors of GenAI adoption in both jurisdictions, and the two figures presented here reveal a pattern that is as striking as it is consistent: the higher a worker's earnings,

the more likely they are to report intentional use of GenAI in their work. This relationship holds in both the Republic of Ireland and in Northern Ireland, though the form it takes and differs between the two jurisdictions.

In the Republic of Ireland, the income–adoption relationship is strikingly clear and increasingly growing across the eight salary bands. Among workers earning under €15,000 per year, just 8.5% report using GenAI in their work. This figure rises to 13.1% in the €15,000–€29,999 band, 27.6% among those earning between €30,000 and €44,999, and 35.4% in the €45,000–€59,999 band. The gradient steepens further at higher income levels: 46.2% of workers in the €60,000–€74,999 band use GenAI, rising to 52.4% among those earning €75,000–€89,999, 57.1% for the €90,000–€109,999 band, and reaching a peak of 73.8% among workers earning €110,000 or more per year.

The scale of this income divide is remarkable. Workers in the highest salary band are almost nine times as likely to use GenAI as those in the lowest band. The overall adoption rate for the RoI of 29.3% thus reflects an aggregate that masks very profound inequality in exposure to, and use of, generative AI technologies across the earnings distribution. In broad terms, it is only from approximately the €30,000–€44,999 band onwards that adoption begins to approach or exceed the all-island average, suggesting – perhaps - that the benefits of GenAI in the workplace are, at least at present, disproportionately accruing to higher-earning workers.

The relationship between salary and GenAI adoption in the RoI is not, of course, independent of the education and occupational gradients documented elsewhere in this report. Higher-earning workers are, by definition, more likely to be in professional, managerial and associate professional roles, the very occupational categories that show the highest rates of adoption, and to hold postgraduate qualifications. Disentangling the independent contribution of earnings from that of occupation and education will require multivariate analysis.

Figure 1: GenAI use by salary bands in the Republic of Ireland

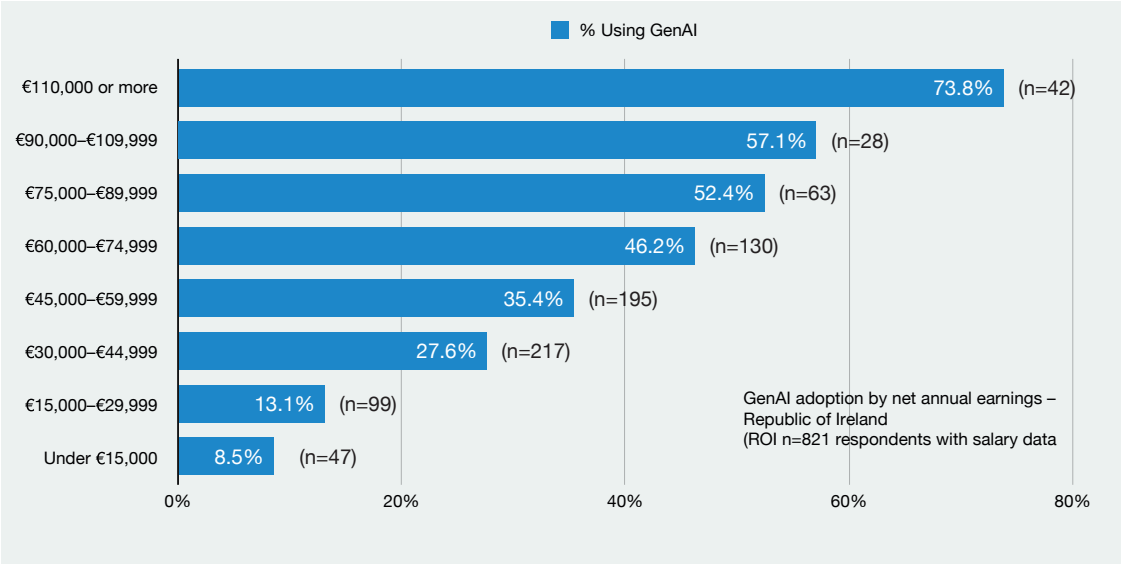
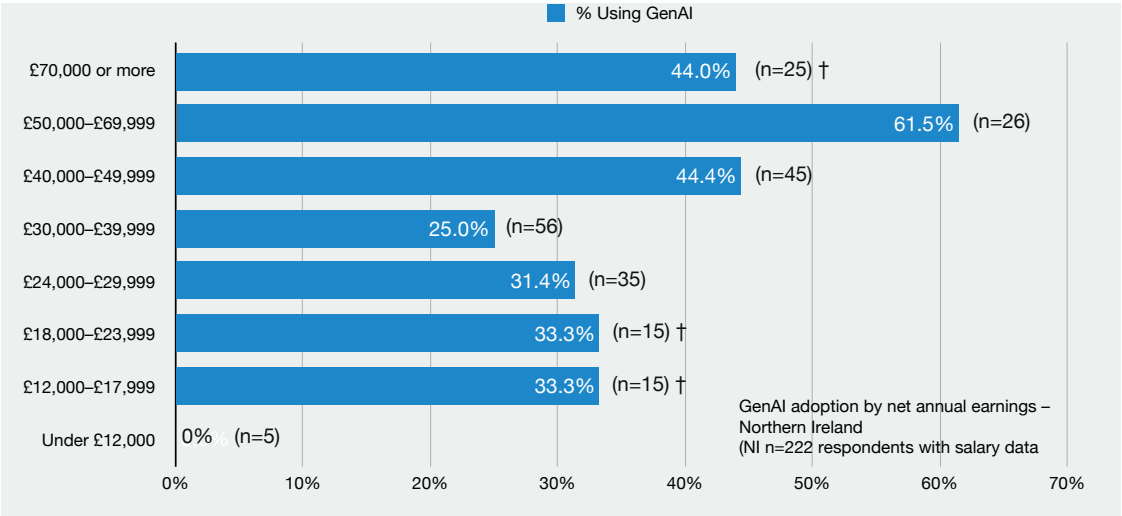


Figure 2: GenAI use by salary bands in Northern Ireland



In Northern Ireland, the income–adoption relationship is broadly similar in direction but less smooth in its progression, a feature that may reflect in part the smaller overall sample size available for the salary analysis (n=222 respondents with usable salary data, compared with n=821 in the RoI). Three salary bands, under £12,000, £12,000–£17,999, and £18,000–£23,999, each contain fifteen or fewer respondents and should be interpreted with particular caution. The under-£12,000 band, with only five respondents and zero reported GenAI users, is noted for completeness but carries no reliable evidential weight.

Setting aside the three lowest bands, the pattern in NI is broadly consistent with that observed in the RoI. Among workers earning £24,000–£29,999, adoption stands at 31.4%; it is 25.0% in the £30,000–£39,999 band, a slight dip that may reflect sampling variability given the modest band size of 56 respondents. Adoption rises to 44.4% in the £40,000–£49,999 band and reaches its highest recorded rate of 61.5% among workers earning between £50,000 and £69,999. The highest band, £70,000 or more, records a somewhat lower figure of 44.0%, which, given a base of only 25 respondents, likely reflects sampling variation rather than any genuine reversal of the earnings gradient.

The NI data thus tell a story that is broadly consistent with the RoI: GenAI adoption is markedly higher among better-paid workers, with the £50,000–£69,999 bracket showing the sharpest concentration of use. Direct comparison of absolute adoption rates across the two salary systems is not straightforward given that the earnings bands are calibrated to different currencies and different overall wage distributions. It is nonetheless notable that, for bands at comparable points in the respective distributions, mid-career, middle-income workers, adoption rates in NI appear to be somewhat lower than equivalent bands in the RoI, consistent with the overall all-island picture of modestly higher adoption in the Republic.

Taken together, the salary data for both jurisdictions point to a clear and consistent conclusion: GenAI adoption in the workplace is strongly stratified by income. This income gradient is in

all probability a reflection of occupational and educational stratification rather than an independent effect of earnings per se, but its scale, nearly nine-fold between the lowest and highest bands in the RoI, underlines the extent to which the current wave of AI adoption is concentrated among workers who are already relatively advantaged in the labour market. Whether and how this concentration changes over time, as AI tools diffuse more widely across occupational hierarchies, is among the most important empirical questions facing researchers and policymakers with an interest in the future of work.

Which GenAI tools do workers use and for what tasks?

A little over half of RoI workers (53.3%) use standalone tools that are publicly available, while 60.6% of NI workers do so, a difference worth noting. In the RoI, 16.5% use integrated tools embedded by their employer into production or service processes, compared with 11.3% in NI. The remainder use both types: 30.2% in the RoI and 28.1% in NI.

By some measure, the most widely used publicly available tool is ChatGPT, used by 74.8% of RoI GenAI users and 75.8% in NI, near-identical rates in both jurisdictions. Microsoft Copilot is used by 41.1% in the RoI and 44.4% in NI; Google Gemini by 16.2% and 16.1% respectively; Claude by 4.6% in the RoI and notably higher at 7.9% in NI; and DeepSeek by 3.4% in the RoI compared with 1.6% in NI. Around 18% in both jurisdictions use a diverse range of other AI tools.

Among workers who report using GenAI tools in their work, the overwhelming majority in both jurisdictions confine their use to a single tool. In the Republic of Ireland, 74.4% of the 259 workers for whom valid data are available use only one GenAI tool. In Northern Ireland, the equivalent figure is 60.9% of the 23 valid respondents. Across both jurisdictions combined, 73.3% of GenAI-using workers report using just one tool.

The second most common pattern is the use of two tools. In the RoI, 13.6% of workers report using two GenAI tools, giving a combined figure of 88.0% who use either one or two tools. In NI, only 8.7% report using two tools, with 69.6% using one or two. On an all-island basis, 86.5% of GenAI users work with either one or two tools. The picture that emerges is thus one of considerable concentration: the great majority of workers who have adopted GenAI have done so through a single platform, and only a small minority have diversified their use across multiple tools.

A small but notable group report using three or more tools. In the RoI, just 2.7% of GenAI users, seven individuals in the sample, use three or more tools, with one respondent reporting use of as many as six. In NI, the proportion is higher at 13.0%, including one respondent who reports using seven tools, though this figure must be treated with extreme caution given the very small NI base of 23 respondents. These multi-tool users represent an emergent group of highly engaged AI adopters whose behaviour may be indicative of where broader workforce adoption is heading, but they currently constitute a small minority in both jurisdictions.

The predominance of single-tool use is consistent with international evidence showing that ChatGPT's early market

dominance has led a large proportion of first-wave GenAI adopters to work almost exclusively within one ecosystem. In the WIIS 2025 data, ChatGPT is used by approximately three-quarters of all GenAI users in both the RoI and NI, and it is reasonable to infer that for the majority of single-tool users, ChatGPT is that tool. The emergence of a minority of multi-tool users, combining, for instance, ChatGPT with Microsoft Copilot or Google Gemini, may signal the beginning of a more pluralistic phase of AI adoption as workers begin to select different tools for different task types.

Who pays for the GenAI tool subscription?

The data indicate that a substantial proportion of workers use advanced versions of these models that require monthly subscriptions or custom pricing. Of those who use advanced GenAI tools, almost one in two workers (49% in the RoI) pay themselves in the case of ChatGPT, while the other half have their subscription paid by their employer. See Table 2 presents the breakdown of subscription payment provision across the different GenAI tools. Employer subscription payment is considerably higher for integrated GenAI tools such as MS Copilot.

Tasks GenAI tools are used for

To examine the range of tasks for which workers deploy GenAI, we asked respondents to indicate, from a list of fifteen activities, which they use GenAI to assist with in their work. Following a taxonomy adapted from Chatterji et al. (2025) and OpenAI's conversation classifier approach, we group these activities into six categories: Writing and Media; Instruction and Guidance; Research and Analysis; Coding; Support Functions; and Other. The results, presented in Figure 3, reveal both the breadth of GenAI's application and a number of striking differences between the Republic of Ireland and Northern Ireland.

Writing and media-related tasks constitute the most prevalent domain of GenAI use in both jurisdictions, and within this category, writing communications, emails, correspondence and similar outputs, is the single most widely reported use of GenAI. It is reported by 39.6% of RoI GenAI users and 48.6% of NI users, giving an all-island figure of 40.4%. Summarising text is the second most common writing task: 27.4% in the RoI and 30.0% in NI. Structuring ideas and writing is reported by 22.6% of RoI users but by a strikingly higher 51.4% of NI users, the largest single jurisdictional gap in the entire task battery. Writing detailed reports or instructions is used by

Table 2. Who pays for GenAI tool subscriptions by tool type

	ChatGPT	MS Copilot	Gemini	Claude	Other AI
I pay myself — RoI	49%	6%	18%	27%	35%
I pay myself — NI	30%	—	—	0%	—
Employer pays — RoI	47%	93%	82%	60%	56%
Employer pays — NI	50%	100%	—	100%	—
N (RoI)	129	117	24	15†	50
N (NI)	10†	9†	3†	5†	4†

Note: NI sub-samples for Gemini and other tools are very small (n<5); percentages should be treated with caution. † Sub-sample n<20 — interpret with caution.

17.0% in the RoI and 21.4% in NI.

Less frequently reported writing tasks include language translation (14.0% in both jurisdictions), generating images or video (9.6% RoI; 15.7% NI), and transcription from audio or video files (7.7% RoI; 15.7% NI). In each of these latter three tasks, NI workers report higher rates of use than their RoI counterparts, a pattern that is consistent across much of the task battery and to which we return below.

The second category, Instruction and Guidance, encompasses tasks in which workers use GenAI as a source of information or learning support. Searching for facts or information is the more prevalent of the two tasks in this category: 28.1% of RoI users and 32.9% of NI users report this use, giving an all-island figure of 28.5%. Tutoring and educational assistance is reported by 12.6% in the RoI and 12.9% in NI, a rare instance of near-identical rates across the two jurisdictions, suggesting that the use of GenAI for learning and development purposes is broadly comparable on both sides of the border.

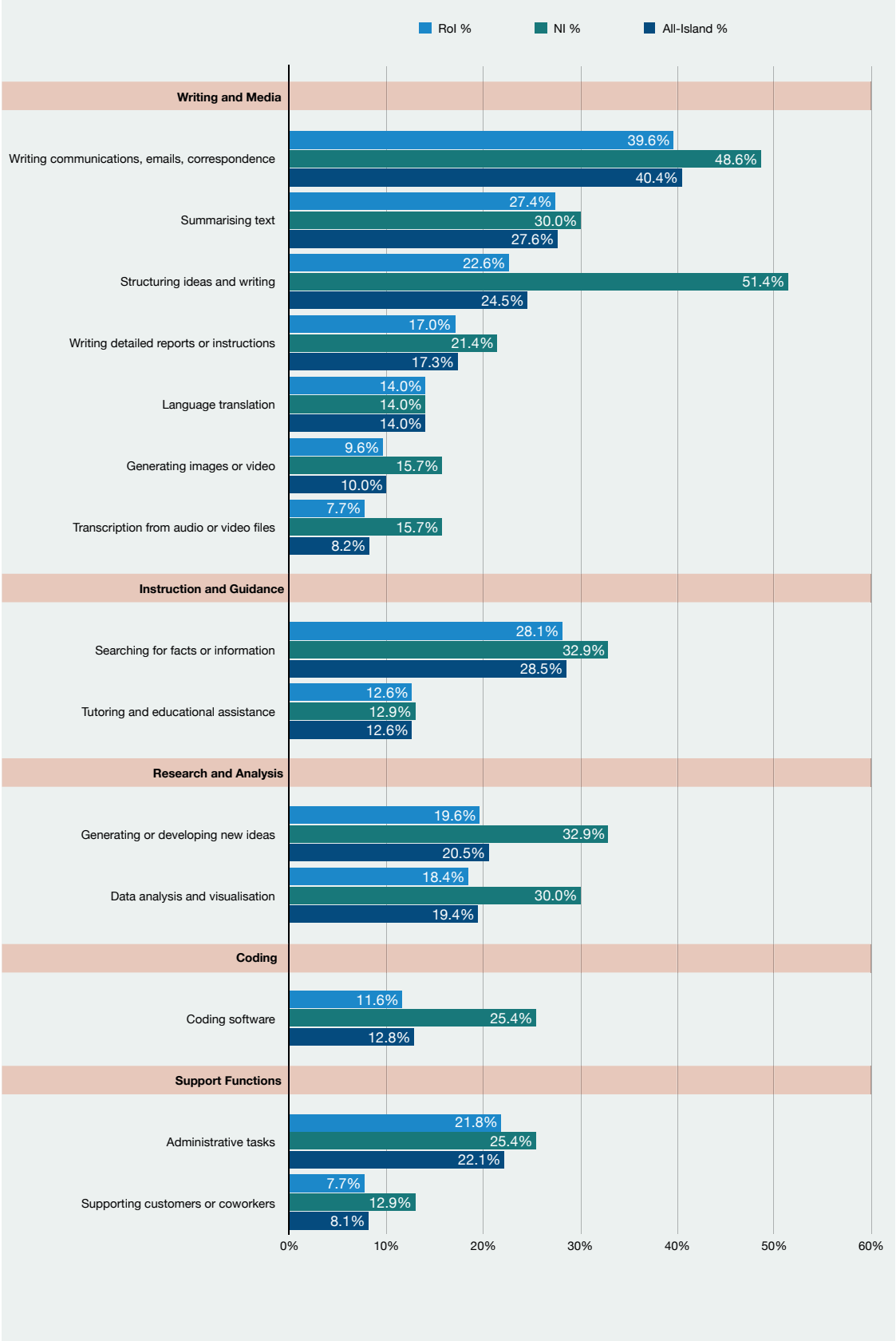
The research and analysis category captures two of the most knowledge-intensive applications of GenAI in the workplace. Generating or developing new ideas is reported by 19.6% of RoI users, rising to 32.9% in NI, a difference of over 13 percentage points. Data analysis and visualisation similarly shows a pronounced jurisdictional gap: 18.4% in the RoI compared with 30.0% in NI, with an all-island figure of 19.4%. Taken together, these findings suggest that NI workers are considerably more likely than their RoI counterparts to deploy GenAI for higher-order analytical and creative tasks.

Coding software is used by 11.6% of RoI GenAI users and 25.4% of NI users, again, a gap of almost 14 percentage points, and one of the most pronounced jurisdictional differences in the entire figure. The all-island figure is 12.8%. The higher rate of coding use in NI is likely to reflect, at least in part, the sectoral and occupational profile of GenAI users in NI, who appear to be disproportionately concentrated in ICT and professional services roles in which coding is a routine task. It may also reflect the greater propensity of NI GenAI users to engage with more technically demanding applications of the technology, consistent with the broader pattern observed across the research and analysis and instruction and guidance categories.

Support functions, comprising administrative tasks and customer or coworker support, represent a distinct mode of GenAI use oriented towards operational rather than knowledge-intensive activities. Administrative tasks are used by 21.8% of RoI GenAI users and 25.4% in NI (all-island: 22.1%), while supporting customers or coworkers is reported by 7.7% in the RoI and 12.9% in NI. These are among the lower-frequency task types, suggesting that while some workers do deploy GenAI to assist with operational support functions, this is currently a less common application than writing, analysis or information-seeking.

Taken together, the task battery data present a picture of GenAI as a versatile and widely deployed tool across a broad range of work activities. Writing and communication tasks dominate in both jurisdictions, consistent with the prominence of text-generation capabilities in the leading GenAI platforms. However, a

Figure 3: Tasks performed using GenAI at work



consistent and substantively important pattern emerges throughout the data: NI workers report higher rates of use than RoI workers across almost every task category, and the gaps are particularly pronounced in structuring ideas and writing (51.4% vs 22.6%), coding (25.4% vs 11.6%), generating new ideas (32.9% vs 19.6%), and data analysis (30.0% vs 18.4%). Whether this reflects differences in the occupational composition of GenAI users in the two jurisdictions, differences in the depth of engagement with the technology, or other factors, is a question to which we return in future multivariate analysis.

Intensity of GenAI use

To measure the intensity of AI use, we first asked respondents to reflect on their use within the last week. The results are reported in Table 4. A large proportion of RoI users, 45.1%, use it every day or most days (every day: 26.9%; most days: 18.2%). In NI, the comparable figure is 43.6% (every day: 29.1%; most days: 14.5%). A further 38.2% of RoI users and 38.5% of NI users use it on some days. Just under one in five in both jurisdictions had not used GenAI in the past week (RoI: 16.7%; NI: 17.9%).

Among those who used GenAI in the past week, the length of time they used it for is relatively modest in both jurisdictions. The majority use it for 30 minutes or less per day: 54.4% in the RoI and 52.8% in NI. A further 29.1% of RoI users and 37.0% of NI users spend between 30 minutes and an hour per day. Those who might be considered substantial users, between one and three hours per day, account for 12.8% in the RoI and 9.1% in NI, while only 3.7% and 1.1% respectively use it for more than three hours per day.

We ran Spearman's rank-order correlation between our two measures of use intensity: frequency of use in the previous week and average daily duration on days GenAI was

Table 4. Frequency and duration of GenAI use (last week)

	RoI %	NI %
Frequency of use		
Every day	26.9	29.1
Most days (3–4 days)	18.2	14.5
Some days (1–2 days)	38.2	38.5
No days last week	16.7	17.9
N	**750**	**73**
Daily duration (among those who used GenAI last week)		
30 minutes or less	54.4	52.8
30 minutes to 1 hour	29.1	37.0
1 to 3 hours	12.8	9.1
More than 3 hours	3.7	1.1
N	**610**	**64**

Notes: Weighted column percentages; N = unweighted respondents. Asked only of GenAI users who opted into the follow-up module. Duration asked only of those who used GenAI in the past week.

used. Spearman's rho is appropriate because both variables are ordinal with each one measured across four ordered categories. Because duration was asked only of those who used GenAI in the past week, the correlation in practice covers three frequency categories. With both variables coded so that higher values mean more use, the correlation is statistically significant (rho = .31, $p < .001$, two-tailed; n = 674 respondents with valid data on both). As such, workers who use GenAI on more days also tend to use it for longer on the days they use it: more intensive users are intensive on both dimensions.

The magnitude of the correlation is modest but meaningful. It indicates that while frequency and duration of use are positively associated, they are far from perfectly correlated, and a sizeable proportion of (other) workers combine high frequency with short daily duration, or conversely, infrequent use with relatively long sessions on the days they do engage with the technology. This heterogeneity in patterns of use is consistent with the diversity of tasks for which GenAI is deployed, as documented in the preceding section: workers who use GenAI primarily for quick communications or fact-checking may use it daily but briefly, while those who deploy it for more complex analytical or coding tasks may engage less frequently but for more sustained periods.

The finding that the two dimensions of use intensity are only moderately correlated has implications for how we conceptualise and measure AI engagement in the workplace. A single-item measure of either frequency or duration alone would provide an incomplete picture of use intensity.

Intensity of GenAI use: multiple tools and frequency of use

We also examined whether and how the intensity of GenAI use was related to the number of AI tools that a worker may use. Here again we use the same measures of use intensity as above: frequency of use during the past week and average daily duration of use.

We first examine those who only use standalone GenAI tools. These tools are distinct from those which an employer may install or embed within their production or service processes and systems. We then turn to multi-tool users.

Among users of standalone tools, we find that the number of standalone tools used by respondents correlates positively in the RoI with both frequency of use (rho = .20, $p < .001$, n = 625) and daily duration (rho = .20, $p < .001$, n = 512). The more GenAI tools a worker uses the more likely they are to use them on more days and for longer periods of time on the days they use them. These associations are modest and weaker than the link between frequency and duration themselves (rho = .31), but they are consistent.

We define multi-tool users as those who use two or more GenAI tools: either two or more standalone tools, or standalone tools together with tools integrated into to their work by their employer. Single-tool users are those who use one standalone tool only, or employer-integrated tools only. On this measure, 52% of RoI users and 47% of NI users are multi-tool users. In the RoI, being a multi-tool user correlates with both frequency of use (rho = .20, $p < .001$, n = 745) and daily duration (rho = .20, $p < .001$, n = 605). Among

RoI workers who used GenAI in the past week, 21% of multi-tool users did so for an hour or more per day, against 11% of single-tool users. In addition, 60% of multi-tool users used GenAI every day or most days, as against 48% of single tool users.

The same pattern is evident in NI. Among past-week users, 14% of multi-tool users used GenAI for an hour or more per day, as against 7% of single-tool users, and 60% used it every day or most days, against 46%.

The number of standalone tools also correlates positively with frequency (rho = .30, p = .015, n = 65) and daily duration (rho = .44, p < .001, n = 56) of GenAI use. Being a multi-tool user correlates with daily duration (rho = .26, p = .036, n = 64), but its link with frequency is not statistically significant (rho = .18, p = .128, n = 73). These estimates rest on 35 multi-tool and 29 single-tool users, so they confirm the direction of the RoI findings but should not be used to compare the two jurisdictions.

Taken together, these significant correlations point to a coherent underlying dimension that might be described as intensity and depth of GenAI engagement. Workers who score highly on this dimension use GenAI on more days, for more hours per day, and across more tools. While none of the individual correlations is large, their consistency and statistical significance suggest that multi-tool use is a meaningful marker of more intensive and embedded AI adoption, rather than simply an incidental feature of a worker's platform choices.

Who are the multi-tool users?

These findings have practical significance for understanding the distribution of AI capability within the workforce. Multi-tool use is not confined to a small minority: 52% of RoI GenAI users and 47% of NI users use two or more tools. A narrower group, 12% of standalone-tool users, use three or more standalone tools. Because multi-tool use is so common, we enquire which workers are more likely to be multi-tool users. Table 5 reports the share of multi-tool users in each group, alongside frequent and intensive use. Given the small NI bases (73 GenAI users in the follow-up module), the narrative profile below draws on the RoI data. We do, however, include the NI figures in Table 5, but most cells are too small to interpret in any meaningful or reliable manner.

Gender does not distinguish multi-tool users. In the RoI, 53% of men and 51% of women who use GenAI use two or more tools. NI shows a larger gap (54% vs 33%), but it rests on very few women and should not be interpreted. These data therefore offer no evidence that the gender gap in AI engagement widens as use deepens: the near-parity in adoption reported earlier holds for multi-tool use as well.

Multi-tool use is also similar across the core working ages: between 52% and 54% of users aged 25–64 use two or more tools. It is lower among the youngest workers (40% of those aged 16–24) and, on a small base, among those aged 65–74 (32%).

Education is a clearer marker of GenAI use. The share of multi-tool users rises from 46% among those with upper secondary education to 48% among those with a bachelor's degree, 58% with a master's and 66% with a doctorate. The gradient is concentrated at postgraduate level, where the most demanding knowledge work is found.

Occupation shows the sharpest differences. 62% of managers, directors and senior officials and 57% of professionals are multi-tool users, compared with 50% of associate professionals, 37% of administrative and secretarial workers and 36% of skilled trades workers. Rates are lower still in elementary occupations (38%), caring, leisure and other services (29%) and sales and customer service (19%), though these rest on fewer than 20 users each. The diversification of AI tool use is, to a considerable degree, a feature of high-skill managerial and professional work.

By industry, multi-tool use is highest in ICT, professional, scientific and technical services (60%), transport and hospitality (56%) and manufacturing (55%), and lowest in public administration and defence (30%) and agriculture, forestry, fishing and mining (27%, small base). Private-sector users are more likely than public-sector users to use multiple tools (55% vs 41%). Organisation size, by contrast, makes little difference: 52% of users in small firms, 57% in medium-sized firms and 51% in large firms use two or more tools. The finding that larger organisations are more likely to host GenAI adopters does not extend to multi-tool use.

Employment conditions matter more. Permanent employees are more likely than those on non-permanent contracts to be multi-tool users (53% vs 43%), and the gap is wider by working hours: 54% of full-time workers compared with 34% of part-time workers. This raises the question of whether the productivity benefits associated with multi-tool use accrue disproportionately to workers in more secure, full-time employment.

Salary, however, shows no consistent gradient. Across RoI salary bands with at least 20 users, the share of multi-tool users ranges from 45% to 66% without rising steadily with net earnings: it peaks in the €75,000–€89,999 band (66%) and falls to 45% in the top band (€110,000 or more). Multi-tool use is not simply a feature of the highest earners.

Overall, multi-tool users are more likely to be found in managerial and professional occupations, among those with postgraduate education, in full-time and permanent jobs and in the private sector. They are not distinguished by gender, age, organisation size or salary. Whether the productivity and innovation gains that appear to accompany more intensive GenAI use serve to widen or narrow existing inequalities over time is a question that warrants sustained attention in future waves of the Working in Ireland Survey.

Table 5: Intensity of GenAI use by worker characteristics, RoI and NI

	Frequent use (Every/Most days)		Intensive use (1+ hours per day)		Multi-Tool users (2+tools)	
	RoI	**NI**	**RoI**	**NI**	**RoI**	**NI**
Total sample						
Total	45%	44%	16%	10%	52%	47%
Gender						
Men	46%	59%†	18%	12%	53%	54%
Women	43%	20%†	15%	7%†	51%	33%
Employment contract						
Permanent	45%	44%	17%	11%	53%	49%
Non-permanent	46%	39%†	16%	—	43%	—
Age group						
16–24	42%	46%†	19%	—	40%	—
25–34	55%	34%†	18%	11%	54%	41%
35–44	41%	61%†	18%	19%	53%	71%
45–54	46%	38%†	13%	4%†	52%	54%†
55–64	30%	12%†	14%	—	53%	12%†
65–74	25%†	—	7%†	—	32%†	—
75+	33%†	—	—	—	—	—
Education (full categories)						
Primary education	—	—	—	—	—	—
Lower secondary education	47%†	—	—	—	35%†	—
Upper secondary education	49%	47%†	31%	12%†	46%	9%†
Post-secondary non-tertiary	30%†	—	13%†	—	43%†	—
Short-cycle tertiary	39%	31%†	13%	25%†	47%	59%†
Bachelor's or equivalent	44%	44%	18%	14%	48%	50%
Master's or equivalent	47%	29%†	15%	—	58%	65%†
Doctoral or equivalent	52%	—	12%	—	66%	—
Occupation						
Elementary occupations	53%†	—	24%†	—	38%†	—
Professional occupations	43%	50%	16%	15%	57%	54%
Associate professional occupations	53%	21%†	19%	16%†	50%	37%†
Administrative and secretarial	50%	—	14%	—	37%	—
Skilled trades occupations	27%	46%†	22%†	—	36%	9%†
Caring, leisure and other services	34%†	—	10%†	—	29%†	—
Sales and customer service	22%†	—	37%†	—	19%†	—

Process, plant and machine operatives	—	—	—	—	—	—
Managers, directors and officials	46%	38%†	13%	—	62%	67%†
Sector of employment						
Private sector	53%	42%	18%	15%	55%	60%
Public sector	27%	45%†	10%	—	41%	46%†
State-owned company	40%†	—	14%†	—	73%†	—
Not-for-profit / NGO	35%	_	24%	_	54%	_
Industry sector						
Agriculture, forestry, fishing & mining	14%†	—	—	—	27%†	—
Energy & Construction	33%	49%†	13%	19%†	44%	37%†
Wholesale & retail	47%	—	21%	—	43%	—
Transport & hospitality	42%	—	17%	—	56%	—
ICT, prof., scientific, tech., admin & support, arts & other services	56%	57%	20%	20%	60%	58%
Financial services & real estate	50%	34%†	14%	—	52%	25%†
Public administration & defence	37%	—	7%	—	30%	—
Education	24%	46%†	7%	—	48%	49%†
Human health	39%	46%†	26%	16%†	44%	42%†
Manufacturing	48%	—	12%	—	55%	—
Organisation size*						
Small (1–49 employees)	42%	47%†	11%	14%†	52%	41%†
Medium (50–249 employees)	48%	37%†	24%	9%†	57%	67%†
Large (250+ employees)	47%	40%	17%	14%	51%	48%
Working hours						
Full-time	46%	45%	17%	9%	54%	48%
Part-time	33%	29%†	13%	—	34%	29%†
Salary — Republic of Ireland (euros)						
Under €15,000	63%†	—	—	—	64%†	—
€15,000–€29,999	34%†	—	8%†	—	56%†	—
€30,000–€44,999	54%	—	23%	—	46%	—
€45,000–€59,999	43%	—	20%	—	51%	—
€60,000–€74,999	48%	—	9%	—	59%	—
€75,000–€89,999	49%	—	25%	—	66%	—
€90,000–€109,999	45%†	—	22%†	—	39%†	—
€110,000 or more	71%	—	26%	—	45%	—

Salary — Northern Ireland (pounds sterling)						
Under £12,000	—	—	—	—	—	—
£12,000–£17,999	—	—	—	—	—	—
£18,000–£23,999	—	—	—	—	—	—
£24,000–£29,999	—	—	—	—	—	—
£30,000–£39,999	—	57%†	—	—	—	88%†
£40,000–£49,999	—	33%†	—	25%†	—	69%†
£50,000–£69,999	—	90%†	—	26%†	—	33%†
£70,000 or more	—	90%†	—	7%†	—	90%†

Notes: Weighted percentages. Frequent use: every day or most days in the past week. Intensive use: 1+ hours per day, among those who used GenAI in the past week . Multi-tool users: two or more GenAI tools, i.e. standalone and employer-integrated tools or two or more standalone tools. All items asked only of GenAI users who opted into answering additional questions in the follow-up module.

*— = fewer than 5 cases or no users in the group. † = fewer than 20 cases; interpret with caution. *Organisation size note as in the report.*

Intensity and GenAI tool integration

We turn to examine the relationship between the type of GenAI tool used – they being standalone publicly available tools, employer-integrated tools, or both – and the two measures of use intensity.

In the RoI, workers who rely exclusively on standalone tools record a frequent use rate of 37% and an intensive use rate of 10.8%. Among those whose employer has embedded GenAI into production or service processes (integrated tools only), frequent use rises to 41.8% and intensive use to 20.2%, nearly double the standalone rate. The most intensive users are those who draw on both tool types: 62.2% use GenAI every or most days and 25.0% use it for one or more hours daily, figures that substantially exceed both the standalone and integrated-only groups. Because users of both types use at least two tools, this group overlaps with the multi-tool users discussed above.

The NI pattern is directionally consistent. Standalone-only users record 37.2% frequent use and 2.9% intensive use, while both-type users record 52.6% and 23.5% respectively. The integrated-only NI group shows high frequent (50.0%) and intensive (25.0%) use rates, though the sub-sample of just eight respondents precludes reliable inference.

Taken together, these findings support the interpretation that organisational embeddedness, the deliberate integration of GenAI into employer workflows, is associated not merely with adoption but with the depth and regularity of use, consistent with the broader literature on technology diffusion in the workplace.

Is AI used responsibly? Training, competence and oversight

We use a number of indicators to assess whether workers use GenAI responsibly. First, we enquired of their level of training and competence.

Table 6: Intensity of GenAI use in standalone and integrated tools

	Republic of Ireland			Northern Ireland		
	Standalone	Integrated	Both	Standalone	Integrated	Both
N	397	122	225	43	8	19
Frequent use (Every/Most days)						
% frequent users	37.0%	41.8%	62.2%	37.2%†	50.0%†	52.6%†
Intensive use (1+ hours per day)						
% intensive users	10.8%	20.2%	25.0%	2.9%†	25.0%†	23.5%†

Note: † Sub-sample n<20 — interpret with caution.

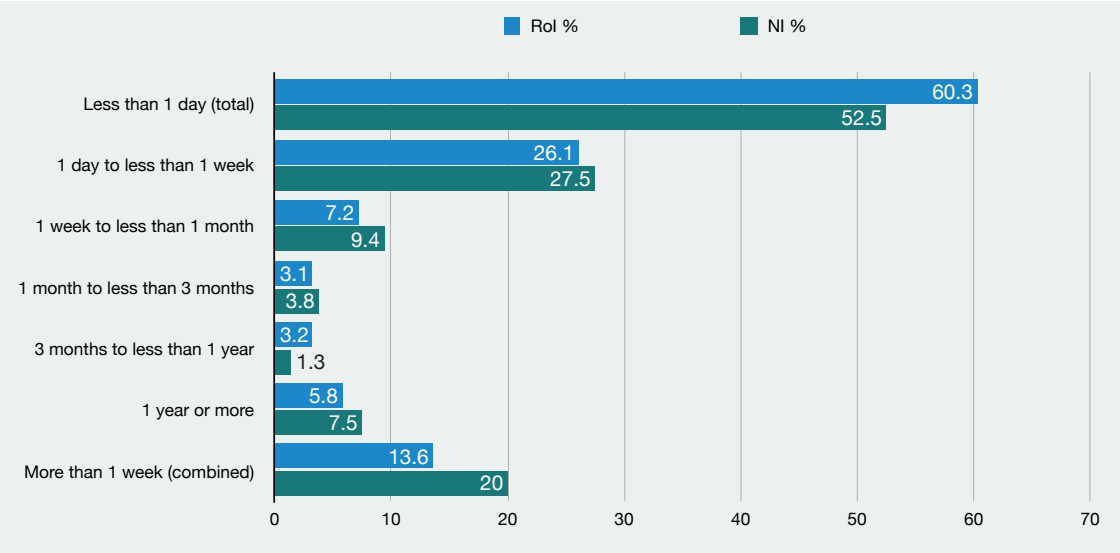
Of employees, 42.8% of RoI workers indicated they had or were in the process of receiving training from their employer in the use of GenAI. In NI, the proportion is lower at 37.7%, giving a combined total of 42.4% (RoI n=701; NI n=53).

We also enquired of respondents, employees and self-employed, if they had ever tried to teach themselves in the use of AI either by reading newsletters, watching YouTube tutorials or by some self-directed means. In RoI, 65.2% had done so, compared with 57.4% in NI (RoI n=751; NI n=70). The proportion among self-employed workers was considerably lower than among employees in both jurisdictions: in RoI, 49% of self-employed workers had taught themselves compared with 66% of employees; in NI the equivalent figures were 41% and 62% respectively, though the NI sub-samples are small and should be interpreted with caution. It also bears emphasis that the proportion of employees who are teaching themselves about AI use is substantially larger than those who have received training from their employer: 43% in RoI and 38% in NI.

We then asked respondents how extensive their training had been to reach their current level of expertise in GenAI (combining both employer and self-provided training). The extent of training in GenAI among workers in both jurisdictions is modest, though NI workers are somewhat more likely to have undertaken more extensive training. In the RoI, almost three-fifths (60.3%) report training of less than one day in duration. In NI, the equivalent is 52.5%. Only 13.6% of RoI workers report training lasting more than one week, compared with 20.0% in NI. A notable feature in both jurisdictions is that a small but non-trivial group reports one year or more of training: 5.8% in the RoI and 7.5% in NI, a group that is likely to have developed specialist expertise in GenAI tools. See Figure 4.

Among workers who have received employer training in the use of GenAI, we asked them to rate the quality of that training on two dimensions: first, how well it informed them of the advantages and benefits of using GenAI, and second, how well it addressed its disadvantages and risks. Responses were recorded on a five-point scale from 'very poor' to 'very good'. The results, presented in the figure above, reveal that the majority of trained workers in both jurisdictions rate the quality of

Figure 4. Extent of training to reach current GenAI expertise level

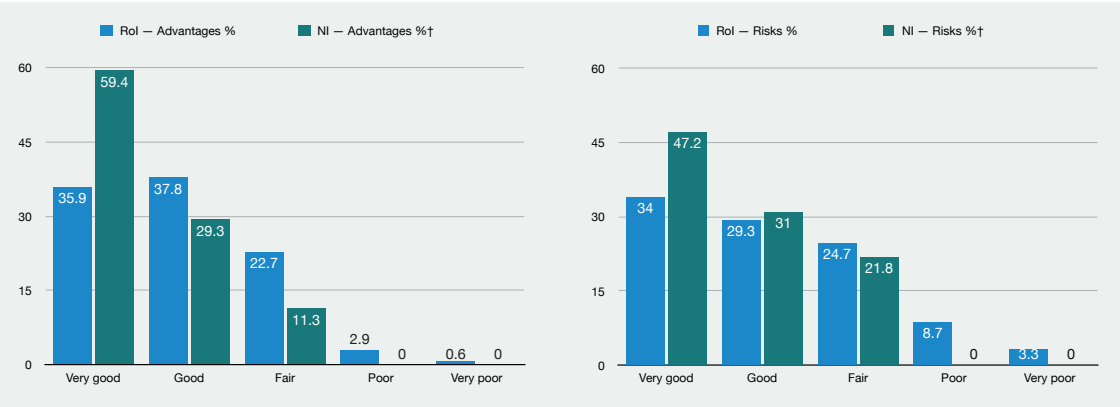


their employer training positively, but with notable differences both between jurisdictions and between the two dimensions of training. See Figure 5.

In the Republic of Ireland, the distribution of ratings for training on the advantages and benefits of GenAI is broadly positive but far from overwhelmingly so. Just over a third of RoI workers who received training rate it as 'very good' (35.9%), with a further 37.8% rating it as 'good', giving a combined positive rating (good or very good) of 73.7%. Just under a quarter rate it as 'fair' (22.7%), while a small minority rate it as 'poor' (2.9%) or 'very poor' (0.6%). The modal response is thus 'good', and the distribution suggests that while most trained workers find the coverage of GenAI's advantages adequate, a substantial minority considers it only moderately satisfactory.

In Northern Ireland, the picture is considerably more positive, though the very small base of 19 respondents demands extreme caution in interpretation. No NI worker in the sample rates the training on advantages as poor or very poor, and the distribution is heavily skewed toward the upper end of the scale: 59.4% rate it as 'very good' and a further 29.3% as 'good', giving a combined positive rating of 88.7%. Only 11.3% rate it as 'fair'.

Figure 5: Quality of training in informing workers of the advantages and benefits, and of the disadvantages and risks, of using GenAI



Whether this reflects a genuine difference in the quality of employer GenAI training in NI relative to RoI, perhaps reflecting a higher concentration of training in large, internationally-owned private sector firms, or whether it is an artefact of the very small and potentially unrepresentative NI sample cannot be determined from the data alone. The finding is directionally consistent with the broader pattern of NI workers reporting somewhat more positive outcomes from their engagement with GenAI throughout this report, but it should not be overstated.

The pattern of ratings for training on the disadvantages and risks of GenAI, covering issues such as security, reliability, bias, and the limitations of AI-generated outputs, tells a somewhat different story. In the RoI, the distribution is more evenly spread across the upper three categories than was the case for training on advantages. The proportion rating this dimension as 'very good' (34.0%) is similar to the equivalent figure for advantages training, but a higher proportion rate it as 'poor' (8.7%) or 'very poor' (3.3%), and fewer rate it as 'good' (29.3%). The net result is that training on disadvantages and risks is rated somewhat less positively than training on advantages in the RoI: 63.3% rate it good or very good, compared with 73.7% for advantage training, a gap of approximately 10 percentage points.

This divergence is significant. It suggests that where employer training on GenAI falls short, it does so more acutely in its coverage of risks and limitations than in its communication of benefits and opportunities. This is a concern from a responsible AI governance perspective: workers who are well-informed about the productive potential of GenAI but less well-equipped to identify and manage its risks may be more likely to deploy AI outputs uncritically, to expose sensitive data inadvertently, or to produce AI-assisted work that does not meet accuracy or quality standards. The finding that 12% of RoI trained workers rate their training on disadvantages as poor or very poor is a particularly pointed indicator of this gap.

In Northern Ireland, training on risks is again rated more positively than in the RoI, though again with the strong caveat of a very small sample. No NI respondent rates this training dimension as 'very poor', and 47.2% rate it 'very good', a figure that, if reliable, would substantially exceed the RoI equivalent. A further 31.0% rate it 'good', giving a combined positive rating of 78.2%. As with the advantages dimension, the NI distribution is skewed toward the upper end of the scale in a way that outstrips the RoI pattern, though the interpretive weight that can be placed on an n of 19 is very limited.

Self-assessed GenAI competence

As to workers' level of competence in using GenAI, we enquired of respondents "How would you rate your level of competence in using the GenAI tool(s) that you use in your work?" Results are broadly similar across both jurisdictions. In the RoI, 54.9% rate themselves as good or very good (good: 29.9%; very good: 25.0%); in NI the equivalent is 58.6% (good: 28.6%; very good: 30.0%). Approximately a third in each jurisdiction rate their competence as fair (RoI: 28.5%; NI: 27.0%), and around one in seven rate it as poor or very poor (RoI: 16.6%; NI: 14.4%). The distributions are thus similar across the two jurisdictions.

We ran the Spearman's rank-order correlation between the overall extent of training undertaken to reach a worker's current level of GenAI expertise and their self-assessed competence in using GenAI tools. The correlation coefficient is rho = .324, significant at the 0.01 level ($p < .001$, two-tailed), based on a pairwise valid sample of 659 respondents. This is a positive and statistically robust relationship: the more extensive a worker's training, whether employer-provided, self-directed, or a combination of the two, the higher they rate their own competence in using GenAI.

The magnitude of rho = .324 is modest to moderate, which is both theoretically expected and substantively informative. It is expected because training and competence are not interchangeable: workers differ substantially in the rate at which they convert training time into usable skill, and prior experience, cognitive engagement, and the quality of the learning environment all mediate the training-competence relationship. It is informative precisely because the association, while positive and significant, leaves a considerable proportion of the variance in self-assessed competence unexplained by training volume alone. In practical terms, this means that some workers report high competence despite relatively limited training, likely reflecting those who have acquired skills through intensive hands-on use rather than formal learning, while others report low competence despite more extensive training investment.

The difference in sample size between the two variables is worth noting. Length of training has a valid N of 659 for the correlation, compared with a base of 892 for self-assessed competence. This reduction reflects the fact that length of training was asked only of workers who indicated they had received some form of training in GenAI, whether from their employer or through self-directed means, whereas self-assessed competence was asked of all GenAI users. The correlation is therefore estimated on the sub-population of trained workers rather than all GenAI users, and its magnitude should be interpreted in that context. Among workers who have no training at all, the relationship between training and competence is, by definition, undefined; it is entirely plausible that the correlation would be stronger if it could be estimated across the full range of training experience, including a notional zero category.

The finding that training extent is positively associated with self-assessed competence provides qualified support for employer investment in GenAI training programmes. It suggests that training does, in workers' own

Table 7. Self-assessed competence in using GenAI (% of GenAI users)

Competence level	RoI %	NI %
Very good	25.0	30.0
Good	29.9	28.6
Fair	28.5	27.0
Poor	12.0	10.0
Very poor	4.6	4.4
N	752	70

assessment, translate into greater capability, though the modest size of the correlation serves as a reminder that training volume is only one of several determinants of GenAI competence. Taken together with the finding that the majority of workers in both the RoI and NI have undertaken only very limited training, the modal category in both jurisdictions being less than one full day, this correlation implies that the current level of training investment is unlikely to be producing the levels of competence that the widespread and responsible deployment of GenAI in the workplace would require. The policy implication is not simply that more training is needed, but that the quality, depth and continuity of that training matters as much as its quantity.

Workers' knowledge on specific aspects of GenAI tools

We further interrogated workers' knowledge of specific aspects of GenAI by putting a series of statements to them. There were asked to indicate their level of agreement with these statements. Such attitudinal scales are often referred to as a 'battery'. They covered their knowledge of GenAI's benefits and limitations, their views on the reliability and completeness of AI-generated information, their attitudes towards security risks, the value they place on human oversight, and their expectations regarding the employment consequences of AI adoption. The results, presented in Figure 7, reveal a coherent and internally consistent pattern of attitudes that is broadly similar across the two jurisdictions, with a number of specific differences worth drawing out.

Knowledge of Benefits and Limitations

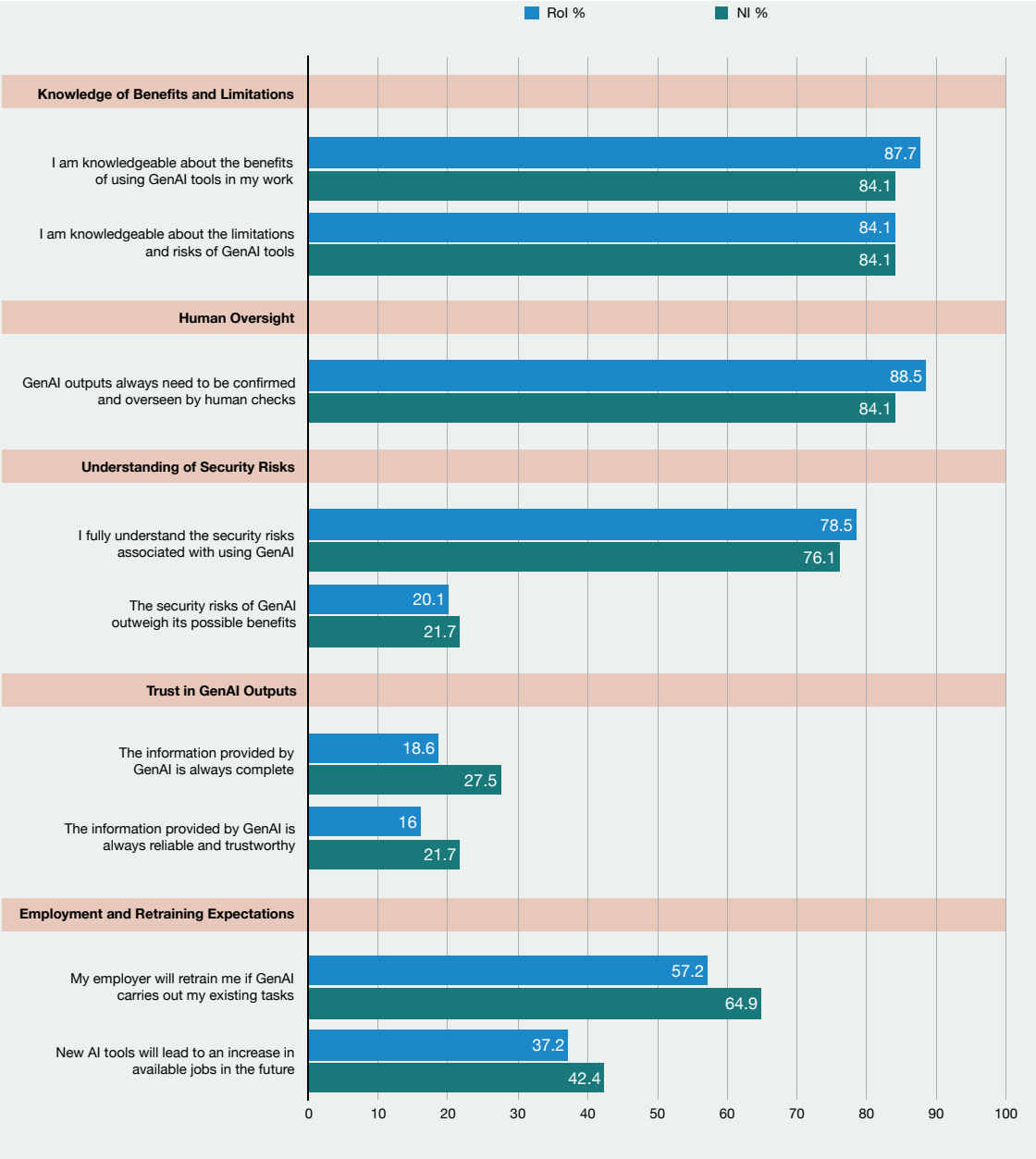
The highest agreement rates in the battery (list of statements) are recorded for the two items measuring workers' self-reported knowledge of GenAI. In the RoI, 87.7% of GenAI users agree or strongly agree that they are knowledgeable about the benefits of using GenAI tools in their work, and 84.1% agree they are knowledgeable about the limitations and risks. In NI, the equivalent figures are 84.1% for both items, a near-identical distribution across the two dimensions and across both jurisdictions. These are notably high levels of self-reported knowledge for a technology that has only recently entered widespread workplace use. And yet, they are broadly consistent with the finding that the majority of workers in both jurisdictions have engaged in some form of self-directed learning about AI, as documented in the training section of this report.

It is worth noting, however, that self-assessed knowledge and actual knowledge are not the same thing. The high proportion of workers who report knowing the limitations and risks of GenAI must be read alongside the finding, discussed below, that a sizeable minority simultaneously express trust in the completeness and reliability of AI outputs. Whether workers' self-assessed knowledge of limitations translates into appropriately cautious behaviour in practice is a question that survey data of this type cannot fully resolve.

Human Oversight

The strongest level of agreement is recorded for the statement that GenAI outputs always need to be confirmed and overseen by human checks: 88.5% of RoI workers and 84.1% of NI workers agree or strongly agree with this proposition. In the RoI, the majority response is 'strongly agree' (56.3%), making this the only item where strong agreement exceeds

Figure 7: Attitudes towards GenAI in the Republic of Ireland and Northern Ireland



simple agreement, a particularly emphatic endorsement of the principle of human oversight. These findings are reassuring from a responsible AI governance perspective and suggest that, whatever their levels of enthusiasm for GenAI's productive potential, workers are not naively deferring to AI outputs without critical scrutiny. The high endorsement of human oversight is consistent with the equally high self-reported knowledge of limitations and risks, and together these two items describe a workforce that, at least attitudinally, approaches GenAI with a high degree of critical awareness and reflection.

Understanding of Security Risks

A large majority of workers in both jurisdictions, 78.5% in the RoI and

76.1% in NI, agree that they fully understand the security risks associated with using GenAI. This is a high figure that sits in interesting tension with the much lower proportion who believe those risks outweigh the benefits. In the RoI, only 20.1% agree that security risks outweigh the possible benefits of GenAI, and in NI the figure is 21.7%, broadly similar across the two jurisdictions and representing a clear minority view. The combination of widespread self-reported security awareness and widespread rejection of the view that risks outweigh benefits suggests that the dominant attitude among GenAI-using workers is one of informed optimism: they believe they understand the risks, and they believe the benefits justify continued use nonetheless.

Trust in GenAI Outputs

In sharp contrast to the high agreement rates for knowledge, oversight and security awareness, agreement with the two statements about the reliability and completeness of GenAI information is very low, and this is among the most important findings in the entire attitudes battery. In the RoI, 18.6% agree that the information provided by GenAI is always complete, and 16.0% agree that it is always reliable and trustworthy. The equivalent figures in NI are somewhat higher, 27.5% and 21.7% respectively, suggesting that NI workers are moderately more likely to place greater trust in GenAI outputs, though in both jurisdictions the clear majority actively rejects these propositions.

These figures need to be framed and read in two ways. First, while 'only' a minority of respondents believe GenAI outputs are reliable and trustworthy, they still represent a substantial number – between a sixth and a quarter of the workforce. This has to be of concern. Second, an alternative framing would encourage a positive reading from the data. That the great majority of GenAI users in both jurisdictions do not regard AI-generated information as inherently complete or reliably accurate, is encouraging and reassuring and, sensu stricto, is the epistemically correct position. Taken together with the near-universal endorsement of human oversight, they suggest that the attitudinal prerequisites for responsible GenAI use, critical awareness, scepticism about output reliability, and support for human verification, are widely held within the GenAI-using workforce. Whether these attitudes translate reliably into practice, whether workers who express scepticism about GenAI reliability actually check outputs systematically, or whether the endorsement of human oversight is more aspirational than behavioural, is a question that future research will need to address.

Employment and Retraining Expectations

Workers are considerably more divided on the employment-related items in the battery than on the knowledge and oversight items. In the RoI, 57.2% are confident that their employer will retrain them to complete different tasks if GenAI carries out their existing ones; in NI the figure is higher at 64.9%. While these are majority positions in both jurisdictions, a substantial minority, over 40% in the RoI and 35% in NI, does not share this confidence. The NI advantage on this item is consistent with the somewhat more positive picture of workplace training and employer engagement with GenAI that emerges from other parts of this report, and may also reflect the more concentrated sectoral and occupational profile of NI GenAI

users, who are disproportionately located in large private sector firms with greater capacity to invest in workforce adaptation.

The item on job creation is the most contested in the entire battery, with agreement and disagreement running in close proximity. In the RoI, 37.2% agree that new AI tools will lead to an increase in available jobs in the future, while 41.1% disagree, making this the only item in the battery where the disagreement rate exceeds the agreement rate. In NI, 42.4% agree and 36.9% disagree, a slight reversal of the RoI pattern, though still a closely divided picture. The roughly equal split in both jurisdictions between optimists and pessimists on the job creation question reflects the genuine uncertainty that characterises public and expert debate on the long-run employment consequences of AI, and suggests that GenAI-using workers, who are among the most directly exposed to the technology, are themselves far from settled in their views on this question.

Therefore, the attitude survey questions as a whole present a coherent portrait of the GenAI-using workforce in both jurisdictions. Workers are knowledgeable, or at least perceive themselves to be; they strongly endorse human oversight; they are sceptical about the unconditional reliability of AI outputs; and they do not regard security risks as disqualifying. On the forward-looking questions of employer retraining and job creation, they are more divided, with a sizeable minority in both jurisdictions uncertain or pessimistic about the employment consequences of continued AI adoption. Across all nine items, the RoI and NI distributions are broadly similar, with NI workers marginally more trusting of AI output quality and marginally more confident about employer support, differences that are directionally consistent throughout but that should be treated with caution given the smaller NI sample.

GenAI Official Policy at Organisational Level

We then enquired whether employees' employer has an official policy or set of guidelines to inform how they should use GenAI at work. Here, a notable jurisdictional difference emerges. In the RoI, 52.2% of employees report that such a policy is in existence, compared with only 36.5% in NI, a gap of over 15 percentage points. This finding is consistent with the broader picture of relatively less formalised governance of GenAI use in NI workplaces.

The vast majority of GenAI users in both jurisdictions report that their employer is aware of their use: 92.7% in the RoI and 94.3% in NI. However, awareness becomes considerably thinner when it comes to knowing what they are using GenAI for and to what extent. In the RoI, 83.8% report their employer knows exactly what they use it for, while 82.1% say their employer is aware of the extent to which they use it. In NI, these figures are somewhat higher: 92.2% and 89.8% respectively, suggesting marginally better oversight in NI workplaces for those where awareness exists.

A central question in the governance of AI use in the workplace is whether employer oversight of workers' GenAI activities is associated with greater worker knowledge of the risks and limitations of the technology. We performed Spearman's rank-order

Table 8: Employers' awareness of GenAI use

Awareness dimension	RoI	NI
Employer aware GenAI used	92.7%	94.3%
Employer aware of what used for	83.8%	92.2%
Employer aware of extent of use	82.1%	89.8%

Note: RoI N = 684; NI N = 53

correlations between three measures of employer awareness, whether the employer knows that the worker uses GenAI, whether the employer knows what the worker uses it for, and whether the employer knows the extent to which the worker uses it, and the worker's self-assessed knowledge of the limitations and risks of GenAI. The analysis was conducted separately for RoI and NI.

In the RoI, the correlation between basic employer awareness of GenAI use and workers' self-assessed knowledge of limitations is rho = .108, significant at the 0.01 level (p = .003, n = 747). This is a weak but statistically significant positive association: workers whose employers are aware of their GenAI use are modestly more likely to report knowing the limitations and risks of the technology. However, the very small magnitude of this correlation, explaining less than 1.2% of the variance in self-assessed knowledge, suggests that simple employer awareness of use, in itself, has only a marginal bearing on the depth of workers' risk literacy.

The associations become more substantive when we turn to the two measures of deeper employer oversight. The correlation between employer knowledge of what the worker uses GenAI for and workers' self-assessed limitations knowledge is rho = .113 (p = .003, n = 677), and between employer knowledge of the extent of use and the same outcome, rho = .157 (p < .001, n = 673).

While these coefficients remain modest in absolute terms, they are consistently positive and statistically significant, and the growing gradient through the different levels of awareness (from .108 to .157) is meaningful: the more detailed and substantive the employer's awareness of a worker's GenAI activities, the more strongly it is associated with the worker's own knowledge of GenAI's limitations and risks.

This gradient is consistent with the hypothesis that it is not mere awareness of GenAI use but active employer engagement with that use, knowing what workers do with AI and how extensively they do it, that is associated with greater worker risk literacy. Employers who know the scope and nature of their workers' AI activities are more likely to be engaging in some form of oversight, guidance or governance that, in turn, may be fostering or reinforcing workers' awareness of the risks involved. The direction of causality cannot be determined from cross-sectional data: it is equally plausible that workers with greater risk knowledge are more likely to disclose the details of their GenAI activities to their employer. However, the consistency of the positive correlations across all three employer awareness measures lends weight to the interpretation that employer engagement and worker risk literacy are mutually reinforcing dimensions of responsible AI governance in the workplace.

The strong correlation between the two employer awareness depth

measures themselves (what use and the extent of use), rho = .627 ($p < .001$, n = 666) confirms that employers who know what workers use GenAI for also tend to know the extent to which they use it. These two dimensions of oversight co-vary closely and might reasonably be treated as indicators of a single underlying construct of employer engagement with workers' AI activities.

The NI results present a more complex picture, in part due to the considerably smaller sample sizes available for the analysis (n=53; n=49–50; n=65). The correlation between employer awareness of GenAI use and workers' knowledge of limitations in NI is rho = −.195, which is not statistically significant ($p = .170$, n = 51). The negative sign is unexpected and difficult to interpret substantively given the small base; it is most plausibly an artefact of sampling variability rather than a genuine negative relationship, particularly as the same association in the RoI is positive.

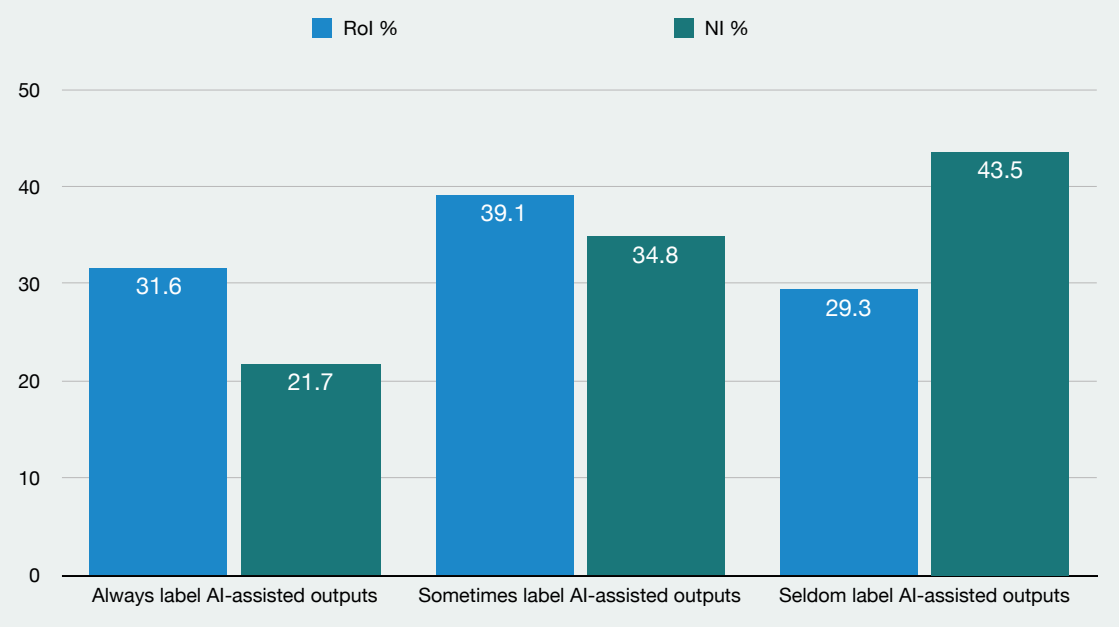
By contrast, the correlations between the deeper employer awareness measures and workers' knowledge of limitations are positive and statistically significant in NI, consistent with the RoI pattern. The correlation between whether the employer knows what AI is used for and workers' knowledge of GenAI limitations and risks is rho = .408 ($p = .004$, n = 48), and between employer's awareness of extent of use and workers' knowledge of GenAI limitations and risks is rho = .386 ($p = .007$, n = 47). These are substantially larger coefficients than the equivalent RoI figures, suggesting a stronger association between detailed employer oversight and worker risk knowledge in NI, though the small NI sample means these estimates carry considerable uncertainty and should be interpreted with caution. The very strong correlation between employer's awareness of use and employer's awareness of extent of use in NI (rho = .798, $p < .001$, n = 49) mirrors the RoI pattern, confirming that the two dimensions of employer oversight depth are closely interrelated in both jurisdictions.

Hence, the correlation analysis supports a qualified but consistent conclusion: employer awareness of the scope and nature of workers' GenAI activities is positively associated with workers' self-assessed knowledge of GenAI's limitations and risks, in both the RoI and NI. The association is stronger for deeper forms of employer awareness, knowledge of what AI is used for and to what extent, than for simple awareness of use, and the magnitudes, while modest in the RoI, are more pronounced in NI. These findings suggest that employer oversight functions not merely as a compliance mechanism but may also play a role in fostering or reinforcing the risk literacy of workers, at least as workers themselves perceive it. In the context of a workforce in which formal training provision remains limited and the majority of workers are self-taught, the quality and depth of employer awareness emerges as a potentially important determinant of whether workers engage with GenAI in an informed and responsible manner.

Labelling of GenAI-assisted work

We also enquired whether, when workers produce work using GenAI, they clearly label it as having been produced with AI assistance. A third of RoI workers (31.6%) indicate they always do so, compared with 21.7% in NI. The proportion who sometimes

Figure 8: Labelling of GenAI-assisted work



label their AI-assisted work is 39.1% (RoI) and 34.8% (NI), while 29.3% of RoI workers and 43.5% of NI workers say they seldom do so. NI workers are thus considerably less likely than their RoI counterparts to consistently acknowledge their use of AI in their outputs.

GenAI outputs: large or small?

We asked respondents a series of questions in respect of the gains obtained from using GenAI in their work. We used three measures: time savings made, whether by using GenAI workers considered themselves to be more or less innovative in their work, and finally whether by using GenAI they had seen the quality of their work improve or not.

Time savings

First we asked *'which of the following best describes the amount of time saved, if any, by using Gen AI in your work?'* In administering the questionnaire, the interviewer prompted the respondent that each statement approximated to a corresponding proportion, *"i.e., that's more than ... but less than..."* as an aid to the respondent to specify the time savings involved.

In both jurisdictions, the great majority of GenAI users report some degree of time saving. In the RoI, 6.7% attain no time savings, while 27.1% obtain savings they describe as 'little' (greater than zero but less than 10%), 33.2% obtain 'some' (10–24%), 21.3% obtain 'large' (25–49%), and finally 11.8% obtain 'very large' time savings (50% or more). The NI distribution is notably more skewed toward higher savings: only 1.4% report no savings, while 31.9% report large savings and 20.3% report very large savings, compared with 21.3% and 11.8% respectively in the RoI. When we then review the sum of the responses to the last three response categories – some, large and very large – we find that very considerable proportions of those who use GenAI derive sizeable time savings – that is, two-thirds in the RoI and three-quarters in NI. This equates to between 4 hours and up to 20 or more hours per week. This is significant and is not out of line with

Table 9. Time savings from GenAI use

Time saving	RoI %	NI %
No time saved	6.7	1.4
A little time (<10%)	27.1	21.7
Some time (10–24%)	33.2	24.6
Large saving (25–49%)	21.3	31.9
Very large saving (≥50%)	11.8	20.3
N	**748**	**69**

international evidence (Humlum and Vestergaard, 2024). However, the findings for NI should be treated with caution given the smaller sub-sample, but they are directionally consistent with a picture of NI workers who are, on average, either using AI for more time-intensive tasks or reporting its benefits more liberally.

Factors associated with GenAI driven time savings

We ran Spearman's rank-order correlations between the amount of time saved through GenAI use and the three variables that capture different dimensions of workers' engagement with and investment in the technology: the perceived quality of training on the advantages and benefits of GenAI; self-assessed competence in using GenAI; and the overall extent of training undertaken. The analysis is conducted separately for the RoI and NI. The pattern of results differs substantially between the two jurisdictions and merits careful interpretation.

In the RoI, two of the three correlations with time saved are statistically significant. The strongest association is between self-assessed competence and time saved: rho = .178, significant at the 0.01 level ($p < .001$, $n = 821$). This is the most substantively important finding in the analysis for the RoI: workers who rate their GenAI competence more highly report saving more time through its use. While the magnitude is modest, the direction and significance of the relationship are unambiguous and theoretically coherent: more competent users are better able to leverage GenAI effectively for time-saving purposes, whether through more skilful prompting, more appropriate task selection, or more efficient integration of AI outputs into their workflow.

The second significant correlation in the RoI is between training extent and time saved: rho = .137 ($p < .001$, $n = 619$). Workers who have undertaken more extensive training report greater time savings from GenAI use. This finding complements the competence–time saving relationship: training builds competence, and competence translates into time savings. By contrast, the correlation between time saved and quality of training on advantages (rho = .095, $p = .087$, $n = 327$) does not reach statistical significance in the RoI. While directionally positive, it suggests that it is the quantity and depth of training investment, rather than the perceived quality of formal employer training, that drives productivity gains.

The NI correlation analysis presents a strikingly different pattern, though the very small sample sizes involved (time saved: n = 65; training on GenAI advantages: n = 18–19; self-assessed GenAI competence: n = 65–67; extent

of GenAI training: n = 36–37) mean that all NI findings must be treated with considerable caution. None of the correlations between time saved and the three predictor variables reaches statistical significance in NI, and the absence of significant correlations should not be interpreted as evidence of no relationship

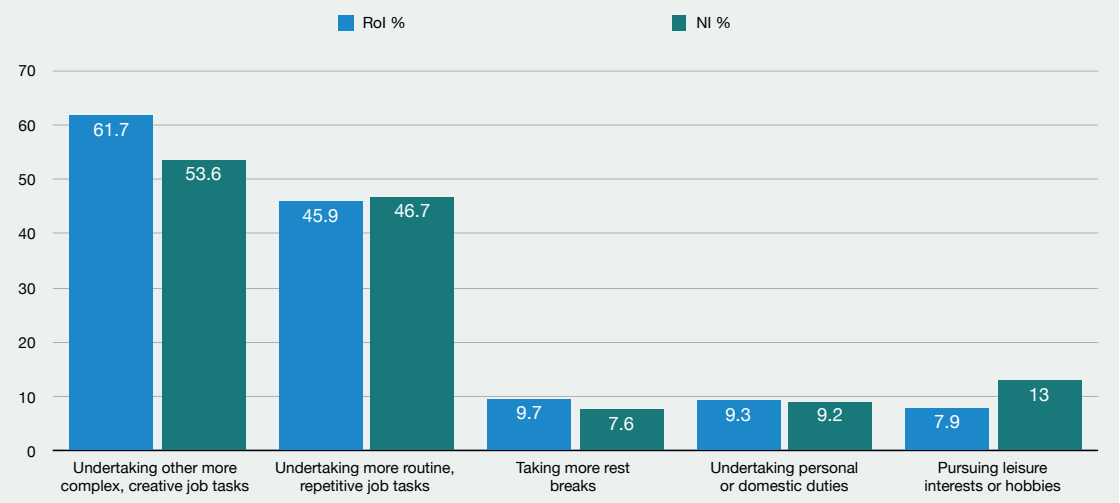
Time saved: where did it go?

Mindful of the limitations of using time savings as a proxy for productivity gains we then enquired of those who reported that they saved time by using AI, what they did with the time saved. This was an attempt to see if the time savings gained accrued to the employer or the employee. Respondents were presented with a list of six activities and invited to select all that applied. The results, presented in Figure 9, reveal a clear and practically significant pattern: the overwhelming majority of workers in both jurisdictions direct their GenAI-generated time savings back into productive work activities, and specifically into higher-order tasks, but also more routine tasks, rather than using the time saved for rest, personal matters or leisure.

The most commonly reported use of time saved by GenAI is undertaking other more complex, creative job tasks, selected by 61.7% of RoI workers and 53.6% of NI workers who report time savings. This is the only activity that receives a clear majority response in both jurisdictions and, notably, it is the only item in the battery that sits above the 50% majority threshold in the RoI.

The second most common use of saved time is undertaking more routine, repetitive job tasks, reported by 45.9% of RoI workers and 46.7% in NI, near-identical rates in the two jurisdictions, and the only item in the battery where the RoI and NI are essentially indistinguishable. That nearly half of all workers in both jurisdictions use their GenAI-generated time savings to carry out more routine work may initially seem counterintuitive, given the common assumption that AI tools liberate workers from exactly this type of activity. However, it is consistent with the reality that most jobs contain a mixture of task types, and that completing AI-assisted tasks more quickly can free up capacity for a broader range of activities, including those that are themselves routine but

Figure 9: How the time saved was invested



that had previously been deferred due to time pressure. It also reflects the heterogeneity of GenAI applications in the workplace: workers who use AI primarily for cognitively demanding tasks such as drafting or analysis may find that the time saved is reinvested in the more administrative and operational dimensions of their role.

A closer examination of the joint distribution of these two items reveals that the routine complex and creative categories are not mutually exclusive in practice. In the RoI, 20.9% of GenAI users with time savings report undertaking both more routine and more complex/creative tasks with the time freed up, a figure that directly supports the interpretation that GenAI-generated time savings are being reinvested across the full range of job activities rather than channelled exclusively into higher-order work. The largest single group in the RoI, 40.7%, report doing more complex/creative tasks only, while 24.9% report more routine tasks only and 13.3% report neither. In NI the pattern is directionally similar though the sub-sample is small: 42.6% report complex/creative tasks only, 36.8% routine tasks only, and 10.3% both though the NI both-type figure should be treated with considerable caution given a base of only seven respondents.

The RoI finding that one in five GenAI users with time savings reinvests those savings across both task types simultaneously lends empirical support to the claim that AI tools do not simply displace routine work but can enable workers to attend to a broader portfolio of activities.

The remaining three activities, taking more rest breaks, undertaking personal or domestic duties, and pursuing leisure interests or hobbies, are each reported by fewer than 15% of workers in both jurisdictions. In the RoI, rest breaks are taken by 9.7% of time-saving workers, personal or domestic duties by 9.3%, and leisure interests by 7.9%. In NI, the equivalent figures are 7.6%, 9.2% and 13.0% respectively, with the leisure category being somewhat higher in NI than RoI, though the difference is modest and the NI base warrants caution.

The low rates of time redirection to non-work activities are striking and deserve comment. They suggest that the time savings generated by GenAI are being captured almost entirely within the sphere of paid work rather than being translated into reduced work effort, increased personal time, or a general expansion of work-life balance. Whether this reflects workers' genuine preferences, implicit or explicit employer expectations about time use, or simply the nature of the work contexts in which GenAI-using workers are typically employed, professional, full-time, salaried roles with high task demands, is a question that the data cannot fully resolve. What can be said is that, at present, the benefits of GenAI-generated time savings appear to accrue predominantly to the employer in the form of greater work output rather than to the worker in the form of reduced effort or expanded personal time. This finding is consistent with the broader literature on the distribution of productivity gains from technological change and underlines the importance of attending to how the benefits of AI adoption are divided between workers and organisations.

Further, the findings suggest that the time freed up by GenAI is being reinvested mainly in more demanding and cognitively intensive work. However

alongside this almost half of workers in both jurisdictions use the time savings to do more mundane, repetitive tasks. While this is not an even split it is a close one. It would appear then that GenAI is functioning, at least in workers' own accounts, as a complement to rather than a substitute for higher-order human judgement and creativity. Workers are not simply doing the same tasks in less time; the majority, particularly in the RoI, are using the time released by AI assistance to engage with more complex aspects of their roles.

This finding has important implications for the debate on the productivity effects of AI. Where AI tools are deployed primarily to automate routine or repetitive elements of a job, the reallocation of freed time to more complex tasks implies a qualitative upgrading of the work that humans perform, a pattern that, if sustained at scale, could contribute to skill development and job enrichment rather than deskilling. It also provides some grounds for optimism about the longer-run employment consequences of AI adoption: if the dominant response to AI-generated time savings is to engage more intensively with complex and creative work, the aggregate demand for skilled human labour may prove more resilient than some displacement scenarios anticipate. However, we need to be cautious and not over-read our findings as many workers use AI to do yet more routine tasks. Here, this might lead to job displacement: if the technology permits a worker to do more of the repetitive work of a colleague, that colleague may no longer be necessary.

Finally, we examine the expectation that employer-integrated tools would generate greater time savings than standalone tools finds only partial support in the RoI data. Integrated-only users in the RoI are broadly similar to standalone users in their time savings profile, 29.5% of workers save 25% or more of their working time, compared with 29.9% for standalone users, a negligible difference. It is workers who use both tool types who stand apart: 40.6% of both-type users save 25% or more of their working time, and 17.4% save 50% or more of their time, nearly double the standalone rate of 9.0%. In NI, the pattern is directionally similar though all sub-samples are small: both-type users (50.0%) and integrated-only users (42.9%) save more time than standalone users (57.1% standalone NI is notably high but based on only 42 respondents).

In sum, then, the time use data presented here show that the GenAI-generated time savings are being deployed both into more complex and creative work and by undertaking additional routine tasks. Non-work uses of saved time remain marginal. Taken together with the finding that a substantial majority of GenAI users report at least some time savings, these results suggest that GenAI is, in workers' own assessment, functioning primarily as a productivity-enhancing technology.

GenAI and innovation at work

We asked respondents whether their use of GenAI had made them more or less innovative in their work. The results in Table 10 indicate that while the majority in both jurisdictions reported it had helped them be more innovative, there are differences in degree. In the RoI, 18.5% report becoming a great deal more innovative, and 36.2% moderately more innovative, a combined 54.7% reporting meaningful

Table 10. Impact of GenAI on innovativeness at work

Level of innovativeness	RoI %	NI %
A great deal more innovative	18.5	21.0
Moderately more innovative	36.2	50.0
A little more innovative	35.4	24.0
No more innovative	8.4	5.0
Less innovative	1.5	0.0
N	420	34

innovation gains. In NI, these figures are notably higher: 21.0% and 50.0% respectively, giving a combined figure of 71.0%. Both figures stand in contrast to a small minority who report no change or reduced innovativeness.

We also asked respondents whether they had used AI to generate particular innovation outcomes. The results are reported in Table 11. A pronounced jurisdictional difference emerges in respect of the type of innovation pursued. In the RoI, the great majority (75.9%) use GenAI to make improvements to work processes that lead to increased efficiencies or productivity. Only 15.8% use it to improve existing products or services, and 8.3% to develop entirely new products or services. In NI, by contrast, while process improvement remains dominant (64.7%), a higher proportion pursue product improvement (20.6%) and new product or service development (14.7%). This suggests NI workers are more oriented towards product and service innovation relative to their RoI counterparts.

We turn next to examine whether the types of innovations undertaken by workers varies by whether they use standalone GenAI tools, integrated GenAI tools, or both. In the RoI, integrated-only users are the most process-oriented of the three groups: 80.0% report process improvements as their main innovation outcome, compared with 74.4% for standalone users and 77.2% for both-type users. New product development is lowest among integrated users (3.6%), well below standalone (8.2%) and both-type (8.9%) users. In NI the integrated-only sub-sample is too small to interpret reliably (n=3), but the both-type NI users show the highest rate of new product development (25.0%).

The RoI finding that employer-integrated tools are more strongly associated with process improvement, and less with product innovation, than standalone tools is surprising given the organisational investment implied by integration. One plausible interpretation is that employers who embed GenAI into production processes do so precisely

Table 11: GenAI use for innovation purposes

Innovation Type	RoI	NI
Make improvements to work processes–increase efficiencies/ productivity	75.9%	64.7%
Make improvements to existing products/services	15.8%	20.6%
To develop new products/services	8.3%	14.7%

Note: RoI N = 324; NI N = 34

to drive efficiency gains in existing workflows, rather than to stimulate product innovation. The tool design reflects the employer's intent: integrated systems are engineered for operational improvement, while workers using standalone tools may exercise more discretion in directing their GenAI use toward creative and innovative ends. This finding has implications for how organisations frame their AI investment strategies, and may warrant further exploration in the multivariate analysis.

Improvements in the quality of people's work outputs

With respect to whether workers' use of GenAI is associated with improvements in the quality of their work, similar patterns emerge across both jurisdictions, though NI workers report more substantial gains. See Table 12. In the RoI, 16.7% report large quality improvements, 37.1% moderate, and 35.1% small. Very few believe their use of AI is associated with no quality improvements or a deterioration: 9% in the RoI. In NI, 34.5% report large quality improvements, a figure more than twice the RoI equivalent, while 36.2% record moderate improvements and 24.1% small improvements.

We performed Spearman's rank-order correlations between the overall extent of training they have undertaken to develop GenAI expertise as well as their self-assessed competence in using GenAI and workers' assessment of the impact of GenAI on the quality of their work. The correlation between training extent and work quality improvement is rho = −.092 (p = .083, n = 358), which does not reach statistical significance at the conventional 0.05 threshold. Training volume, in other words, does not independently predict perceived work quality improvement in this sample. This finding is consistent with the pattern observed for time savings in the preceding section, where training extent was significantly correlated with time savings but at a weaker level than competence. The non-significance of the training-quality relationship here, combined with the significant competence-quality relationship, is consistent with a mediated model in which training influences quality outcomes primarily through its effect on competence, training builds skill, and skill improves quality, rather than through any direct effect of training volume on quality perceptions.

The borderline p-value of .083 and the reduced sample size of n=358, reflecting the sub-population of workers who both undertook training and rated quality impact, suggest that the absence of significance should not be interpreted as strong evidence of no relationship. With a larger sample,

Table 12. Impact of GenAI on work quality

Quality impact	RoI %	NI %
Large improvement	16.7	34.5
Moderate improvement	37.1	36.2
Small improvement	35.1	24.1
No improvement	5.7	3.4
Some reduction in quality	4.5*	1.7
N	372	29

* Combines 'small', 'moderate' and 'large' reduction categories in the RoI.

a modest positive association between training extent and quality outcomes might well emerge. The finding is better characterised as inconclusive than as a definitive null result.

On the other hand, the correlation between self-assessed competence and perceived work quality improvement is rho = −.282, significant at the 0.01 level ($p < .001$, $n = 428$). The negative sign requires careful interpretation. The question is coded so that lower values correspond to greater quality improvement, that is, 'large improvement' is coded as 1 and 'some reduction in quality' as 5. The negative coefficient therefore indicates a positive substantive relationship: workers who rate their GenAI competence more highly are more likely to report larger improvements in the quality of their work as a result of using GenAI. This is the strongest and most directly interpretable finding in the correlation analysis.

The magnitude of rho = −.282 is modest but substantively meaningful. The consistency of direction is notable: competence is positively associated with both of the principal productivity outcomes examined in this report, time savings and work quality improvement, lending further weight to the possibility that the development of genuine GenAI skill is an important mediating factor between AI adoption and the realisation of productivity gains. Workers who have invested in developing their GenAI capabilities, whether through formal training or self-directed learning, appear to be substantially better placed to benefit from the technology than those who use it with limited preparation.

Impact of the use of GenAI on working conditions

We further enquired of the effects the use of GenAI had on various aspects of people's job quality. In most respects the effects are similar across both jurisdictions, though two dimensions stand out. First, earnings: while only 4.7% of RoI workers report that GenAI has increased their earnings, the figure is substantially higher in NI at 20.0%, though this should be interpreted cautiously given the small NI sub-sample. Second, autonomy: 24.3% of NI workers report an increase in their level of autonomy in organising their work, compared with 14.8% in the RoI.

The most widely reported impact across both jurisdictions is on skill levels: about half of GenAI users in both the RoI and NI report that their skill levels have increased. Work pace or intensity has increased for 33.7% of RoI users and 30.4% of NI users. Very few in either jurisdiction report a shortening of their working day (RoI: 10.5% report a decrease; NI: 17.4%).

Workers' attitudes towards GenAI

Finally, we examine the reasons why workers, who use AI in their work currently, would envisage that they will not use it more extensively in the future. We first asked if *"Over the next two years, do you think your usage of GenAI for your work will greatly increase, moderately increase, stay the same, moderately decrease, greatly decrease, or stop entirely."* The great bulk of GenAI users in both jurisdictions expect to increase their use of AI tools over the next two years. In the RoI, 33.3% expect to greatly increase their usage and 28.5% moderately increase, giving a combined increase of 61.8%,

Table 13. Effects of GenAI on working conditions

	RoI (n≈739–749)				NI (n=69)			
Working condition	**Increased**	**No change**	**Decreased**	**N**	**Increased**	**No change**	**Decreased**	**N**
Your skill levels	47.3%	50.7%	2.0%	749	50.0%	47.1%	2.9%	70
Pace or intensity of work	33.7%	59.4%	7.0%	748	30.4%	56.5%	13.0%	69
Your level of autonomy	14.8%	83.3%	1.9%	748	24.3%	72.9%	2.9%	70
Interaction with colleagues	12.4%	81.9%	5.7%	741	15.9%	79.7%	4.3%	69
Chance of losing your job	12.4%	81.6%	5.9%	740	8.7%	81.2%	10.1%	69
Length of working day	2.5%	86.9%	10.5%	749	1.4%	81.2%	17.4%	69
Amount of money you earn	4.7%	93.6%	1.7%	749	20.0%	77.1%	2.9%	70

alongside 22.4% who expect a slight increase. Taken together, 84.2% of RoI GenAI users anticipate at least some increase in their use. In NI, the figures are very similar: 35.7% expect to greatly increase usage, 28.6% moderately, and 21.4% slightly, a combined 85.7% expecting some increase. Only small minorities in either jurisdiction expect to decrease or cease their use.

We asked this latter group of workers, 16% of GenAI users *"Why do you think your use of GenAI for your work will not increase over the next two years?"* The primary reason workers report is that their work is not suitable for using AI or they can undertake their work without the assistance of AI. Other impediments relate to the perceived reliability and trustworthiness of AI outputs, and inadequate training provision. It is of interest that few if any workers report fears relating to job security or job satisfaction.

Table 15 presents the reasons given by workers across the island of Ireland, combining respondents from the Republic of Ireland and Northern Ireland, for not planning to increase their use of GenAI, or for currently not using it. The combined all-island sample for this battery is 129 respondents (RoI n=119; NI n=10),

Table 14. Future intentions for GenAI use over the next two years

Intention	RoI %	NI %
Greatly increase	33.3	35.7
Moderately increase	28.5	28.6
Slightly increase	22.4	21.4
Stay the same	12.8	11.4
Decrease or stop	3.0	2.9
N	745	70

Table 15: Reasons for GenAI use not increasing over the next two years

Reason for not increasing / not using GenAI	% Yes (N)
My work is not suitable for using GenAI	35.7% (46)
I can do my work perfectly well without using GenAI	29.5% (38)
The input data is of insufficient quality to generate usable output	16.3% (21)
I do not trust AI generated outputs	13.2% (17)
I am worried about the data security risks of using GenAI	11.6% (15)
I have not been trained to use GenAI	9.3% (12)
Don't know	5.4% (7)
If I use GenAI I would gain less satisfaction from my work	4.7% (6)
My employer actively discourages me from using GenAI	1.6% (2)
I am afraid GenAI would replace me and I would lose my job	0.8% (1)
Other	42.6% (55)

and all figures should be treated with considerable caution given the small base. The NI sub-sample of ten is too small to permit separate jurisdictional analysis, and results are therefore presented on a combined all-island basis throughout this section.

Among the structured response options, the two most commonly cited reasons relate to task relevance rather than fear or distrust. Just over a third of all-island respondents (35.7%, n=46) indicate that their work is not suitable for using GenAI, and 29.5% (n=38) state that they can do their work perfectly well without it. These findings are important as they suggest that the primary barrier to further GenAI adoption among current GenAI users is not technological anxiety, mistrust or organisational constraint but rather a pragmatic assessment of fit: workers who do not use or plan to increase their use of GenAI largely believe that the technology does not add value in their specific work context.

Technical and quality concerns account for a smaller but non-trivial share of responses. Sixteen per cent of respondents (n=21) indicate that input data is of insufficient quality to generate output they can reliably use, and 13.2% (n=17) state they do not trust AI-generated outputs. These findings point to a distinct category of barrier, not task unsuitability but rather dissatisfaction with the current quality and reliability of GenAI outputs in their specific application contexts. Security concerns are cited by 11.6% (n=15), a figure that sits in interesting contrast with the much higher proportion of GenAI users, 78.5% in the RoI, who report fully understanding security risks. Among the non-increasing group, security awareness appears to translate more directly into a behavioural constraint, suggesting that risk knowledge and risk aversion are not always aligned in the broader user population.

Training absence is cited by 9.3% (n=12) of respondents as a reason for not increasing their GenAI use, a figure that is modest in absolute terms but meaningful in the policy context of this report. In a survey where nearly three-fifths of all GenAI users in the RoI have undertaken less than one day of training in total, the relatively low salience of training as a stated barrier among non-increasing

users might initially seem surprising. It is, however, consistent with a pattern in which training absence is not necessarily perceived as a primary obstacle, particularly among workers who have already concluded that GenAI is not well-suited to their work, but which may nonetheless function as an implicit barrier by limiting workers' awareness of the range of tasks for which AI tools could be productively deployed.

At the lower end of the distribution, fear of job replacement, the concern that using GenAI would ultimately lead to the worker being replaced by the technology, is cited by just 0.8% of all-island respondents (n=1). Reduced job satisfaction is cited by 4.7% (n=6), and employer discouragement by 1.6% (n=2). These would then appear to be marginal concerns among the non-increasing user group. The near-absence of displacement anxiety as a stated barrier to increased GenAI adoption as reported here in Table 15 should however be read and interpreted alongside the finding from the attitudes battery above where a substantial number of current GenAI users, 41% (RoI) and 37% (NI), believe that new AI tools will not create more jobs. Our reading of this evidence is that workers who use GenAI tools and who intend to continue to use them in the future are watchful and mindful of the employment risks that accompany their use of AI tools.

Perhaps, the most striking feature of the data is the scale of the 'Other' category, selected by 42.6% of respondents (n=55). This is the most frequently selected response in the battery and suggests that a substantial proportion of non-increasing users hold reasons for their position that are not adequately captured by the structured response options. The open-text responses associated with this category, while not reported quantitatively here, reveal a diverse set of motivations including practical constraints on further use, task saturation, scepticism about GenAI's applicability to specific job types, concerns about over-reliance, and in some cases moral or professional objections. The prevalence of this category underlines the heterogeneity of non-increasing users and suggests that any account of barriers to GenAI adoption that relies solely on structured survey items risks underestimating the complexity of workers' reservations.

Therefore, the barriers data paint a picture of non-increasing GenAI users as a group whose position is driven primarily by pragmatic task assessments and, to a lesser degree, by quality and security reservations, rather than by fear, distrust or employer constraint. The dominance of task-fit considerations as a barrier is an important finding for AI adoption policy: it implies that interventions aimed at expanding GenAI adoption through training provision or awareness-raising will have limited effect among workers whose work is genuinely unsuited to current AI capabilities. Sustainable expansion of AI use across the workforce will require not only investment in skills and training but also the continued development of AI applications that are relevant to the full range of occupational tasks, including those that are currently considered beyond the technology's effective reach.

9. Implications for policy makers and organisations

AI isn't coming, it is here and it is spreading rapidly. Are we ready for it? Have we the governance systems in place? Are people trained to use it responsibly? Will it benefit us? If it is to, how can we ensure that the gains are not disproportionately acquired by one party but that they are distributed fairly so as to improve the conditions of employment and living standards of those who use it? These are among the pressing questions confronting policy makers, employers, employee representatives and workers. The answers, however, are not self-evident. One of the telling lessons of the history of the introduction of new technologies is that they have no automatic effect: progress is not preordained (Acemoglu and Johnson, 2023; Frey, 2025). Outcomes depend on the choices WE make.

The findings from the Working in Ireland Survey 2025 come an important time for public policy formulation in respect of AI this small island. Our report details the extensive use of this new technology across workplaces both in the Republic of Ireland and Northern Ireland. However, we find its adoption to be uneven and unequal. We further find that training provision is chronically insufficient and organisational governance is patchy and weak. The productivity gains from AI adoption are considerable but at this point they are flowing predominantly to employers and not to workers. These findings occur against a backdrop of an evolving and still-unsettled European and national regulatory landscape for artificial intelligence, one that, at the time of writing (May 2026), has produced significant legislative activity at EU level but whose translation into substantive protections for workers in their everyday encounters with AI remains incomplete. The circumstances in this regard are not dissimilar in Northern Ireland. We address the implications for both policy-makers and organisations in turn drawing on the evidence from WIIS 2025 and on the relevant legislative and policy frameworks.

The EU AI Act and Its Implications for Workers

We turn first to look at the regulatory context in respect of AI adoption and use as it pertains to the Republic before then examining the regulatory context in Northern Ireland.

The primary legislative instrument governing AI in the European Union is Regulation (EU) 2024/1689, commonly referred to as the EU AI Act, which entered into force on 1 August 2024 and has applied in full since 2 August 2025, with certain provisions for high-risk systems phased in across a two-year transitional period. The Act establishes a risk-based regulatory framework that categorises AI systems into unacceptable risk (prohibited), high risk, limited risk and minimal risk, with corresponding obligations on providers and deployers. For workplace AI, the most immediately relevant provisions are those governing high-risk AI systems, which include AI tools used

in employment and human resources management contexts, for example, for recruitment and selection, work allocation, monitoring of workers' performance, or decisions about promotion, dismissal and access to training (Annex III, Article 6).

Under the Act, deployers of high-risk AI systems in employment contexts are subject to a series of obligations including: designating a responsible person for AI governance; ensuring adequate human oversight; conducting conformity assessments and maintaining logs; notifying workers and their representatives of the use of high-risk AI systems that affect or may affect them; and ensuring that workers operating high-risk systems have appropriate training in AI literacy (Article 4, Article 26). The obligation on Member States to promote AI literacy is broadly stated in Article 4: providers and deployers shall take measures to ensure, to the best of their ability, that their staff and other persons dealing with the operation of AI systems on their behalf have a sufficient level of AI literacy, taking into account their technical knowledge, experience, education and training, and the context the AI systems are to be used in.

These provisions are directly pertinent to the WIIS 2025 findings. The survey documents a workforce in which the majority of GenAI users are self-taught, formal employer training is typically limited to less than a day, and training on the disadvantages and risks of AI is rated 10 percentage points less positively than training on its benefits. The AI Act's AI literacy obligation, however broadly worded, provides a legislative foundation for requiring employers to invest in substantive training that equips workers not merely to use AI productively but to do so responsibly, with awareness of its limitations, biases and risks. The challenge is that the Act's literacy provision is framed as a best-efforts obligation rather than a hard minimum standard, and its implementation in practice will depend heavily on enforcement by National Competent Authorities. In Ireland, responsibility for enforcement of the AI Act in the employment context has yet to be definitively assigned, and the institutional architecture for oversight remains under development at the time of writing.

A further provision of relevance to workers is Article 26(7), which requires deployers to inform workers' representatives, where applicable, of the use of high-risk AI systems in the workplace before bringing them into use. This provision has the potential to strengthen the role of trade unions and employee representatives in the governance of AI adoption within enterprises, but it applies only to high-risk systems as classified under the Act, and many of the GenAI tools documented in WIIS 2025 (ChatGPT, Gemini, Copilot, Claude, etc.) are general-purpose AI (GPAI) systems that may or may not be deployed in high-risk contexts depending on their specific application. The Act imposes obligations on GPAI model providers (Articles 51–56) but its protections for workers in everyday workplace AI use, which falls below the high-risk threshold in most cases, are less robust.

The Algorithmic Management Directive and Transparent Working Conditions

A more directly worker-centred set of provisions is contained in the revised Platform Work Directive, Directive (EU) 2024/2831 adopted in November

2024, which, while primarily directed at platform and gig workers, contains provisions on algorithmic management and transparency that are of broader significance for AI governance in the workplace. The Directive requires that platform workers be informed about the use of automated monitoring and decision-making systems affecting their work, be afforded the right to request human review of automated decisions, and that their representatives have access to information about such systems. These provisions represent the most advanced example in current EU law of algorithmic transparency obligations directed specifically at workers.

The more general instrument on transparent working conditions is Directive (EU) 2019/1152 on transparent and predictable working conditions, transposed into Irish law through the Employment (Miscellaneous Provisions) Act 2018 as amended and the European Union (Transparent and Predictable Working Conditions) Regulations 2022. While this Directive predates the widespread adoption of GenAI, its principle that workers must be informed of the essential aspects of their working arrangements, including the tools and systems used in their work, provides a basis on which obligations of AI disclosure and transparency might be further developed in national law. As of the time of writing, Irish employment law does not contain a general right for workers to be informed of the use of AI systems in the management of their work, outside the specific provisions applicable to platform workers and the limited high-risk notifications under the AI Act.

Data Protection Law and the Use of GenAI at Work

The use of GenAI in the workplace raises significant data protection concerns that are directly relevant to the WIIS 2025 findings. The General Data Protection Regulation (GDPR), Regulation (EU) 2016/679, which is directly effective in Ireland and given further effect through the Data Protection Acts 1988–2018, imposes obligations on employers - as data controllers - with respect to any personal data processed through the use of AI tools by their workers. Where workers input personal data, including data relating to colleagues, clients or customers, into GenAI systems such as ChatGPT or Gemini, whose training and processing architecture involves data transfer to third-country providers, the employer may be in breach of its GDPR obligations unless appropriate data processing agreements are in place and workers are trained not to input personal data into non-approved systems.

The findings from the WIIS 2025 survey document a workforce in which only 52.2% of RoI workers and 36.5% of NI workers are covered by an official employer policy on GenAI use, and in which the training on security risks is among the least highly rated dimensions of employer provision. The Data Protection Commission (DPC) in Ireland has issued guidance on the use of GenAI tools and the obligations of data controllers. However, its translation into workplace policies and worker training remains inadequate based on the evidence of the WIIS 2025. The 11.6% of workers who cite security concerns as a reason for not increasing their GenAI use, combined with at least a fifth of the workforce who concede they do not fully under-

stand the understand the security risks pertaining to AI use, suggests an awareness-action gap that workplace governance and training must address. Under Article 39 of the GDPR, the role of the Data Protection Officer within organisations encompasses employee training and awareness. However, the absence of adequate AI-related training documented in WIIS 2025 may constitute a governance loophole that exposes organisations to regulatory risk as well as to the substantive data protection harms the GDPR is designed to prevent.

The Irish Government's AI Strategy and the National AI Action Plan

The Irish Government's National Artificial Intelligence Strategy, AI: Here for Good, was first published in 2021 and updated in 2023. It sets out a vision for Ireland to be a global leader in the development and deployment of human-centric and trustworthy AI, building on Ireland's position as a host to many of the world's leading technology companies. The Strategy's emphasis on human-centric AI and trustworthy deployment is broadly aligned with the values underpinning the EU AI Act, and it acknowledges the importance of AI literacy and skills development across the workforce. Responsibility for implementation sits with the Department of Enterprise, Tourism and Employment, which chairs an AI Ambassador programme and funds a range of enterprise digitalisation supports through Enterprise Ireland and the IDA.

The recently published Department of An Taoiseach report entitled, Digital Ireland Connecting our People, Securing our Future (2026), rehearses the ambitions outlined in previous strategy reports. It also recognises the importance of equipping the country's workforce with the requisite digital skills to use AI responsibly. It further recognises the possibility that AI may lead to job displacement and of the need for the Government to support any workers that may so loose their jobs with "agile, accessible and fit-for-purpose upskilling and reskilling opportunities" (p.08). To this end, too, the Strategy commits to the establishment of a National Skills Observatory to research labour market trends and skills needs, as well as an Observatory for Business AI Readiness which will examine the use of AI by enterprises in Ireland. While the ambitions set out in these various strategy reports are noble and worthy, they must be set against the WIIS 2025 findings. Certainly the 2021 and 2023 Strategy documents aspirations for a broadly skilled, well-governed AI workforce are not yet matched by conditions on the ground.

The Strategy's workforce skills pillar focuses primarily on the supply of technical AI talent, data scientists, machine learning engineers, AI researchers, rather than on the AI literacy needs of the much larger population of workers who are using GenAI tools in non-technical roles. The finding that 65.2% of RoI GenAI users have taught themselves, and that only four in ten employees have received employer training on GenAI use, suggests there is a significant implementation gap between the Strategy's ambitions and the lived reality of AI adoption in the Irish workplace. The Government's updated National Action Plan, published in 2024, makes provision for awareness campaigns and literacy initiatives through Skillnet Ireland and the tertiary education sector, but these are directed primarily

at businesses and at those entering the workforce, rather than at the existing workforce in which, as WIIS 2025 documents, GenAI is already extensively deployed.

A further gap in the Irish policy response concerns the distributional dimensions of AI adoption. Neither the National AI Strategy nor the Action Plan addresses with any specificity the findings, confirmed by WIIS 2025, that AI adoption is highly concentrated among higher-earning, more highly educated workers in larger firms, and that the productivity gains it generates are being captured predominantly by organisations rather than by workers. The broader economic literature, and other European countries overseeing actors such as the French Government's AI Commission (2024), suggests that AI's potential to increase aggregate productivity is considerable, but that the realisation of this potential in terms of broadly shared economic welfare depends on deliberate policy choices about distribution, bargaining and labour market governance. The Irish Government's AI strategy does not, at present, engage with these distributional questions in any depth.

Northern Ireland: A Distinct Policy Context

Northern Ireland's AI policy context is distinct from that of the Republic in two important respects. First, as part of the United Kingdom following Brexit, Northern Ireland is outside the direct application of the EU AI Act, though it remains subject to GDPR (retained in UK law as the UK GDPR under the Data Protection Act 2018) and to the UK Government's AI governance framework. The UK has adopted a sector-led, principles-based approach to AI regulation, articulated through the AI Safety Institute and a series of pro-innovation policy documents, rather than the more prescriptive risk-based regulatory approach of the EU. At the time of writing, the UK has not introduced legislation equivalent to the EU AI Act, though a draft AI Bill has been under consideration. This regulatory divergence between the RoI and NI creates a differential governance environment for employers operating across both jurisdictions, a consideration of direct relevance given WIIS 2025's documentation of lower employer policy coverage in NI (36.5%) than in the RoI (52.2%).

Second, the Northern Ireland Executive's own AI strategy, AI Strategy for Northern Ireland, published in 2022, emphasises the role of AI in economic growth and public service improvement, with a particular focus on skills development through Invest NI, the Department for the Economy and further education institutions. The strategy acknowledges the workforce dimension of AI adoption but, like its Irish counterpart, is primarily focused on AI as a business and economic opportunity rather than on the distributional and governance challenges that the WIIS 2025 data document. The finding that only 36.5% of NI employees work in organisations with an official GenAI policy suggests that the Strategy's governance ambitions are not yet translating into workplace reality.

Implications for Government

Drawing together the WIIS 2025 findings and the legislative and policy context reviewed above, we identify five priorities for government action. First, the Republic of Ireland and Northern Ireland governments should both develop, or substantially strengthen, national workplace AI gov-

ernance frameworks that go beyond the minimum requirements of the EU AI Act and UK equivalent. The WIIS 2025 data document that the most consequential governance failures in Irish workplaces are not in high-risk AI deployment, the primary focus of the Act, but in the everyday use of general-purpose AI tools by workers without adequate training, policy guidance or oversight. A national code of practice for employer AI governance, developed in partnership with employer bodies, trade unions and civil society, and given legal underpinning through employment legislation, would represent a proportionate and practically effective response. Such a code should require, at minimum: the publication of a workplace AI policy by employers above a threshold size; adequate and documented training for all workers who use AI tools; clear protocols for AI output labelling and human oversight; and the establishment of consultation mechanisms through which workers and their representatives can raise concerns about AI deployment.

Second, the Republic of Ireland government should substantially increase investment in GenAI training provision for the existing workforce, with particular attention to lower-paid, lower-skilled and part-time workers who are currently the least likely to receive employer training and the most likely to be disadvantaged by AI-driven labour market change. The current provision through Skillnet Ireland, SOLAS and the National Training Fund is insufficient in scale and is disproportionately directed at upskilling for technical AI roles rather than at AI literacy for the broader workforce. A dedicated programme of workplace AI literacy training, delivered through employer-union/employee partnerships and accessible to workers at all skill levels, would help to address both the competence deficit documented in WIIS 2025 and the equity dimensions of AI adoption. In Northern Ireland, the Department for the Economy and Invest NI should take equivalent action through the further education sector and through the Skills Strategy for Northern Ireland.

Third, both governments should act to ensure that the distributional implications of AI adoption, who benefits and who bears the costs, are placed firmly on the policy agenda. The WIIS 2025 finding that productivity gains from GenAI are being captured predominantly by organisations, and that only 4.7% of RoI workers report any increase in earnings from AI use, raises important questions of economic justice that the current policy frameworks do not adequately address. Options for government action include: requiring large employers to report on the workforce impacts of AI adoption as part of annual reporting obligations; extending the remit of the Low Pay Commission to include assessment of AI's effects on wages and working conditions in low-pay sectors; and exploring, in partnership with employers and unions, whether AI-driven productivity gains should be linked to improvements in workers' terms and conditions through collective bargaining or profit-sharing mechanisms.

Fourth, the Republic of Ireland government should ensure that the transposition and enforcement of the EU AI Act is accompanied by specific guidance for employers and workers on its application in employment contexts, and that the National Competent Authority designated to oversee the Act's employment provisions has adequate resources

and expertise to fulfil this role. The Act's AI literacy obligation (Article 4) and the high-risk worker notification requirement (Article 26(7)) are potentially significant instruments for improving workplace AI governance, but their effectiveness depends entirely on enforcement. Given the documented gap between existing governance obligations (under GDPR, working conditions law and health and safety legislation) and actual employer practice, there is no basis for assuming that the Act's new obligations will be complied with voluntarily and without active regulatory engagement.

Fifth, the Irish Government should consider the implications of the WIIS 2025 findings for its public procurement and state aid policies. A growing number of European governments are conditioning access to public contracts and state supports on compliance with specific labour standards, including training obligations and worker consultation requirements. Extending this principle to AI governance, requiring, for example, that firms receiving state support through Enterprise Ireland, IDA Ireland or Invest NI have a documented workplace AI policy and adequate training provision in place would leverage the State's purchasing and investment power to raise governance standards across the economy, and would be consistent with the EU's procurement directives and with Ireland's commitments under the European Social Pillar.

Implications for Organisations

The WIIS 2025 findings also carry direct implications for the practices of employing organisations, independently of the regulatory requirements discussed above.

The finding that self-assessed competence, not training extent, may be an important driver of productivity gains from GenAI should cause employers to think again about AI training investment. The correlation evidence in this report is consistent with a model in which short, compliance-driven training, a briefing session, an online module or a policy document, produces little measurable benefit for workers or for the organisation. What workers need, and what the data suggest organisations are failing to provide, is substantive, sustained training that develops genuine ability to use AI tools effectively, critically and responsibly. This means training that covers not just the productive applications of GenAI but also its hallucination risks, its implicit biases, its data protection implications, its output reliability limitations and the circumstances in which human judgement must override AI-generated content. The 10-percentage-point gap in training quality ratings between advantages and disadvantages training in the RoI is a direct indicator of where the greatest training deficit lies: in risk literacy, not in capability promotion.

The governance findings are equally stark. Barely half of RoI workers and fewer than four in ten NI workers are covered by an official employer policy on GenAI use. This is not merely a compliance failure but a strategic risk for organisations. Workers who use GenAI without policy guidance may inadvertently breach GDPR by inputting personal data into third-party AI systems; may produce AI-assisted outputs that are inaccurate, biased or confidential; may expose the organisation to reputational, legal or financial liability; and may undermine the quality standards that the organisation itself is seeking to maintain. The finding

that around three-quarters of workers report understanding security risks, yet only a half work under a policy framework that provides guidance on those risks, describes an organisational governance gap that leaves workers exposed and organisations unprotected. Developing and implementing a clear, accessible and regularly updated AI use policy is among the most straightforward steps organisations can take to improve this situation, and the investment required is modest relative to the risks of inaction.

The distributional findings raise a more challenging set of implications for organisations that go to the heart of the employment relationship. The evidence that workers are directing GenAI-generated time savings predominantly back into productive work, rather than to rest or personal time, is consistent with a pattern in which the organisation, not the worker, is the primary beneficiary of AI-driven productivity gains. This pattern is not inevitable. Where organisations choose to share AI productivity gains with workers, through shorter working hours, reduced task loads, higher pay, or investment in workers' development, the evidence from the broader economics and management literature suggests they are likely to see returns in the form of greater employee commitment, lower turnover and higher trust (Brynjolfsson et al., 2025b). The question of how AI productivity gains are shared is, at its core, a question about the employment relationship and about how organisations understand their obligations to the workers on whom those gains depend.

Finally, the WIIS 2025 data on worker attitudes should give organisations grounds for measured optimism. Workers are not fearful of AI; they are not resistant to its use; and they are not naïvely uncritical in their engagement with it. The near-universal endorsement of human oversight, the low trust in unconditional AI output reliability, and the pragmatic rather than principled objection to adoption together describe a workforce that is well-positioned to engage constructively with AI governance frameworks, if such frameworks are provided. The challenge for organisations is not to persuade a reluctant workforce to accept AI, but to match the workforce's existing pragmatic sophistication about AI with the governance, training and policy infrastructure that responsible and productive AI use requires.

Conclusion

The Working in Ireland Survey 2025 documents a workforce that has adopted generative AI at a faster pace than many anticipated. It is already giving rise to substantial productivity effects, albeit in ways that disproportionately benefit those whose work-related tasks are more prone to be augmented by GenAI. In the main, too, these are workers who already enjoy an advantaged position in the labour market. The legislative and policy landscape, the EU AI Act, the GDPR, the National AI Strategy, and the emerging body of AI governance guidance in the Republic and Northern Ireland, provides important foundations for better outcomes. But the gap between regulatory aspiration and workplace reality, documented across almost every dimension of this survey, is substantial. Closing that gap will require sustained and coordinated effort from government, employers, trade unions and civil society. It will require investment in training that builds genuine competence rather than nominal compliance; governance frameworks that protect workers as well as organisations; and deliberate choices about how the economic gains from AI are shared. The Working in Ireland Survey will continue to monitor these dimensions in future waves, and we hope the evidence it provides will inform and sharpen the policy response.

An addendum – Workers' use of automated equipment and robotics

We provide this brief report on workers' use of automated equipment and robotics in their work as an addendum to our GenAI report. Both GenAI and robotic/automated machinery are key features of the use of digitalised equipment in the workplace. While the former, as we outline above, is often associated with work tasks involving writing, idea-generation, analytical reasoning and coding, as well as being more pronounced in its use in service-based industries, the use of automated machinery, including robotics, is more often related to physical tasks in manufacturing and logistics. The capital costs associated with robotic technologies are also considerably more expensive than those required in the use of GenAI tools.

WIIS 2025 asked respondents: "Does your job involve working with or using automated machinery, equipment or robots to carry out complex physical tasks?" The interviewer also prompted respondents thus: "This might include, for example, computer-controlled machines, virtual assistants, or robotic process automation."

The results indicate that whereas GenAI use is concentrated among knowledge workers, the use of automated machinery and robotics follows a markedly different pattern. Overall incidence is considerably lower than GenAI: 13.4% of RoI workers and 9.3% of NI workers report that their job involves working with or using automated machinery, equipment or robots, against the 29.3% (RoI) and 26.1% (NI) recorded for GenAI use. This is consistent with the expectation that physical automation technologies, unlike GenAI, are not general-purpose tools accessible from any desk or device but are tied to specific production and operational contexts.

The gender pattern for automated machinery use diverges sharply from that observed for GenAI. Where the GenAI gender gap was notably modest (1.2 percentage points all-island), the gap for automated machinery and robotics use is substantially wider and consistent in direction across both jurisdictions: men are roughly twice as likely as women to report working with automated machinery or robots in both the RoI (17.2% vs 9.2%) and NI (14.4% vs 3.5%). This is unsurprising given that automation and robotics use is concentrated in manufacturing and physical production roles, which remain male-dominated occupational categories.

Unlike GenAI, where adoption shows a clear inverted-U pattern peaking among 25–34 year-olds, automated machinery and robotics use declines more steadily and gradually with age in the RoI, from 16.8–17.0% among workers under 35 to around 9% among those aged 55–64, with the apparent uptick among 75+ workers (25.0%) reflecting a very small base (n=20) and warranting caution. In NI, the pattern is broadly similar though somewhat flatter, again falling away among older workers and dropping to near zero in the 65–74 and 75+ bands.

There is little difference in automated machinery use by employment contract type in either jurisdiction (RoI: 13.5% permanent vs 12.9% non-permanent; NI: 9.6% vs 9.1%), a pattern that contrasts with GenAI, where non-permanent workers in NI showed markedly lower adoption (19.0% vs 26.6%). This suggests that exposure to automated machinery is less tied to the security or seniority of one's contractual position than is exposure to GenAI tools.

For both jurisdictions, the educational pattern is the reverse of that found for GenAI. In the RoI, workers with up to short-cycle tertiary education report somewhat higher rates of automated machinery use (15.3%) than those with a college degree or above (12.2%), a finding consistent with the expectation that automated machinery and robotics are disproportionately encountered in production, manufacturing and operative roles rather than in the graduate-dominated professional and managerial occupations that drive GenAI adoption. The same direction holds in NI, though the gap is considerably narrower (10.2% vs 9.2%). This is an important point of contrast for the report to draw out: GenAI adoption is steeply stratified upward by education in both jurisdictions, while automated machinery use, if anything, is mildly stratified in the other direction, and consistently so across the island.

Private sector workers are markedly more likely to report automated machinery or robot use than those in the public sector or not-for-profit sector, in both jurisdictions (RoI: 16.8% private vs 8.3% public vs 4.4% not-for-profit; NI: 10.6% vs 8.4% vs 2.7%). This mirrors the broad direction of the GenAI sectoral findings, though the gap between private and public sector use is proportionally larger for automated machinery than for GenAI.

The industry-level findings provide the clearest illustration of where automated machinery is used. Manufacturing records by far the highest incidence of automated machinery and robotics use in both jurisdictions, 40.3% in the RoI and 17.7% in NI and dwarf those recorded in most other sectors. Agriculture, forestry, fishing and mining also record a comparatively high rate of use in the RoI (20.8%), though the NI base is too small to interpret (n=1). By contrast, sectors that recorded the highest GenAI adoption, ICT/professional services, financial services, and education, show comparatively low or middling rates of automated machinery use (13.0%, 10.8% and 4.0% respectively in the RoI), reinforcing that these are two largely distinct technological exposures concentrated in different parts of the workforce. Public administration and defence records the lowest rate in the RoI (3.5%).

Automated machinery and robotics use rises with organisation size in the RoI, from 11.0% in small firms to a peak of 15.5% in medium-sized firms, before easing slightly to 14.5% in large firms, broadly consistent with the positive size gradient observed for GenAI adoption, though the relationship here is less strictly monotonic. The NI pattern is essentially flat across firm sizes (between 7.8% and 10.6%), mirroring the comparatively weak or inverted size gradient already noted for GenAI use in NI.

As with GenAI, the relationship between earnings and automated machinery use should be examined separately for each ju-

risdiction given the different salary band structures and currencies. In the RoI, the relationship with salary is far less clear-cut than the striking, near-monotonic gradient observed for GenAI. Automated machinery use ranges narrowly between 7.0% and 24.2% across salary bands without a consistent upward trend, peaking in the €75,000–€89,999 band (24.2%, n=62) rather than at the very top of the distribution as GenAI adoption does. This is consistent with the broader picture that automated machinery use is tied to occupational and sectoral context (manufacturing, production) rather than to the income-linked, professional/managerial profile that characterises GenAI adoption. In NI, the salary sub-samples are very small throughout (most bands n<20) and the apparent 60.0% figure in the lowest band (n=5) should not be treated as reliable; the only bands with adequate sample sizes, £30,000–£39,999 (21.1%, n=57) and £40,000–£49,999 (11.1%, n=45), do not show a clear pattern either.

Table 1: Use of automated machinery, equipment or robots by demographics in the Republic of Ireland and Northern Ireland

	RoI	NI
Total sample		
Total	13.4% (n=3,032)	9.3% (n=1,245)
Gender		
Men	17.2% (n=1,586)	14.4% (n=666)
Women	9.2% (n=1,426)	3.5% (n=579)
Employment contract		
Permanent	13.5% (n=2,728)	9.6% (n=1,176)
Non-permanent	12.9% (n=303)	9.1% (n=77)
Age group		
16-24	16.8% (n=339)	11.7% (n=137)
25-34	17.0% (n=612)	10.5% (n=276)
35-44	13.2% (n=763)	9.2% (n=304)
45-54	12.4% (n=669)	10.8% (n=288)
55-64	9.1% (n=518)	7.9% (n=189)
65-74	9.0% (n=111)	1.9% (n=52)
75+	25.0%† (n=20)	0.0%† (n=6)
Education		
Up to short-cycle tertiary	15.3% (n=1,276)	10.2% (n=638)
College degree or above	12.2% (n=1,723)	9.2% (n=563)

Sector of employment		
Private sector	16.8% (n=1,698)	10.6% (n=593)
Public sector	8.3% (n=819)	8.4% (n=419)
Not-for-profit / NGO	4.4%† (n=90)	2.7%† (n=37)
Sector		
Agriculture, forestry, fishing & mining	20.8% (n=125)	0.0%† (n=1)
Energy & Construction	13.2% (n=280)	14.5% (n=110)
Wholesale & retail	10.8% (n=372)	11.1% (n=199)
Transport & hospitality	9.1% (n=319)	8.6% (n=128)
ICT, prof., scientific, tech., admin & support, arts & other services	13.0% (n=647)	10.3% (n=234)
Financial services & real estate	10.8% (n=139)	4.4%† (n=45)
Public administration & defence	3.5% (n=170)	5.0% (n=80)
Education	4.0% (n=278)	5.0% (n=121)
Human health	10.3% (n=379)	6.6% (n=211)
Manufacturing	40.3% (n=290)	17.7% (n=96)
Organisation size		
Small (1-49 employees)	11.0% (n=692)	10.6% (n=273)
Medium (50-249 employees)	15.5% (n=471)	7.8% (n=193)
Large (250+ employees)	14.5% (n=1,327)	9.4% (n=522)
Salary - Republic of Ireland (euros)		
Under €15,000	14.9%† (n=47)	-
€15,000-€29,999	7.0% (n=100)	-
€30,000-€44,999	7.9% (n=215)	-
€45,000-€59,999	15.5% (n=194)	-
€60,000-€74,999	17.6% (n=131)	-
€75,000-€89,999	24.2% (n=62)	-
€90,000-€109,999	14.3%† (n=28)	-
€110,000 or more	16.3%† (n=43)	-
Salary - Northern Ireland (pounds sterling)		
Under £12,000	-	60.0%† (n=5)
£12,000-£17,999	-	7.7%† (n=13)
£18,000-£23,999	-	0.0%† (n=15)
£24,000-£29,999	-	5.9%† (n=34)
£30,000-£39,999	-	21.1% (n=57)
£40,000-£49,999	-	11.1% (n=45)
£50,000-£69,999	-	15.4%† (n=26)
£70,000 or more	-	0.0%† (n=25)

Endnotes

1 Three points of comparison are worth noting. The EWCS 2024 (Eurofound) asked workers whether they use "artificial intelligence that simplifies complex mental tasks or makes recommendations", a formulation broader than generative AI that may capture AI-powered recommendation and decision-support systems as well as generative models, yielding an average adoption rate of 12% across 35 European countries. The survey was administered face-to-face (CAPI). The Eurostat ICT Households Survey 2025, the first edition to include GenAI questions, asks about generative AI use across all contexts (personal and work-related) in the three months prior to interview, estimating that approximately 15% of working-age Europeans used GenAI for work purposes. The survey was conducted by National Statistical Institutes using a mix of modes including CAPI and online. The WIIS 2025 question on the use of GenAI in work differs from both in that it explicitly names GenAI technologies, restricts the scope to work use, and was administered by telephone to a working population sample in RoI and NI. The higher adoption rates recorded in the WIIS (29% RoI; 27% NI) relative to the EWCS 2024 are consistent with the later fieldwork date, the more technology-intensive occupational profile of survey respondents, and the greater public familiarity with GenAI by 2025. Direct comparisons across surveys should be made with caution given differences in question wording, reference period, mode of data collection, and target population.

2 The term general-purpose technology is often used differently to its original formulation which equated it with meeting three criteria: improvement over time, pervasive throughout the economy, and the ability to generate complementary innovations (Lipsey et al., 2005). GenAI is now widely seen to meet these requirements (Eloundou et al., 2023).

3 There are many other enterprise functions AI can be used for, but these provided are an illustration of the variety of possible applications it can undertake. This listing of tasks is drawn from a number of sources including Lightcast (2025) which identifies GenAi as being composed of a particular skill cluster that includes: Adobe Sensei, ChatGPT, CrewAI, DALL-E, image generator, generative adversarial networks, generative AI agents, generative artificial intelligence, Google Bard, image inpainting, image super-resolution, LangGraph, large language modeling, Microsoft Copilot, multimodal learning, multimodal models, prompt engineering, retrieval-augmented generation, Stable Diffusion, text summarization, text to speech (TTS), variational autoencoders (VAEs). Krakowski (2025) also provides a very good and comprehensive technical review of the abilities and limits of GenAI.

4 Eloundou et al. (2023)'s paper refers to large language models (LLM s) and generative pre-trained transformers (GPTs) which for our purposes are similar to GenAI models such as ChatGPT.

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