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Squandered skills? Bridging the digital gender skills gap for inclusive growth in Ireland – A comparative European perspective

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BLOCK W

AN INSTITIÚID UM THAIGHDE EACNAMAÍOCHTA AGUS SÓISIALTA
ESRI ECONOMIC & SOCIAL RESEARCH INSTITUTE

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ABOUT THE ESRI

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ABOUT BLOCKW

BlockW's mission is to ensure that all available talent, regardless of gender, contributes to Ireland's digital and economic future. The organisation focuses on three main pillars:

The first pillar is advocacy and partnerships. BlockW works in partnership with government, agencies, employers, education providers and European initiatives to highlight the importance of inclusive digital transformation and to position gender equality as a core element of Ireland's competitiveness. Recent activities include contributions to the EU's Women in Digital (WiD) Forum, engagement with the development of Ireland's next National Digital and AI Strategy, and collaboration with industry and education stakeholders on digital skills initiatives.

The second pillar is showcasing female role models and leaders. BlockW organises networking and panel events that profile women working across the digital economy, highlighting their leadership, innovation and career pathways in technology and related sectors. These events aim to make opportunities in emerging technologies more visible and to support women and girls at every stage of the talent pipeline.

The third pillar is research. BlockW undertakes and supports research to generate data-informed insights that can guide decision-making, policy development and funding priorities. BlockW commissioned and funded *Parenting in a digital era: A narrative review*, undertaken by the Economic and Social Research Institute (ESRI), which informed the work of the Department of Health Online Health Taskforce report, *Online health and rights for Ireland's children and young people*. Through BlockW's joint research programme with the ESRI – Workforce Gaps in a Digital Economy: Ireland and Europe – BlockW is investing in a multiphase study (2025–2027) to provide an evidence base for policy interventions at organisational, sectoral, national and European levels. BlockW also contributes to international work through the International Association for Trusted Blockchain Applications (INATBA), particularly on areas related to future skills.

BlockW is a company limited by guarantee and a registered charity.

Further information is available at www.blockw.ie.

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FOREWORD

As Chair of BlockW, I am pleased to introduce *Squandered Skills? Bridging the Digital Gender Skills Gap for Inclusive Growth in Ireland – A Comparative European Perspective*. Produced in partnership with the Economic and Social Research Institute (ESRI), this study is published at a pivotal moment for Ireland and for Europe.

Under the EU Digital Decade, Member States have committed to building a digitally capable workforce of 20 million information and communications technology (ICT) specialists by 2030, with significantly greater participation by women. Ireland aligns with these ambitions through Harnessing Digital – The Digital Ireland Framework. While Ireland performs strongly on many digital indicators, this research asks a more fundamental question: Does everyone participate equally in the digital economy?

The distinctive contribution of this study is its focus on tasks rather than job titles. Using European data from the European Skills and Jobs Survey (ESJS), the authors show that while women and men use basic digital tools at similar rates, a substantial gap emerges in advanced tasks such as programming, AI development and complex IT systems work. Women are around 15 percentage points less likely than men to perform these tasks, and most of this gap cannot be explained by education, occupation or sector. Instead, it may reflect how work and opportunity are structured within organisations.

For Ireland, these findings should give us pause. As a country that prides itself on being a global digital leader, we cannot afford to overlook the potential underutilisation of talent that this research exposes. Competitiveness, innovation and resilience depend not only on attracting investment or building infrastructure but on ensuring that the full breadth of our population can contribute to and benefit from digital transformation.

Ireland records the largest gender gap in advanced digital task use among other European economies. This is not because women lag behind their European peers, but because men are far more likely to be concentrated in highly digital, advanced roles. In an economy close to full employment, and one that relies heavily on international ICT talent, failing to fully utilise the advanced digital capability of women already in the labour market is inefficient and unsustainable.

From a gender equality perspective, the findings are equally clear. The gap identified is not primarily about participation or capability, but evidence suggests that it is as a result of other factors, possibly including access to opportunity, advanced tasks, high-value projects and progression pathways. When women are excluded from advanced digital work, organisations lose skills, economies lose productivity, and societies lose diverse voices in shaping technologies that increasingly govern our lives.

For BlockW, this research reinforces a core message: Education remains vital, but it is not sufficient. The persistence of unexplained gaps suggests deeper organisational and cultural barriers – how work is designed, how tasks are allocated, whose expertise is trusted and who is sponsored into roles of influence.

For policymakers and business alike, this represents both a delivery risk and a missed opportunity. In the context of skills shortages and demographic pressures, failing to make full use of women's advanced digital skills is an avoidable constraint on Ireland's capacity for growth. *Squandered Skills?* provides a timely evidence base to inform the National Digital and AI Strategy and wider policy action.

I would like to thank the ESRI research team, the steering committee, partners and funders for their support. The findings are challenging, but they present a clear opportunity. With ambition and focus, Ireland can lead not only in digital innovation, but in how equitably the opportunities of the digital economy are shared.

BlockW is proud to have partnered with the ESRI on this work, and we hope this publication will prompt action by all those with a stake in building a digital future that is innovative, inclusive and just.

Professor Joyce O'Connor

Chair and Co-Founder, BlockW

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

CIL	Computer and information literacy
CT	Computational thinking
ESJS	European Skills and Jobs Survey
IMF	International Monetary Fund
JDII	Job Digital Intensity Index
RIF	Recentred influence function
STEM	Science, technology, engineering and maths

EXECUTIVE SUMMARY

Rapid digital transformation, reflected in the growing use of digital technologies across jobs, is reshaping work in Ireland and Europe. This makes it essential to understand digital skill use in order to ensure inclusive economic growth, where the benefits of technological change are widely shared. Persistent gender gaps in access to advanced digital tasks matter because exposure to these tasks is often a stepping stone to higher-quality jobs, leadership pathways, and more productivity-enhancing work, so such disparities can reinforce wider labour market inequalities.

This report examines the gender gaps in workplace digital task use, with a specific focus on Ireland, using the European Skills and Jobs Survey (ESJS) (Cedefop, 2021). We distinguish between basic digital tasks such as routine use of internet, word processing and spreadsheets, and advanced digital tasks including programming, AI/machine learning, and IT system management. We also construct a Job Digital Intensity Index (JDII) , which captures how digitally intensive jobs are overall, based on the range of digital tasks performed.

Our analysis combines regression-based estimates, decomposition techniques, and distributional analysis to examine gender differences in digital task use and digital job intensity. Across Europe, women are around 15 percentage points less likely than men to perform advanced digital tasks in their jobs. Differences in observable worker and job characteristics, such as education, field of study, occupation and sector, explain only a minority of this gap, accounting for around 30 per cent on average. The remaining difference is not explained by the factors observed in the data, indicating that additional influences (not captured in the survey) may also play an important role.

We find that gender disparities widen significantly at the very upper end of the distribution. While the lower and middle levels of digital intensity show more modest differences, the gap becomes most pronounced for jobs requiring the most digitally intensive range of tasks, pointing to a 'digital glass ceiling' within workplaces. Across Europe, the analysis also shows that gender gaps are larger and less well explained by observable characteristics among younger cohorts (aged under 35). This suggests that the under-representation of women in advanced digital roles is not a legacy issue confined to older cohorts, but one that continues to emerge early in careers.

Ireland stands out in the European context. It exhibits the largest gender gap in advanced digital task use, with approximately 44 per cent of men versus 18 per cent of women performing advanced digital tasks, a difference of 26 percentage points, close to double the European average. Importantly, women in Ireland use advanced digital skills at rates broadly comparable to women elsewhere in Europe. Ireland's large gap instead reflects particularly high rates of advanced digital task use among men. While differences in the types of jobs men and women do (often referred to as occupational sorting) explains a somewhat larger share of the gap in Ireland than in other European countries, a substantial portion remains unexplained, highlighting the potential influence of unobserved structural, cultural or other organisational factors specific to the Irish labour market.

Overall, the evidence shows that closing the gender gap in digital skill use at work will require more than increasing women's participation in science, technology, engineering and maths (STEM) education or occupations. While education and access to digital jobs are important, the results highlight the need for further research into other factors that may shape opportunities to develop and apply advanced digital skills, including workplace organisation, task allocation, progression pathways, and broader organisational practices. Addressing these issues will be important not only for gender equality, but also for productivity, innovation and inclusive economic growth in Ireland.

CHAPTER 1

Introduction

Ireland's economy is undergoing a rapid digital transformation (such as greater use of data analytics, cloud-based systems, automation and, increasingly, AI-enabled tools), influencing the nature of work and the skills demanded across all sectors. Digital competencies have become increasingly important in modern labour markets and knowledge economies. Possessing digital skills has transitioned from being a distinct advantage to being a prerequisite for effective economic and social participation (Reddy, Sharma and Chaudhary, 2020; Fraillon et al., 2020; Falck et al., 2021). Research shows that employers seek a workforce that is highly adept in a broad range of digital tools, and lacking these skills is associated with negative consequences in terms of wages and career prospects (OECD, 2024a; Reddy, Sharma, and Chaudhary, 2020). Recent International Monetary Fund (IMF) analysis using online vacancy data shows that roughly one in ten job postings in advanced economies now requires at least one 'new' skill that was rare a decade ago, highlighting how quickly skill requirements are changing (Jaumotte et al., 2026). The same analysis emphasises that building skills supply is not enough on its own, and that adoption and effective use within firms also matters. An understanding of who gets access to and/or performs digitally intensive work is therefore crucial for designing policies that ensure women are not left behind as the digital economy advances.

Digital skill gaps not only hinder individual career advancement but also pose barriers to broader economic development by constraining the talent pool.[1] As digital tools diffuse beyond information and communications technology (ICT) into areas such as health, finance, manufacturing and public services, upskilling is relevant across sectors not as 'digitisation for its own sake', but because digital task exposure increasingly shapes progression into higher-quality roles (OECD, 2024a; Garcia-Lazaro et al., 2025; Leopold et al., 2025).[2]

Reflecting these concerns, policymakers in Ireland and across Europe recognise the critical importance of digital skills for future development. EU strategies and initiatives such as the Digital Education Action Plan (2021–2027), the Digital Skills

[1] Studies of skill underutilisation have long shown that when workers' abilities are not fully deployed, it hampers both individual progression and overall productivity. Parallels can be drawn with digital skills, where underuse in the workplace, particularly among certain groups, may signal missed opportunities for innovation, efficiency, and inclusive economic growth.

[2] Sector-specific competency frameworks are already being developed in areas such as healthcare, where EU policy work sets out core digital skills and training pathways for health professionals (Williams et al., 2025). As well as this, Ireland's Women in Finance Charter provides a local example of firm-level target-setting and annual reporting to track progress in representation and progression, which is analogous to the type of transparency that could support equitable access to advanced digital tasks (Slevin and Russell, 2025).

and Jobs Coalition, and the EU Gender Equality Strategy 2020–2025 aim to strengthen digital capabilities and support women's participation in digital education and employment. Under the EU Digital Decade, Member States have committed to building a digitally capable workforce of 20 million ICT specialists by 2030, with significantly greater participation by women. In parallel, LEADSx2030 (Leading Europe's Advanced Digital Skills to 2030), part of the Digital Europe Programme, supports the development of roadmaps and guidance on advanced digital skills needs and promotes reskilling and upskilling pathways and collaboration between industry and education and training providers. Monitoring frameworks such as the Women in Digital (WiD) Index track women's participation across the digital skills 'pipeline' (from education and training to entry into digital occupations, and progression into senior and leadership roles) and suggest that Ireland performs strongly on several of these indicators. However, these pipeline measures do not account for differences in the task content of jobs and the day-to-day use of digital skills at work.

This study examines Ireland's digital skills use at work with the emphasis on inclusive workforce development, with a particular focus on gender disparities in digital skill use and how Ireland compares to other European countries. Prior research and EU initiatives have highlighted the 'digital gender divide' as a policy concern, noting that women are often underrepresented in science, technology, engineering and maths (STEM) education and technical occupations. This study adds to the literature by analysing how these disparities are observed within the workplace and how Ireland compares to other European countries.

Despite the growing literature, very little research investigates how this gender digital divide plays out in the workplace. To examine this, we use Cedefop's[3] European Skills and Jobs Survey (ESJS), Wave 2 (2021), a rich dataset that collects information on employees' skillsets, job task content and educational background, with European-wide coverage. This enables us to conduct cross-country analyses and to document cross-country heterogeneity in conditional gaps. The current literature includes a mix of independent papers using different methods in a limited pool of countries. Naturally, performance metrics from different tests and data from different surveys may not yield consistent results. Our contribution is to apply a uniform methodology using harmonised survey data, in order to deliver comparable cross-country estimates and country-specific conditional gaps in digital skill use, while maintaining a specific focus on Ireland's outcomes in comparative perspective.

While we are the first to study gender differences in digital skills use across the European workforce, prior research on the gender wage gap offers some important

[3] European Centre for the Development of Vocational Training.

context. Studies for Ireland and other countries show that much of the gender pay gap is driven by educational and occupational sorting (the specific education fields and occupations/roles men and women are in), with women underrepresented in STEM fields and high-paying technical occupations (Russell, Smyth, and O'Connell, 2010; Delaney and Devereux, 2019; Doris, 2019). However, sorting into fields of study and occupations may not be solely the result of individual 'choice' but can also be shaped by gender norms and institutional structures. Goldin (2014) further argues that the persistence of gender inequality, especially at the top of the earnings distribution, is linked to rigid job structures that reward long, inflexible hours, penalising those with caring responsibilities. This perspective suggests that unexplained gaps in digital skills use may similarly reflect structural features of workplaces and task allocation that limit women's opportunities to engage more fully in the most digitally intensive roles.

Our key research question is whether women and men in the workforce differ in their use of digital tasks on the job, and if so, to what extent can the gap be explained by observable characteristics (e.g. occupation, education). While many studies have documented gender gaps in ICT education and in STEM occupations (Card and Payne, 2021; Cimpian et al., 2020; Beede et al., 2011; Tandrayen-Ragoobur and Gokulsing, 2022), less is known about gender differences in the digital task content of jobs across the broader labour market in Europe. For example, do female employees use advanced digital tools and perform high-tech tasks at the same rate as male employees with similar backgrounds? If not, what explains the gap? How much of the gap is due to women's lower presence in certain fields of study and/or occupational roles, or does the gap persist even among comparable workers, suggesting other barriers?

Our findings show that, despite near parity in basic digital task usage at work, women remain significantly less likely than men (by 15 percentage points (p.p.)) to engage in advanced digital tasks. Probit regression estimates reveal robust gender differences in digital task use that persist even after controlling for education, occupation, and sector. On our Job Digital Intensity Index (JDII), women's mean score is almost 7 points below that of men. Oaxaca-Blinder decompositions indicate that only about 30 per cent of this gap can be attributed to observable factors such as educational field, industry and occupation. Differences in field of study and sectoral/occupational sorting account for an important share of the gap, although women's relatively higher average educational attainment partly offsets it.

When the analysis moves beyond average digital skill use and considers different levels of digital intensity across jobs, using recentred influence function (RIF) decompositions, the gender gap becomes more pronounced. Women remain underrepresented at the top end of the digital intensity distribution, i.e. higher levels of the JDII, consistent with a 'digital glass ceiling' in access to the most digitally intensive roles. While gender gaps in digital skill use widen in both Ireland and other European countries as jobs become more digitally intensive, the reasons behind these gaps differ. In Europe, much of the gap can be explained by differences in education and occupational sorting, but in Ireland these factors matter less for the most digital jobs, suggesting that other, less visible barriers may play a larger role. This means that closing Ireland's gender digital gap will require more than increasing women's participation in STEM or digital occupations, it will also require a better understanding of how work is organised, how digital tasks are assigned, and how people progress into the most advanced digital roles. Addressing these issues is important not only for gender equality, but also for strengthening productivity, innovation, and inclusive economic growth in Ireland, and Europe.

The remainder of the report is structured as follows. In Chapter 2, we discuss the previous relevant literature. Chapter 3 describes the data in more detail and how our variables are constructed (including the JDII). In Chapter 4, we show the descriptive statistics and display the distribution of the JDII of women and men. Chapter 5 presents the results and Chapter 6 concludes with a summary, reflections on policy implications and directions for further research.

CHAPTER 2

Literature review

This section reviews the main strands of research relevant to our analysis. First, we examine literature on task-based approaches to understanding technological change and inequality. Second, we review research on occupational sorting and gender gaps in digital task usage. Finally, we consider literature on the gender digital divide in education, confidence and attitudes, and discuss how these early-life factors may shape later workplace outcomes.

A growing body of research highlights how technological change affects the task content of jobs rather than simply transforming entire occupations. The task-based approach introduced by Autor, Levy and Murnane (2003) and broadened by Acemoglu and Autor (2011) analyses the bundle of tasks that workers perform (rather than entire occupations) in order to understand how technology reshapes inequality. This lens has seldom been applied to gender gaps in digital work. To our knowledge, no cross-country study directly examines gender differences in the application of digital competencies at work, despite strong evidence of their wage-enhancing effects (Falck et al., 2021). A noteworthy single country exception is Black and Spitz-Oener (2010), who find that women's increased supply of non-routine analytical tasks explained a large share of the declining gender wage gap in Germany. McGuinness et al. (2023) provide related EU evidence on technology-driven changes in skill requirements, highlighting gender differences in exposure to technological change and associated risks of skill obsolescence. Building on these insights and using a task-based approach, we examine whether comparable gender differences exist in the digital task content of jobs across Europe, with a particular focus on Ireland.

A key motivation for this focus is that differences in access to advanced digital tasks can translate into unequal career opportunities. Digital competencies are associated with higher wages and progression partly because they facilitate entry into more digitally intensive roles and higher-productivity tasks (Falck et al., 2021). Recent evidence using job vacancy data likewise suggests that employers explicitly reward digital skill requirements in posted wages, including within-occupation premiums when digital skills are listed in job ads (Garcia-Lazaro et al., 2025). Together, this literature implies that persistent gender gaps in workplace digital task exposure may matter for job quality and progression, not just for equality of participation in digital domains.

Another relevant strand of research concerns how gender occupational sorting interacts with technological change to shape labour market outcomes. Acemoglu (1999) and Acemoglu and Autor (2011) demonstrate how technological change interacts with worker sorting across occupations, contributing to wage dispersion and inequality. More recent studies (Card et al., 2013; Song et al., 2019) highlight how high-wage workers are increasingly concentrated in high-wage firms and tend to work alongside others with similar profiles. While this literature has primarily focused on skill-based sorting, there is growing recognition that gender-based sorting may play a crucial role in explaining disparities in digital skill use. For example, Blau and Kahn (2017) highlight how persistent occupational segregation channels women away from STEM and other technical fields, which are some of the most digitally intensive sectors of the economy. This suggests that men and women may sort into different occupations with varying degrees of digital intensity, whether due to differences in educational choices, social norms and stereotypes about 'appropriate' fields for women, or structural barriers that limit access to more digitally intensive roles (Reuben et al., 2014; Bordalo et al., 2019; Ceci et al., 2014).

Beyond entry into technical roles, evidence from organisational research points to a 'broken rung' at the first promotion step into management that slows women's early progression, including in technical roles (Ellingrud and del Mar Martinez, 2025). Because managerial and higher-responsibility roles often concentrate high-value digital tasks and decision-making, these early promotion bottlenecks may also contribute to gender gaps in advanced digital task exposure within and across occupations. In the Irish context, evidence on gender differences in degree choice is especially relevant where Delaney and Devereux (2019) show that sizeable gender gaps in STEM programme choice persist even among students with similar preparation, which can also shape later occupational pathways and access to digitally intensive work. Our analysis builds on this literature by examining whether gender sorting into fields of study, sectors and occupations accounts for a meaningful share of observed gaps in digital task use and whether gaps persist among comparable workers, consistent with within-occupation differences in task allocation and access to high-value digital work.

While our focus is on digital tasks in the workplace, earlier life-stage factors such as education, confidence and digital exposure may shape the subsequent occupational pathways that become apparent in the workplace. Several studies have explored the gender digital divide in education, often finding a complex pattern. When computers were first introduced to schools, they were often viewed as 'boys' toys' (Master, Meltzoff, and Cheryan, 2021), with an assumption that male students would adapt more quickly to digital technology. However, an expanding body of research challenges this stereotype. For example, Siddiq and Scherer (2019) find a small but significant performance advantage for girls in ICT-based assessments. Similarly, results from the 2013 International Computer and Information Literacy Study (ICILS) show that eighth-grade girls outperform boys in computer and information literacy (CIL) (Gebhardt et al., 2019). Digging deeper, this advantage appears domain specific. While girls excel in CIL, using computers to investigate, create and communicate, the gender differences are reversed when looking at computational thinking (CT), which involves algorithmic problem-solving, where boys tend to demonstrate higher achievement (Kaarakainen et al., 2017; Fraillon et al., 2020). These distinctions matter because the labour market rewards more advanced digital and computational skills (OECD, 2024a; 2024b), and because early differences in confidence and self-perception may shape whether individuals select into (or persist in) technical pathways. For example, Risse (2018) shows that personality traits and confidence-related measures contribute to gender wage differentials, consistent with the idea that attitudinal mechanisms can reinforce sorting patterns and subsequent labour market outcomes.

Gender also has an interesting interaction with age. Literature has shown that while boys and girls have comparable levels of digital competency at school-going age, the gender gap evolves as individuals get older.[4] Bachmann and Hertweck (2025), using German data, find almost no gap at age 14, but a substantial and growing one by the end of secondary school, with men outperforming women in digital skill tests.[5] Notably, this study controls for important confounding factors such as field of study, subject specialisation, and the intensity of digital tool usage in school, indicating that other mechanisms may be driving the divergence. At the European level, too, young adults aged 16–24 report similar digital skill levels, but among older adults, men are more likely to report advanced digital competencies (OECD, 2024b). These early-stage dynamics, differences in confidence, subject choice, and self-perception may also influence later occupational and task-based sorting, reinforcing gender gaps in digital skill use at work.

In summary, the literature highlights several mechanisms through which gender disparities in digital task use can emerge and persist. Task-based frameworks show how technological change reshapes jobs at the task level and how differences in exposure to high-skill digital tasks can further translate into differences in job quality, wages and progression. Occupational sorting literature explains how gender differences in education, degree choice, job roles and workplace assignment may focus women into less digitally intensive pathways. Our study builds on this literature by providing cross-country evidence of gender disparities in actual digital task use at work across Europe.

[4] Similar findings have been shown for achievements in mathematics. See for example, Fryer and Levitt (2010), who find that gender gaps in math performance emerge early and differ significantly across countries, and Niederle and Vesterlund (2010), who argue that differences in competitiveness and preferences partly explain gender differences in math outcomes. Card and Payne (2021) extend this to STEM, showing that even among high-achieving women, structural and social factors continue to deter participation in math-intensive fields. These parallels suggest that observed gaps in digital task use may similarly reflect a combination of educational, occupational and behavioural dynamics.

[5] Similar findings have been shown by Gnambs (2021).

CHAPTER 3
Data and descriptive statistics

In our analyses, we utilise data from the latest wave of Cedefop's European Skills and Jobs Survey (ESJS), conducted in 2021. The ESJS is a comprehensive European cross-country survey designed to capture information on skills requirements, competencies, and initial and ongoing learning among adult employees (aged 24–65) across European labour markets (Cedefop, 2021).[6] This dataset is particularly relevant for our study as it collects detailed information regarding the digital technologies that European employees use in their day-to-day work, alongside extensive background data such as employment characteristics, industry sector, education level, field of education, gender, age, and other job-related attributes. As with most large-scale surveys, these measures are self-reported and may be subject to reporting error and cross-country differences in interpretation. All estimates are therefore produced using the ESJS survey weights to support national representativeness within each country, but the data remain cross-sectional and descriptive.[7]

3.1 MEASURING DIGITAL SKILLS USAGE

A unique feature of the ESJS data is that they contain information on practical exposure to digital technologies for workers in their current job across the 27 EU Member States, less Malta and Cyprus, plus Iceland and Norway.[8] The following question is asked: 'Did you perform any of the following activities as part of your main job in the last month?'

[6] The second wave (ESJS2) was carried out in 2021 across all EU Member States, Iceland and Norway, using harmonised methodology to enable cross-country comparisons across sectors, occupations, and demographic groups. ESJS2 fieldwork took place primarily from May to August 2021 and resulted in approximately 46,213 completed interviews with labour market participants.

[7] The ESJS is designed to be nationally representative of employees within each participating country; Cedefop draws samples using country-specific sampling frames and provides survey weights to correct for selection probabilities and differential non-response. The survey is not mechanically 'balanced' across occupations; instead, representativeness is achieved via the sampling design and weighting. See Cedefop (2021) for full details on sampling, fieldwork and weighting, and https://digital-skills-jobs.europa.eu/en/inspiration/resources/cedefop-european-skills-and-jobs-survey-esjs.

[8] Throughout the report, 'Europe' (or 'Rest of Europe') refers to EU27, less Cyprus and Malta, plus Iceland and Norway (27 countries) in ESJS Wave 2 (2021), unless stated otherwise. Some variables required for our study are not recorded for either Malta or Cyprus, explaining their exclusion.

Respondents indicated yes or no to the following ten tasks:

1. 'Use the internet for browsing, sending emails or using social media for your work.'
2. 'Write or edit text, for instance using Word or similar software.'
3. 'Prepare presentations of your work, for instance using PowerPoint or similar software.'
4. 'Use spreadsheets, for instance using Excel or similar software.'
5. 'Use more advanced functions of spreadsheets, for instance macros or complex formulas.'
6. 'Work with specialised sector- or occupation-specific software, for instance for accounting, legal analysis, inventory control, web design, graphic design, customer relationship management, etc.'
7. 'Manage and merge databases, for instance using Access, Oracle or similar software, and related query techniques (e.g. SQL).'
8. 'Write programmes or code using a computer language, for instance C++, Python, Java, Visual Basic, etc.'
9. 'Write programmes using artificial intelligence methods, for instance machine-learning or deep-learning algorithms.'
10. 'Develop or maintain IT systems, hardware or software.'

For empirical clarity, we group these tasks into three categories based on their complexity and the level of digital proficiency required. Following Cedefop's own categorisation (Cedefop, 2022), we define:

- **Basic technology use:** (1) internet browsing, (2) word processing, (3) presentation preparation, and (4) simple spreadsheet work;
- **Intermediate technology use:** (5) more complex spreadsheet operations (e.g. using macros), (6) working with specialised occupation-specific software, and (7) managing databases;
- **Advanced technology use:** (8) programming, (9) use of artificial intelligence or machine learning methods, and (10) IT system development or maintenance.

3.2 CHARACTERISTICS OF WOMEN AND MEN

At a descriptive level, there are gender differences in the digital task usage reported by individuals in their current jobs. Responses to these questions vary notably by country and gender. Table 1 provides descriptive statistics on the prevalence of each of the ten digital tasks and three broader task categories for workers, disaggregated by gender. A full list of the other key variables and controls used in our analyses can be seen in Appendix Table A.1.

The data show that basic digital activities such as internet browsing and word processing are widely used across both genders. Gender differences become more pronounced as task complexity increases. Specifically, in Ireland, men are more likely to report engagement with advanced digital tasks, including the use of programming (32% compared to 11%), AI or machine learning (17% vs. 6%), and ICT system maintenance (32% vs. 14%). These disparities contribute to the observed gender gap in the advanced technology task grouping. On average, in Ireland, 44 per cent of men report using advanced digital skills at work, compared to only 18 per cent of women, yielding a gap of approximately 26 percentage points. In contrast, basic tasks such as spreadsheet and presentation software show more balanced usage, though still skewed slightly toward men (94% for women vs. 96% for men). Overall, while both genders participate broadly in digital work, a clear and persistent gender gap emerges in the use of higher-level (intermediate and advanced) digital technologies in Ireland. Furthermore, this is consistent with patterns explored in our subsequent empirical analysis.

TABLE 3.1 DESCRIPTIVE STATISTICS OF DIGITAL TASKS BY GENDER

		Ireland			Rest of Europe		
Task	Digital Intensity Classification*	Women (%)	Men (%)	***Diff (Women - Men)***	Women (%)	Men (%)	***Diff (Women - Men)***
Internet browsing	Basic	83.2	88.3	***-5.1****	86.1	83.2	***2.9*****
Word processors	Basic	85.1	80.7	***4.4****	78.8	73.4	***5.4*****
Presentation software	Basic	56.5	59.1	***-2.7***	43.5	44.4	***-0.9***
Spreadsheet software	Basic	75.7	75.6	***0.1***	67.4	69.2	***-1.9*****
Advanced spreadsheet use	Intermediate	33.2	49.6	***-16.4*****	25.8	35.7	***-9.9*****
Occupation-specific software	Intermediate	42.8	57.7	***-14.9*****	55.4	58.4	***-3.0*****
Database management	Intermediate	22.8	40.1	***-17.3*****	22.5	30.3	***-7.9*****
Software programming	Advanced	10.9	32.4	***-21.5*****	11.3	20.3	***-9.0*****
Machine learning/AI	Advanced	6.3	17.4	***-11.1*****	6	9.7	***-3.7*****
ICT infrastructure	Advanced	14.0	32.7	***18.7*****	13.4	24.8	***-11.4*****
BASIC		93.7	95.5	***-1.8***	92.0	90.8	***1.2*****
INTERMEDIATE		57.4	71.8	***-14.4*****	63.7	69.4	***-5.7*****
ADVANCED		18.4	44.3	***-25.9*****	18.4	31.8	***-13.4*****

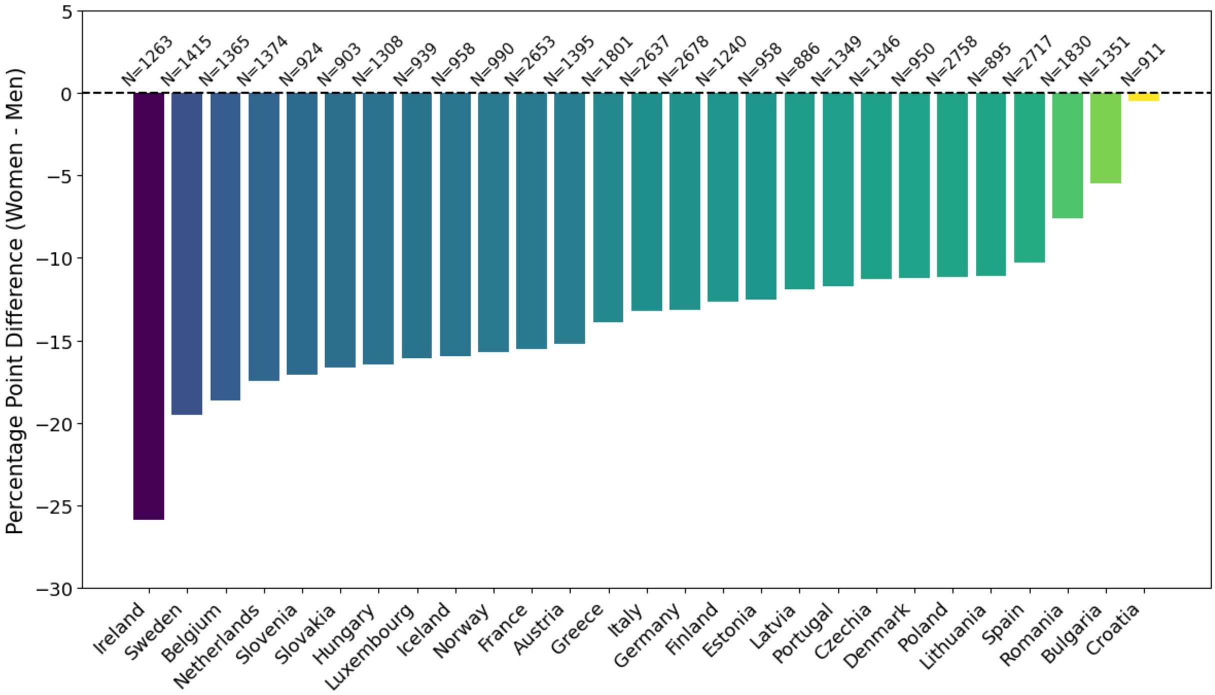
Source: *ESJS (2021), Authors' own calculations.*
Note: *Classification from Cedefop (administrator of ESJS data). Total counts are N=1,388 for Ireland and N=42,791 for rest of Europe. Stars represent the statistical significance of the difference between men and women: *=p<0.1, **=p<0.05, ***=p<0.01. Proportions are weighted.

Overall, Ireland mirrors European patterns with minimal gaps in basic digital task use but substantial female under-representation in advanced digital tasks. However, Ireland's gender gaps are generally larger than the rest of Europe (average). Women's participation in intermediate and advanced digital skills in Ireland is roughly on par with the European average for women, but men in Ireland engage in these high-level digital activities at significantly higher rates than both Irish women and men in Europe overall. This results in a gap for Ireland that is nearly double the European average gap where women in Ireland are especially underrepresented (compared to men) in performing advanced digital tasks on the job.[9]

[9] To validate the gender differences in advanced digital task use observed in the ESJS, we compared results from the same set of European countries with the PIAAC data, which includes a comparable question on programming activity. In PIAAC, 6.9 percentage points more men than women aged 35 and over report programming at least once a month, rising to 8.4 percentage points among younger workers (<35). The corresponding ESJS figures are 8.4 and 12.3 percentage points, respectively, based on whether respondents had programmed in the last month. The similarity in patterns across surveys supports the robustness of the observed gender gap in advanced digital task use, although potential response biases such as men over-reporting and women under-reporting digital skills should be acknowledged (Hargittai and Shafer, 2006; Palczyńska and Rynko, 2021).

Figure 3.1 illustrates the raw gender gaps in the proportion of male and female workers across European countries who report using advanced digital skills in their jobs. The data shows a consistent and substantial gender gap across nearly all countries reflecting a widespread pattern in reported advanced digital task use across countries. While the absolute levels vary across countries, the direction of the gap is universally negative for women, indicating a systemic under-representation of women in highly intensive digital roles. The disparity persists even in countries with relatively high female labour force participation and strong digital infrastructure (for example, Belgium, Ireland, Netherlands and Sweden). The raw gender gap in advanced digital skill usage varies from 26 percentage points in Ireland to less than 1 percentage point in Croatia.

FIGURE 3.1 GENDER GAP IN ADVANCED DIGITAL SKILLS USAGE AT WORK



Source: ESJS2 (2021)

Note: Bars show the difference in weighted proportions (women minus men) reporting any advanced digital task (programming, AI/ML, or IT systems), computed within each country

3.3 JOB DIGITAL INTENSITY INDEX (JDII)

It is important to acknowledge that employees rarely possess skills exclusively in one singular category. Their digital skill profiles typically exhibit a combination of basic, intermediate and/or advanced digital competencies. Therefore, we construct a Job Digital Intensity Index (JDII) to capture a continuous measure of digital competency, reflecting the diversity and intensity of digital tasks performed in the workplace. This index facilitates a more detailed analysis of digital skills across different demographic groups. The JDII is constructed as follows:

$$\mathbf{JobDigitalIntensityIndex}_{\boldsymbol{i}} = 1 \cdot \sum_{j \in \mathbf{B}} x_{ij} + 2 \cdot \sum_{j \in \mathbf{I}} x_{ij} + 3 \cdot \sum_{j \in \mathbf{A}} x_{ij} \qquad (1)$$

Where $x \in \{0,1\}$ is a dummy variable indicating whether employee i engages in task j, B is the set of basic tasks, I is the set of intermediate tasks, and A is the set of advanced tasks (as defined in Table 3.1). This index assigns weights of 1, 2, and 3 to basic, intermediate and advanced tasks, respectively, reflecting the increasing level of digital skill required. The weights are heuristic but reflect the increasing difficulty of task categories.[10] The potential value of the index for each employee runs from 0 to 19.

To facilitate interpretation and comparability, we have rescaled the JDII from its original range of 0 to 19 onto a 1 to 100 scale. This linear transformation enhances readability and enables easier communication of results, particularly when visualising the distribution of digital task intensity across groups.[11] The distribution of the JDII by gender for Ireland and the Rest of Europe is shown in Figure 3.2. The overall distribution of the variable is skewed right, indicating that lower levels of digital intensity are common, and the density of the distribution decreases as the value of the JDII increases (employees with very high scores are rarer).

The distributions show that the overall JDII is higher on average in Ireland than the rest of Europe, indicating that jobs in Ireland tend to involve more frequent and more complex digital task use. However, while women's distribution closely matches that of women in the rest of Europe, men in Ireland are far more concentrated in high-digitally intensive work. This indicates that the increased digital opportunity in Ireland is largely being realised by men, leading to a more

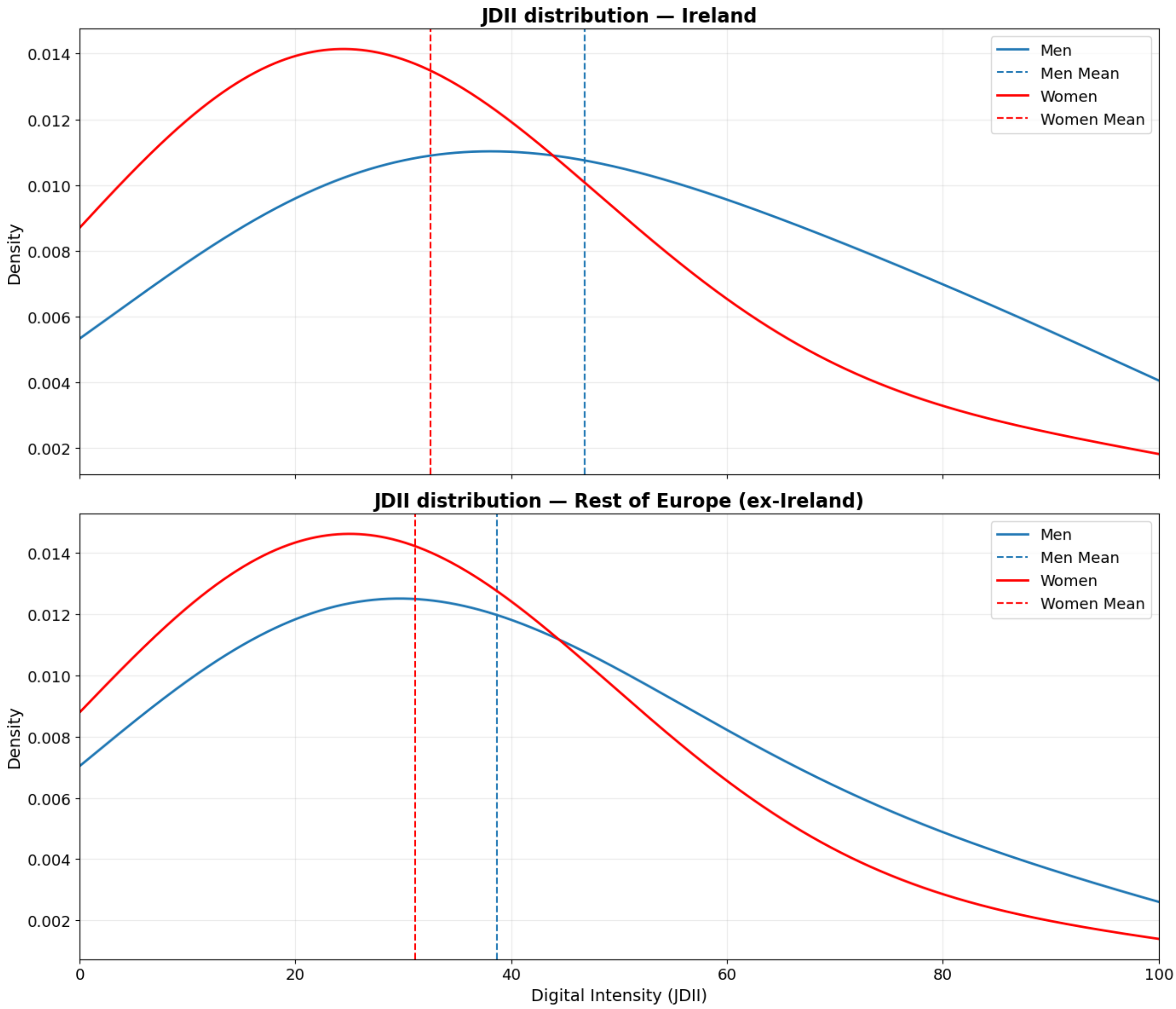
[10] Advanced tasks contribute more to an employee's digital intensity score than intermediate tasks, and intermediate tasks contribute more than basic digital tasks. Even when we construct a more complex index based on task rarity and association with technological under-skilling, the correlation between the two indices is very high (R≈0.975). As such, we have chosen to use the above index in our analyses as it is more intuitive and easier to comprehend.

[11] For Figure 3.2, we apply kernel density smoothing to the JDII to provide a clearer visual representation of the gender-specific distributions, especially in the upper tail of the index. This approach reduces noise and improves interpretability while preserving the underlying distributional patterns. In our regression analysis, we still use the raw JDII scale.

pronounced gender divergence in Ireland than in the rest of Europe.

The raw, unsmoothed version of the JDII distribution, using the original 0–19 scale, is presented in the Appendix for both Ireland and the rest of Europe (Figure A.1 and Figure A.2) for reference, showing that men were more concentrated in the upper JDII raw values (12–19), whereas the distribution for women is more concentrated in the lower-to-mid range (5–12). Men are overrepresented at higher intensity levels, while distributions converge in the lower deciles.

FIGURE 3.2 DISTRIBUTION OF JOB DIGITAL INTENSITY INDEX (JDII) BY GENDER



Source: ESJS2 (2021)

Notes: We have rescaled the JDII from its original range of 0 to 19 onto a 1 to 100 scale. Distributions are shown using a Gaussian kernel density estimate (KDE). For observations $x_1, \dots, x_n$, the estimated density at x is $\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} \phi(\frac{x - x_i}{h})$, where $\phi(\cdot)$ is the standard normal pdf and h is the bandwidth. In implementation, the bandwidth is set to 20 in rescaled JDII units weighted. The raw, unsmoothed version of the JDII distribution is presented in the Appendix (Figure A.1 and Figure A.2) for reference; weighted.

CHAPTER 4

Empirical strategy and methodology

Our empirical approach to quantify and understand the gender gap in digital skills at work uses three complementary tools, implemented separately for Ireland and the rest of Europe: (i) probit and OLS regression models to estimate the conditional likelihood of digital skill use; (ii) Blinder-Oaxaca decomposition to partition observed gender gaps into explained and unexplained components; and (iii) distributional analysis based on unconditional quantile methods, implemented via the recentred influence function (RIF) approach (Firpo et al., 2009), which allows us to assess whether gaps are larger in high digital-intensity jobs than in the middle or lower parts of the distribution. This triangular approach aims to provide a comprehensive view of both the magnitude and sources of digital task inequalities.

Our analysis is based on the following regression:

$$\text{DigitalUsage}_{i,j} = \alpha + \beta_h * H_{i,j} + \beta_p * P_{i,j} + \epsilon_{i,j} \tag{2}$$

The dependent variable takes a number of forms depending on the model being estimated, ranging from a dummy variable for the use of intermediate or above or the use of advanced digital skills, to the constructed continuous index, JDII, for individual i in country j. Our dependent variable is regressed on a vector of human capital, personal, and job characteristics. These include gender, age, education level, field of study, sector (public, private or not-for-profit), contract type (permanent or temporary or none), part-time status, firm size, occupation, and industry. The coefficient on gender from our probit or OLS regression for Equation (2) gives an estimate of the gender digital skills gap at work, controlling for other personal, job and human capital characteristics. We sequentially introduce three model specifications to control for a range of independent variables: Specification 1 includes basic controls (country fixed effects, age, area of residence); Specification 2 adds detailed job and demographic controls (tenure, part-time status, education level, contract type, occupation type, firm size, sector); and, Specification 3 further includes field of education and limits the sample to those with at least upper secondary education. All models are weighted using survey weights. Results are reported as marginal effects (see Table 5.1, 5.2 and 5.3).

Based on our digital usage regression, we carry out two decomposition methods that are explained in the section below. The first is the classic decomposition by Oaxaca (1973) and Blinder (1973), which decomposes the mean digital usage. Second is a method by Firpo et al. (2009) which decomposes the digital usage in the spirit of Oaxaca and Blinder but can be usefully applied at different quantiles of the digital intensity distribution. By focusing only on the mean digital usage, standard OLS and Oaxaca decomposition techniques are limited in their ability to provide insights for other parts of the JDII distribution. Therefore, employing unconditional quantile regression techniques enable us to examine the JDII across the entire distribution.

4.1 OAXACA-BLINDER DECOMPOSITION

To distinguish between the share of the digital skill gap that can be attributed to observable differences in characteristics (e.g. age, education, occupation) versus unexplained components, we employ the Oaxaca-Blinder (1973) decomposition technique. For the binary outcomes: (i) use of intermediate-or-above digital tasks and (ii) use of advanced tasks, we use the Fairlie (2005) nonlinear decomposition, which is appropriate for probit models. For the continuous outcome: (iii) the Job Digital Intensity Index (JDII), we use the standard Oaxaca-Blinder (Oaxaca, 1973; Blinder, 1973) decomposition. Together, these methods decompose the average gender gap into an explained component due to differences in observed characteristics and an unexplained component due to differences in coefficients and unobserved factors.

For ease of exposition, let X_i be a vector which includes the personal, job and human capital characteristics of individual i. Then let $\bar{X}_M$ and $\bar{X}_F$ represent the mean endowments for men and women and denote the corresponding estimated coefficient vectors by $\hat{\beta}_M$ and $\hat{\beta}_F$. The Oaxaca-Blinder decomposition expresses the mean gender gap in outcome as,

$$Y_M - Y_F = (\bar{X}_M - \bar{X}_F) * \beta^* + \left[\bar{X}_F * \left(\hat{\beta}_M - \beta^*\right) + \bar{X}_F\left(\beta^* - \hat{\beta}_F\right)\right], \tag{3}$$

where the choice of the non-discriminatory coefficient vector β^* determines the reference structure. Following Neumark (1988) and Oaxaca and Ransom (1994), we use the pooled coefficients approach, in which β^* is estimated from a regression on the pooled sample of men and women. The pooled method avoids privileging one group's task structure as the normative benchmark and produces decomposition results that are less sensitive to the choice of reference group.

We decompose the gap using the entire pooled sample of employees across 27 countries before proceeding to decompose the gap for Ireland and the rest of Europe separately. This allows us to rank regions by the magnitude of the gap as well as the degree of gender convergence in digital skills-enhancing characteristics. Table 5.4 presents the decomposition results across all outcomes, and Figure 5.1 shows the decomposition by country region.

4.2 UNCONDITIONAL QUANTILE DECOMPOSITION

While the Oaxaca technique allows us to decompose the digital intensity gap at the mean, it does not allow us to assess the degree to which the gap, or the factors that determine it, vary across the digital intensity distribution. To further understand heterogeneity in the gender digital gap across the digital skills distribution, we implement quantile regression analysis on the Job Digital Intensity Index (JDII) (see Figure 5.2). We employ a technique proposed by Firpo et al. (2009) to extend the methodology of Oaxaca and Blinder to decompose the digital intensity across the entire distribution. For more detailed information on decomposition methods, focusing particularly on such decompositions beyond the mean, please see Fortin et al. (2011).

We estimate RIF regressions at selected quantiles of the JDII, using the same control set as in the earlier probit regressions to examine whether the gender gap differs across the unconditional distribution of digital intensity. This allows us to explore whether the gender gap in digital task intensity is larger at the top end of the distribution, as might be expected if men dominate highly digital-intensive roles (e.g. software engineering, AI development).

In a standard OLS regression, the β coefficient can be interpreted as the effect of a change in X on the unconditional mean of Y. As such, OLS regressions can be used in the Oaxaca decomposition to examine the unconditional mean difference in gender digital usage. However, the β coefficient from a quantile regression of Y on X gives the effect of a change in X on the conditional quantile, thereby making the unconditional quantile decomposition less straightforward than a standard Oaxaca decomposition. The method proposed by Firpo et al. (2009) overcomes this difficulty.

The Firpo et al. (2009) technique can be outlined in three stages. In the first stage, the recentred influence function (RIF) of the unconditional quantile of the dependent variable is calculated. Denoting q_τ as the τ^{th} quantile of interest, the RIF is derived by first calculating the influence function (IF) as follows:

$$IF = (\tau - 1\{Y \leq q_\tau\})/f_y(q_\tau) \quad (4)$$

where Y denotes the dependent variable (JDII), $f_y(q_\tau)$ is the density at point q_τ, and $1\{Y \leq q_\tau\}$ is a dummy variable that equals one for observations in which Y is less than or equal to q_τ. To get the RIF, one adds back the quantile to the IF, such that $RIF = q_\tau + IF$.

In the second stage, the RIF is used as a dependent variable in an OLS regression. The resulting β from the RIF regression captures the marginal effect of a change in X on the unconditional quantile of Y. Finally, in the third stage, a standard Oaxaca decomposition is carried out on the RIF regression, which yields the unconditional quantile decomposition. Unlike earlier decomposition approaches (for example, Machado and Mata, 2005), the Firpo et al. (2009) method not only allows for the estimation of the 'explained' and 'unexplained' gap but also allows us to break these down further to identify the contributions of the individual explanatory variables in a more straightforward way.

CHAPTER 5
Results

This section highlights our three key findings on gender disparities in the use of advanced digital skills at work in Ireland compared to the rest of Europe. Overall, women are significantly less likely than men to use advanced digital skills at work across Europe, with Ireland recording the largest gender gap, even after controlling for education, occupation, and other individual and job characteristics. Second, a mean decomposition of the gender digital gap indicates notable differences between Ireland and the rest of Europe. In Ireland, a smaller share of the gap in advanced digital tasks is explained by observable factors, while a larger share of the gap in overall digital intensity is explained relative to the European average. The composition of these explanatory factors also differs, with occupational sorting accounting for more of the gap in Ireland, whereas sorting into different fields of education plays a greater role across the rest of Europe. Third, distributional analysis reveals that the gender gap in digital intensity grows as we move up the skills distribution. In Ireland, the gender gap is particularly pronounced at the upper tail, suggesting that women are especially underrepresented in the most digitally intensive roles compared to men.

Taken together, the findings point to a distinctive pattern in Ireland. Not only is the overall gender gap in digital skill use larger than in many other European countries, but the factors driving this gap also differ. While differences in education, occupation and sector explain a significant share of the gap, a sizeable portion remains unexplained, especially in the most digitally intensive jobs. This suggests that a range of other factors not captured in the survey may also be relevant, including how work is organised, how tasks are distributed within roles, and how opportunities to develop and apply advanced digital skills arise over the course of an individual's career. These patterns highlight the need for further research and monitoring. Understanding gender differences in digital skill use in Ireland requires attention to both differences in education, occupation and sector, and to workplace processes that shape who has access to digitally intensive tasks as digital technologies spread across the labour market.

5.1 PROBIT AND OLS REGRESSION ESTIMATES

Tables 5.1 and 5.2 present the marginal effects from probit regressions estimating the probability that individuals use either intermediate-or-above digital or advanced digital tasks in their job, respectively. Furthermore, Table 5.3 reports coefficients from OLS regressions estimating the continuous digital intensity JDII variable on a 0–100 scale.

Intermediate-or-above tasks capture a broad set of workplace digital activities beyond basic use, while the advanced measure focuses on high-level tasks such as programming, AI/ML and IT systems work. The JDII provides a continuous summary of digital task intensity by combining the range and complexity of tasks performed. Moving from Specification 1 to Specification 3 shows how much of the raw gender gap is accounted for by observed worker and job characteristics (most importantly occupation, industry and field of education) while any remaining gender difference reflects a conditional gap that is not explained by these observed factors.[12]

Across both Ireland and the rest of Europe, the gender coefficient is negative and highly statistically significant, confirming that women are less likely than men to engage in digital work tasks requiring intermediate to advanced skill levels. However, the magnitude of the gap differs between the two samples. In Ireland, the baseline model (Specification 1 on Tables 5.1 and 5.2) shows that being female is associated with a 15 percentage point lower probability of using intermediate-or-above digital tasks and a 24 percentage point lower probability of performing advanced tasks. The corresponding gaps for the rest of Europe are 6 and 13 percentage points, respectively. Adding detailed individual and job controls (Specification 2) reduces the gaps somewhat in both samples, but they remain large and statistically significant. After additionally controlling for field of education and restricting the sample to those with at least upper secondary education (Specification 3), the gaps narrow further to 4 percentage points for intermediate tasks and 9 percentage points for advanced tasks in the rest of Europe, while they slightly widen to 9 percentage points and 20 percentage points in Ireland.

TABLE 5.1 REGRESSION RESULTS FOR DIGITAL SKILLS USE FOR EUROPE: INTERMEDIATE OR ABOVE

	Ireland			Rest of Europe		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.151***	-0.083***	-0.087**	-0.061***	-0.059***	-0.044***
	(0.030)	(0.031)	(0.043)	(0.006)	(0.006)	(0.007)
Detailed controls	NO	YES	YES	NO	YES	YES
Education field controls	NO	NO	YES	NO	NO	YES
Observations	*1,260*	*1,138*	*650*	*38,496*	*36,998*	*23,676*

Source: ESJS2 (Cedefop).
Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1. Detailed controls include ISCO-2 occupation, NACE-1 industry, area of residence, firm size, sector (public, private, etc.), education level, contract type, part-time status, age and country FE. Non-detailed controls include age, area of residence and country FE. Weighted. Field of education is only recorded for a limited sample, thus these specifications only include individuals with upper-secondary education or above.

[12] Note: Specifications that include field of education (Specification 3) are estimated on a restricted sample, because field of study information is only available for respondents with at least upper secondary education (ISCED 3+). Consequently, changes in the gender coefficient between Specifications 2 and 3 reflect both (i) the inclusion of field-of-education controls and (ii) the shift to a more educated subsample. This restriction is nevertheless substantively relevant for our focus on intermediate and especially advanced digital tasks, which are concentrated in jobs that typically require at least upper secondary, and often tertiary, qualifications. For this reason, we treat Specification 3 as our preferred benchmark when comparing gender gaps across Ireland and the rest of Europe.

TABLE 5.2 REGRESSION RESULTS FOR DIGITAL SKILLS USE FOR EUROPE: ADVANCED

	Ireland			Rest of Europe		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.244***	-0.164***	-0.195***	-0.130***	-0.101***	-0.093***
	(0.030)	(0.031)	(0.043)	(0.006)	(0.006)	(0.007)
Detailed controls	NO	YES	YES	NO	YES	YES
Education field controls	NO	NO	YES	NO	NO	YES
Observations	*1,263*	*1,130*	*672*	*38,506*	*37,707*	*23,671*

Source: ESJS2 (Cedefop).
Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1. Detailed controls include ISCO-2 occupation, NACE-1 industry, area of residence, firm size, sector (public, private, etc.), education level, contract type, part-time status, age and country FE. Non-detailed controls include age, area of residence and country FE. Weighted. Field of education is only recorded for a limited sample, thus these specifications only include individuals with upper-secondary education or above.

For the continuous JDII measure, women on average score 8.6 points lower than men in Ireland and 4.5 points lower in the rest of Europe, even after controlling for job and worker characteristics. The gap persists across all specifications: while controls explain part of the disparity, a substantial unexplained component remains. These results suggest that differences in observed characteristics such as education, job type and sector only partially account for the gender gap, particularly at higher levels of digital skill complexity. Notably, women remain significantly underrepresented in more complex digital task components even when they have comparable education and work in similar sectors as men, with the Irish gap consistently larger than that observed elsewhere in Europe.

TABLE 5.3 REGRESSION RESULTS FOR DIGITAL SKILLS USE FOR EUROPE: JOB DIGITAL INTENSITY INDEX

	Ireland			Rest of Europe		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-12.92***	-8.25***	-8.56***	-5.61***	-5.56***	-4.54***
	(1.82)	(1.86)	(2.56)	(0.31)	(0.32)	(0.40)
Detailed controls	NO	YES	YES	NO	YES	YES
Education field controls	NO	NO	YES	NO	NO	YES
Observations	*1,263*	*1,130*	*672*	*38,506*	*37,707*	*23,671*

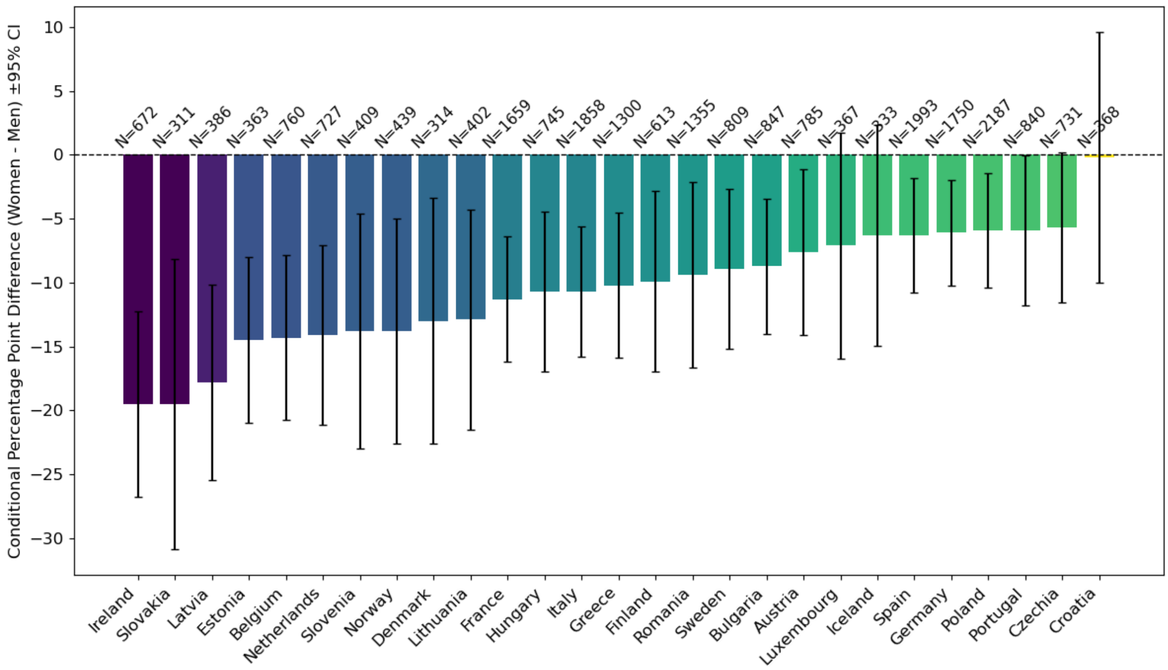
Source: ESJS2 (Cedefop).
Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1.. Detailed controls include ISCO-2 occupation, NACE-1 industry, area of residence, firm size, sector (public, private, etc.), education level, contract type, part-time status, age and country FE. Non-detailed controls include age, area of residence and country FE. Weighted. Field of education is only recorded for a limited sample, thus these specifications only include individuals with upper-secondary education or above.

To provide a sense of scale, we compare the estimated female coefficient in Specification 3 with selected education-field contrasts from the same specification. In Ireland, the estimated female effect on advanced digital task use is approximately twice the magnitude of the difference between workers with an arts/humanities background and those with an ICT background. In the rest of Europe, the female effect is smaller relative to education field, amounting to just over one-third of the corresponding arts–ICT contrast. For the continuous JDII outcome, the estimated female penalty in Ireland is broadly comparable to moving from science/maths to arts/humanities, whereas in the rest of Europe, the female effect is just over half the science/maths–arts contrast.[13]

Figure 5.1 illustrates the conditional advanced digital task gap for Ireland and the rest of Europe, based on the fully controlled specification (Table 5.2, Specification 3). The figure plots the gender difference in the probability of performing advanced digital tasks after accounting for individual and job characteristics, including field of study. The results highlight that the gender gap remains the largest in Ireland, reinforcing the regression findings. The persistence of the gap after controlling for observed characteristics is suggestive of within-occupation task allocation, access to high-impact projects or training, or other unmeasured factors which may appear more pronounced in Ireland than in other European labour markets. Nevertheless, the findings also show that while national labour market structures and education systems influence digital participation on the job, gender-based barriers in high-skill digital employment are widespread and persistent across Europe.

[13] These comparisons are descriptive and are computed within each sample using that sample's coefficients; differences across Ireland and Europe may therefore also reflect differences in how education fields translate into digital task use across labour markets.

FIGURE 5.1 CONDITIONAL ADVANCED DIGITAL TASK GAP BY COUNTRY (INCLUDING FIELD OF STUDY)



Source: ESJS2 (2021).
Note: Coefficients reported are from separate country level probit regressions on advanced task usage. It is the marginal effect of the female variable. Whiskers represent 95% confidence interval. Weighted.

5.2 DECOMPOSING THE GENDER DIGITAL SKILLS GAP

To quantify how much of the observed gender gap can be attributed to differences in characteristics rather than differences in the returns to those characteristics, we conduct a Blinder-Oaxaca decomposition separately for Ireland and for the rest of Europe. Table 5.4 reports the mean decomposition of the average gender gaps in digital task use for both samples, partitioning the gap into the share attributable to observable characteristics (explained) and the residual that reflects differential returns or unobserved factors (unexplained).

For advanced digital tasks, the raw gender gap is approximately 34 percentage points in Ireland and 15 percentage points in the rest of Europe. Of this, 32 per cent is explained in Ireland and 40 per cent is explained in the rest of Europe. For the Job Digital Intensity Index (JDII), the raw gap is approximately 16 in Ireland and 7 in the rest of Europe, with 51 per cent of the gap explained in Ireland compared to 32 per cent in the rest of Europe.

Turning to the composition of the explained component, the patterns differ markedly between Ireland and the rest of Europe. In Ireland's advanced-tasks specification, the gap is driven primarily by occupation and industry, each accounting for roughly 20 per cent, which is consistent with stronger occupational and sectoral sorting into high-tech roles. Field of education contributes very little in Ireland for advanced tasks, which indicates that what job a worker does matters more than what they studied for explaining gender differences at the advanced end of digital work.

In the rest of Europe, the pattern by outcome is different. For advanced tasks, field of education plays a larger role, comparatively, at about 20 per cent, in line with cross-country variation in STEM and ICT specialisation. For the continuous JDII outcome, occupation adds little explanatory power in the rest of Europe once sector and education are controlled for, suggesting that overall digital intensity is not well proxied by broad occupational titles outside Ireland. Other factors, including age, contract type, area of residence and firm size, contribute modestly in both samples. By contrast, education level and sector (private/public/not-for-profit) contribute negatively or only minimally to the explained share, indicating that aggregate qualification levels or sector do not, on their own, account for the observed disparities.

One possible interpretation is that the Irish labour market has a more polarised concentration of digitally intensive work in a narrower set of occupations and industries, so broad occupational sorting captures a larger share of the gender gap. Ireland's industrial structure is characterised by a large presence of multinational, ICT-intensive firms alongside a sizeable domestically oriented services sector, and thus may generate sharper differences in digital task intensity across occupations than in many other European countries. In such a setting, individuals sorting into particular occupations and industries may be a stronger determinant of digital task use, whereas in the rest of Europe, differences in field of study may map more directly into advanced digital tasks through education-to-occupation pathways. At the same time, the finding that occupation explains very little of the JDII gap outside Ireland may reflect greater within-occupation heterogeneity in digital task requirements across countries (i.e. the same broad ISCO-2 category can encompass jobs with very different digital content), so occupational titles are a noisier proxy for digital intensity in a pooled European sample.[14]

These results align with the structure of employment. In both samples, men are more concentrated in ICT-intensive occupations such as ICT specialists, engineering and technical management, while women are relatively more present in services and administrative roles that have lower average digital intensity. Women's tertiary attainment is higher than men's in both Ireland and the rest of Europe, which narrows any gap attributable to education level per se. However, field of study remains important outside Ireland: women are less likely to hold STEM degrees, particularly in ICT and engineering, which contributes more to the explained component in the rest of Europe more than in Ireland, where occupation and industry sorting dominates. If women had the same distribution across industries, occupations and fields of study as men, the gender gap would shrink in both Ireland and the rest of Europe, but it would not disappear because the sizable unexplained component remains.

[14] These explanations are necessarily tentative given the cross-sectional and self-reported nature of the ESJS, but they provide plausible channels to be examined in future work using more granular job and firm information.

The unexplained share of the gender digital skills gap varies notably across outcomes and between Ireland and the rest of Europe[15]. For advanced tasks, Ireland shows a larger unexplained component (around 68%) than Europe average (60%), while for JDII, the opposite holds (49% vs. 68%). In Ireland's advanced-task decomposition, most of the unexplained gap relates to sector and age effects, with smaller positive contributions from part-time status, field of education, and industry, partly offset by negative effects from occupation and the shift term. This suggests that gender differences within sectors and across age groups drive much of the unobserved variation rather than occupational segregation itself.

In contrast, for the rest of Europe, the advanced-task gap is dominated by a large positive shift term, implying a broad unobserved baseline difference once age and occupation are controlled for. For JDII, Ireland's unexplained share reflects within-occupation and age-related differences, whereas in the rest of Europe, the unexplained gap is mainly due to the shift term, with occupation and other characteristics contributing negatively. Overall, Ireland's unexplained components point to unobserved differences within observable categories, while in wider Europe, generic unobserved effects dominate.

Overall, the decomposition patterns point to potentially different underlying correlates of the gender gap in Ireland and in the rest of Europe. In Ireland, the main unobserved margins for advanced tasks run through sectoral context and career stage, while the main unobserved margin for JDII runs within occupations. In the rest of Europe, the residual looks more like a systematic baseline difference that is not well captured by observed characteristics, while field of study remains a comparatively important channel for advanced tasks, and occupation is relatively uninformative for JDII. These patterns are consistent with several possible explanations, such as within-role task allocation, unequal returns to similar experience or credentials and differences in access to informal training, and they indicate that reducing gender disparities in digital work will possibly require both compositional changes and changes in how digital responsibilities are allocated within jobs.

[15] The unexplained component reflects differences not captured by observed variables; it is not evidence of discrimination or structural barriers by itself.

TABLE 5.4 BLINDER-OAXACA DECOMPOSITION FOR THE GENDER DIGITAL GAP FOR EUROPE

Outcome variable	Intermediate or above tasks		Advanced tasks		JDII	
	1	2	3	4	5	6
SAMPLE	**Ireland**	**Rest of Europe**	**Ireland**	**Rest of Europe**	**Ireland**	**Rest of Europe**
Men	74.7%	75.0%	56.2%	36.0%	49.40	38.66
Women	61.6%	67.5%	21.9%	20.6%	33.65	32.01
Difference	13.2 p.p.	7.5 p.p.	34.3 p.p.	15.3 p.p.	15.75	6.65
Explained						
Total	98.5%	40.0%	32.4%	40.5%	50.7%	32.3%
Age	18.2%	0.0%	3.8%	0.7%	4.7%	0.8%
Part-time	-0.8%	2.7%	-2.6%	-3.3%	-1.9%	-1.1%
Field of education	18.2%	22.7%	0.6%	20.3%	10.3%	24.1%
Contract type	0.0%	2.7%	0.3%	1.3%	0.3%	2.4%
Education level	0.0%	-9.3%	0.0%	-3.9%	0.0%	-10.8%
Area of residence	-0.8%	0.0%	-1.7%	0.0%	2.0%	0.6%
Firm size	6.8%	2.7%	1.2%	0.7%	3.0%	2.9%
Sector	-17.4%	-1.3%	-3.5%	-7.2%	-8.7%	-6.5%
Occupation	48.5%	0.0%	20.4%	17.6%	19.6%	0.9%
Industry	25.0%	21.3%	13.7%	13.7%	21.3%	17.6%
Country		0.0%		0.7%		1.5%
Unexplained						
Total	1.5%	60.0%	67.6%	59.5%	49.3%	67.7%
Age	-0.8%	-60.0%	64.1%	-35.3%	48.7%	-54.7%
Part-time	0.8%	2.7%	12.2%	5.9%	12.0%	7.1%
Field of education	0.0%	5.3%	9.9%	0.7%	21.9%	5.0%
Contract type	0.0%	-2.7%	2.9%	7.8%	18.4%	14.0%
Education level	0.0%	5.3%	-0.6%	5.2%	-0.4%	-7.2%
Area of residence	0.0%	4.0%	-2.6%	-2.0%	-0.4%	0.6%
Firm size	0.0%	4.0%	1.2%	0.0%	3.0%	2.1%
Sector	1.5%	-14.7%	85.4%	0.0%	10.8%	-3.2%
Occupation	-0.8%	-66.7%	-34.4%	-92.2%	100.1%	-16.5%
Industry	-1.5%	28.0%	8.2%	-1.3%	-47.5%	-5.9%
Country		-13.3%		-4.6%		-3.6%
Shift component	0.8%	166.7%	-78.4%	173.9%	-117.3%	130.1%
Observations	600	23,943	648	23,939	688	23,917

Source: ESJS2 (Cedefop).
Note: Oaxaca-Blinder decomposition of three outcome variable, for Ireland and rest of Europe. Percentages show the per cent a variable contributes to the gender gap in the outcome variable. Intermediate and above, and advanced specifications show the difference in gender mean %, JDII specification shows the gap in mean JDII value. Raw gaps in Table 5.4 are computed on the decomposition sample restricted to employees with an upper-secondary education or above, hence differ from Table 3.1. Weighted.

We also identify the specific fields of education, occupations and industries (Table 5.5 and 5.6) that contribute most to the explained component of the gender gap in the JDII. The rankings differ across Ireland and the rest of Europe. In Ireland, the industry and occupation lists are headed by education (19%) and production and specialised services managers (10%), followed by health and social work (13%) and ICT professionals (7%). The corresponding field-of-education contributions are comparatively small, which is consistent with the earlier finding that field of education plays a limited role for Ireland once occupational and sectoral sorting is taken into account. In the rest of Europe, field of education is more important, with ICT at 12 per cent at the top of the ranking, and the industry list is led by health and social work at 9 per cent and education at 7 per cent. These patterns reinforce the view that the Irish gap in digital intensity is shaped more by where women and men work, and what roles they hold within sectors, while in the rest of Europe, educational specialisation is a more prominent channel.

Furthermore, we explore how the gender digital gap differs across countries within Europe. Figure 5.2 shows the total gender gap in the JDII and the share explained by gender differences in observable characteristics. While we find that gap is clearly largest in Ireland, a sizable proportion of this gap is explained by differences in characteristics between men and women.

TABLE 5.5 TOP CATEGORIES EXPLAINING GENDER GAP IN JDII – IRELAND

Rank	Field of education	% Expl.	Occupation	% Expl.	Industry	% Expl.
1	Education	4.8%	Production and specialised services managers	10%	Education	18.5%
2	Arts, humanities and foreign languages	2.5%	ICT professionals	7.1%	Health and social work	13%
3	Engineering, manufacturing and construction	1.7%	Building and related trades workers	3.9%	Public admin and defence	1.5%
4	Services (personal, security, transport)	1%	Personal care workers	3.2%	ICT	1.1%
5	Business, administration and law	0.9%	ICT technicians	2.8%	Real estate	0.3%

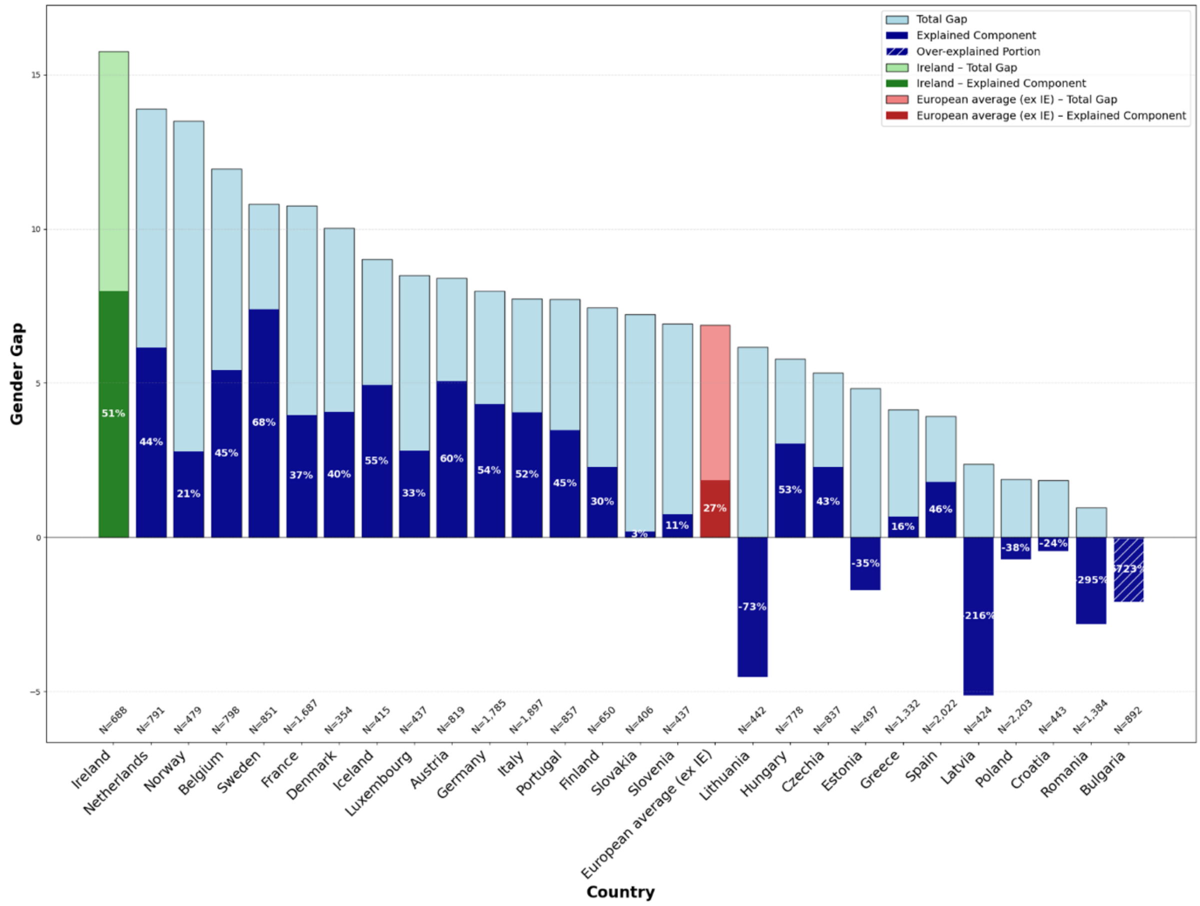
Source: ESJS2 (Cedefop).
Note: Oaxaca-Blinder decomposition of three outcome variable, for Ireland. Percentages show the per cent a variable contributes to the gender gap in the outcome variable. Intermediate and above, and advanced specifications show the difference in gender mean %, JDII specification shows the gap in mean JDII value. Weighted.

TABLE 5.6 TOP CATEGORIES EXPLAINING GENDER GAP IN JDII – REST OF EUROPE

Rank	Field of education	% Expl.	Occupation	% Expl.	Industry	% Expl.
1	ICT	11.7%	ICT professionals	7.7%	Health and social work	9.0%
2	Arts, humanities and foreign languages	3.3%	Production and specialised services managers	3.9%	Education	7.4%
3	Education	2.4%	ICT technicians	3.6%	ICT	2.4%
4	Health and welfare	2.4%	Personal care workers	3.5%	Public admin and defence	1.7%
5	Social sciences, journalism and information	1.8%	Health professionals	2.3%	Mining and quarrying	0.3%

Source: ESJS2 (Cedefop).
Note: Oaxaca-Blinder decomposition of three outcome variable, for rest of Europe. Percentages show the per cent a variable contributes to the gender gap in the outcome variable. Intermediate and above, and advanced specifications show the difference in gender mean %, JDII specification shows the gap in mean JDII value. Weighted.

FIGURE 5.2 BLINDER-OAXACA DECOMPOSITION FOR THE GENDER GAP IN JOB DIGITAL INTENSITY INDEX BY COUNTRY



Source: ESJS (2021).
Note: This figure shows the total gender gap in the JDII and the share explained by gender differences in observable characteristics. Gaps and N here differ from Figure 3.1 as this is limited to those with an upper-secondary education or above. European average just averages gap and explained component over all countries excluding Ireland.

5.3 DISTRIBUTIONAL PATTERNS IN DIGITAL TASKS USAGE

In the final step, we examine the distributional nature of the gender digital-usage gap at three points of the JDII distribution, namely the 25th, 50th, and 75th percentiles (Figure 5.3). The gap is not uniform across the distribution. In both Ireland and the rest of Europe, the gender gap is relatively small at the lower tail and grows as we move up the distribution. It is, however, consistently larger in Ireland, exceeding twice the size of the gap in the rest of Europe at each percentile.

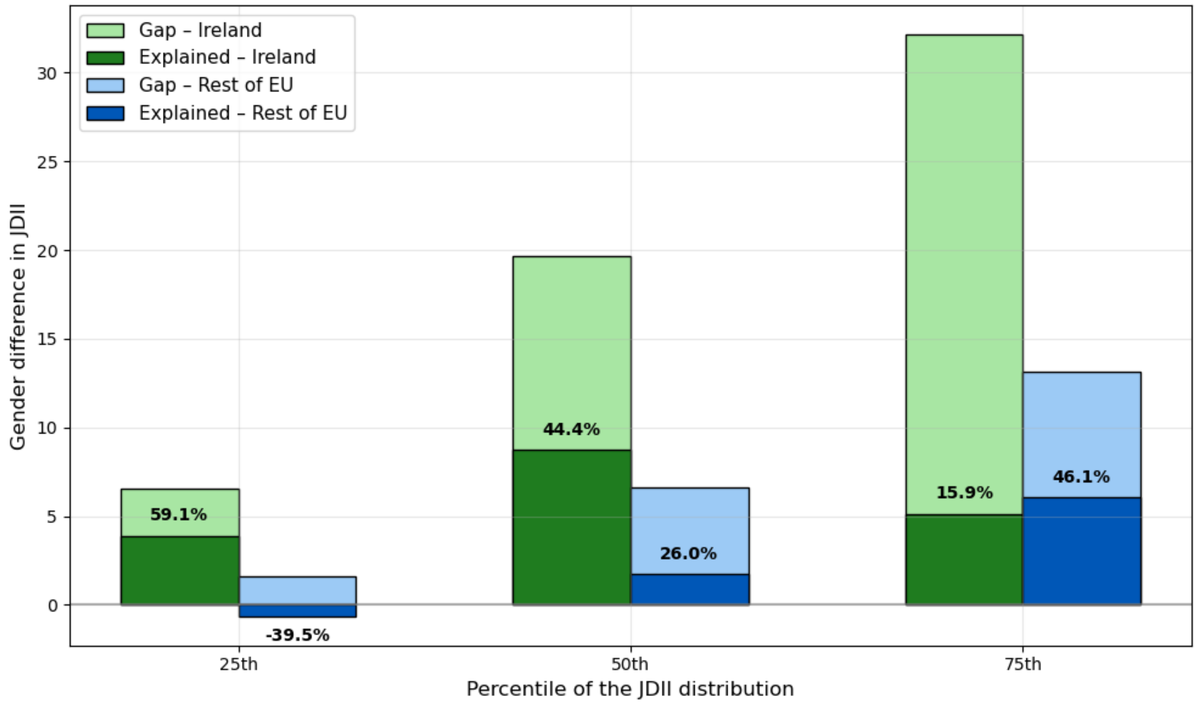
In Ireland, the gender gap at the 75th percentile is approximately 32 points on the 0–100 JDII scale, compared with 20 at the median and 7 at the 25th percentile. In the rest of Europe, the corresponding gaps are 13, 7, and 2. Thus, while the gap widens with digital intensity in both samples, the upper-quartile gap is much larger in Ireland, indicating stronger underrepresentation of women in higher-intensity digital roles. Consistent with this, the raw JDII distributions by gender (Appendix Figure A.1 and Figure A.2) show a visibly thinner upper tail for women, especially in Ireland.

There is also an inverse pattern in how much of the gap is explained by observable characteristics as we move up the JDII distribution. At the 25th percentile, a larger share of the Irish gap is explained than in the rest of Europe (59% vs. −40%). The negative explained share in the rest of Europe indicates that, based on observables alone, women would be predicted to have a small advantage at the lower quartile; the observed male advantage therefore arises entirely from the unexplained component. As we move up the distribution, the explained share declines in Ireland but rises in the rest of Europe. At the median, the explained share in Ireland remains slightly higher than in the rest of Europe. At the 75th percentile, almost one-half of the gap is explained in the rest of Europe, whereas only about 16 per cent is explained in Ireland.

Figure 5.4 decomposes the explained component at each quartile into field of education, occupation and industry. In the rest of Europe, most of the increase in explanatory power from the 25th to the 75th percentile is accounted for by occupation, while the contributions of field of education and industry remain broadly flat. In Ireland, the pattern is the reverse: occupation is the strongest explainer at lower levels of digital intensity but contributes very little at the 75th percentile, and field of education remains small across the distribution.

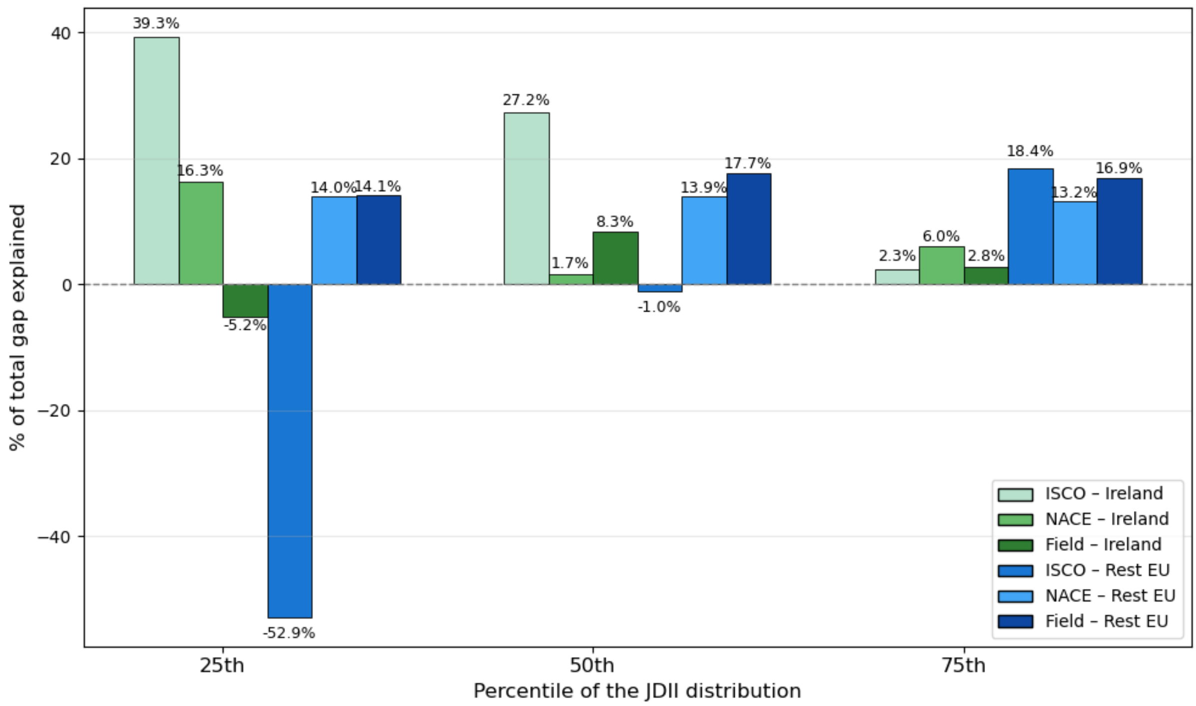
This means that the widening upper-tail gap in the rest of Europe is largely a compositional story of who holds which occupations at the top of the digital intensity distribution. By contrast, the widening upper-tail gap in Ireland is not primarily driven by differential occupational placement. Instead, it points to differences within occupations and sectoral contexts at higher intensities of digital work, consistent with greater roles for task allocation, progression into digitally intensive functions, and returns to experience once workers are already in similar job titles. Consequently, occupational reallocation is likely to yield larger payoffs in the rest of Europe, whereas in Ireland policy will need to focus more on advancing women within occupations and sectors into the most digitally intensive tasks and responsibilities.

FIGURE 5.3 QUANITILE DECOMPOSITION OF JDII BY GENDER, GAP AND % EXPLAINED



Source: ESJS2 (2021).
Note: Component shares can be negative or exceed 100% when explained and unexplained subcomponents offset each other; results should be interpreted in terms of signs and net totals.

FIGURE 5.4 QUANTILE DECOMPOSITION: EXPLAINED COMPONENT BY DRIVER



Source: ESJS2 (2021).
Note: Component shares can be negative or exceed 100% when explained and unexplained subcomponents offset each other; results should be interpreted in terms of signs and net totals.

TABLE 5.7 QUANTILE DECOMPOSITION OF JDII DETAILED RESULTS (EXPLAINED COMPONENTS)

Percentile	25th		50th		75th	
	1	2	3	4	5	6
SAMPLE	Ireland	Rest of Europe	Ireland	Rest of Europe	Ireland	Rest of Europe
Men	26.531	20.576	48.839	35.947	80.28	58.015
Women	19.949	18.95	29.15	29.325	48.117	44.864
Difference	6.582	1.626	19.689	6.622	32.163	13.151
Explained						
Total	59.1%	-39.5%	44.4%	26.0%	15.9%	46.1%
Age	5.1%	1.0%	3.2%	0.4%	2.8%	0.4%
Part-time	7.8%	17.3%	3.5%	3.5%	1.6%	2.0%
Field of education	-5.2%	14.1%	8.3%	17.7%	2.8%	16.9%
Contract type	-0.4%	7.3%	0.2%	2.7%	0.1%	0.9%
Education level	0.3%	-30.3%	-0.1%	-8.7%	-0.1%	-5.4%
Area of residence	2.3%	0.6%	0.0%	0.0%	1.1%	0.4%
Firm size	4.8%	1.3%	3.3%	0.8%	3.4%	1.0%
Sector	-11.6%	-14.1%	-2.7%	-4.0%	-4.1%	-2.9%
Occupation	39.3%	-52.9%	27.2%	-1.0%	2.3%	18.4%
Industry	16.3%	14.0%	1.7%	13.9%	6.0%	13.2%
Country	0.0%	3.1%	0.0%	0.9%	0.0%	0.7%
Unexplained						
Total	40.9%	139.5%	55.6%	74.0%	84.1%	53.9%
Age	36.7%	-137.3%	-12.3%	-106.1%	33.1%	-81.6%
Part-time	20.1%	-4.0%	10.6%	5.2%	6.4%	7.8%
Field of education	34.9%	33.0%	39.8%	7.8%	6.9%	3.2%
Contract type	-62.3%	42.2%	20.3%	18.1%	38.1%	13.1%
Education level	0.9%	12.2%	0.6%	8.7%	0.4%	6.7%
Area of residence	1.5%	1.7%	-0.2%	2.0%	2.0%	1.0%
Firm size	-40.7%	-8.0%	-10.1%	-1.6%	-18.1%	3.9%
Sector	58.1%	-84.3%	0.9%	-21.1%	-20.1%	-3.7%
Occupation	256.8%	-23.6%	119.7%	-35.3%	59.2%	-9.5%
Industry	71.5%	79.5%	-54.5%	9.1%	-12.0%	-13.8%
Country	0.0%	2.2%	0.0%	1.2%	0.0%	0.8%
Shift component	-396.5%	199.8%	-72.4%	178.3%	-30.0%	127.9%

Source: ESJS2 (2021).
Note: Quantile decomposition of JDII, for Ireland and rest of Europe. Percentages show the per cent a variable contributes to the gender gap in the outcome variable. Weighted. Component shares can be negative or exceed 100% when explained and unexplained subcomponents offset each other; results should be interpreted in terms of signs and net totals.

CHAPTER 6

Conclusions

This report examines the gender gap in the use of digital skills at work across Europe, with a specific focus on Ireland, using the European Skills and Jobs Survey (Cedefop, 2021). In doing so, we examine differences not only in the use of specific digital tasks, ranging from basic activities such as internet use, word processing, and simple spreadsheets to advanced tasks including programming, artificial intelligence (AI) or machine learning, and IT systems management, but also in the overall intensity of digital engagement at work. To capture this broader dimension, we construct a Job Digital Intensity Index (JDII), which summarises how digitally intensive a job is based on the range and complexity of digital tasks performed. Consistent patterns emerge across Europe: while women and men use basic digital skills at similar rates, women are significantly less likely to perform advanced digital tasks. These gaps persist even after controlling for key observable factors such as education, field of study, occupation and industry, indicating that observed characteristics alone do not account for the full disparity.

Across Europe, women are approximately 15 percentage points less likely than men to undertake advanced digital tasks in their jobs such as programming, artificial intelligence/machine learning, or IT system management. Differences in observable characteristics explain only a minority of this gap at around 40 per cent on average, leaving roughly 60 per cent unexplained. This equates to a 10 percentage point unexplained gap in the proportions of men and women using advanced digital skills at work. The unexplained component captures differences not measured in the survey and is potentially consistent with a range of mechanisms (such as within-job task assignment, differential access to high-impact projects or training, or because the relationship between characteristics and advanced digital task use differs by gender), but it does not, by itself, identify the underlying causes. Furthermore, analysis of our Job Digital Intensity Index (JDII) shows that gender disparities widen significantly at the very upper end of the distribution. While the lower and middle levels of digital intensity show more modest differences, the gap becomes most pronounced for jobs requiring the most digitally intensive range of tasks, pointing to a 'digital glass ceiling' within workplaces.

Ireland stands out in the European context. It exhibits the largest gender gap in advanced digital task use, with approximately 44 per cent of men versus 18 per cent of women performing advanced digital tasks, i.e. a 26 percentage point difference, close to double the European average. Importantly, women in Ireland use advanced digital skills at rates comparable to women elsewhere in Europe; the distinctiveness of Ireland's gap arises from substantially higher usage among men in Ireland. Decomposition analysis shows that occupational sorting explains a slightly larger share of the gap in Ireland than in other European countries, but a substantial portion remains unexplained, highlighting the potential influence of unobserved structural, cultural or other organisational factors specific to the Irish labour market.

Distributional analysis, using the pooled European sample, further reveals that gender gaps are larger, and less of the gap is explained by observable characteristics among younger cohorts (aged under 35). These cohort patterns are descriptive and should not be interpreted as causal or as evidence of changing 'effects' over time. Nevertheless, they indicate that the issue is not a legacy effect among older workers; rather, early-career women are already less represented in advanced digital roles and face more unexplained disparities than older women. These patterns suggest that shifts in workforce compositions across cohorts alone will not close this digital divide and reinforces the importance of understanding how digitally intensive work is accessed and allocated early in careers.

Several limitations should be borne in mind when interpreting these findings. First, digital task measures are self-reported and may be subject to reporting error and cross-country differences in interpretation. Second, the ESJS is cross-sectional, so the analysis is descriptive and does not support causal inference about the drivers of the unexplained component. Third, the ESJS does not capture some potentially relevant factors, such as detailed information on projects within firms, promotion pathways and managerial responsibilities. Finally, some country-specific estimates may be sensitive to sample sizes, especially when models are estimated separately by country or when restricting to subsamples with field-of-study data. Future research would benefit from linked employer-employee data and/or longitudinal administrative sources that can measure within-firm task allocation, training access, project assignment, promotions into supervisory/manager roles, and more granular worker information.

Overall, the evidence shows that closing the gender gap in digital skill use at work requires more than balancing educational attainment or widening access to STEM fields of study and occupations. A substantial share of the gap remains unexplained by observable characteristics in the ESJS, particularly at the upper end of the digital intensity distribution, pointing to other workplace dimensions, potentially in how digitally intensive tasks are accessed and undertaken. While education and access to digital jobs are important, the results highlight the need for further research into other factors that may shape opportunities and decisions to develop and/or apply advanced digital skills, including workplace organisation, task allocation, progression pathways, and broader organisational practices. Enhanced monitoring of digital task use and improved data linking skills, tasks and labour market outcomes would further support evidence-based policy design. Addressing these issues will be important not only for gender equality, but also for productivity, innovation, and inclusive economic growth in Ireland by ensuring that digital human capital is fully utilised.

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APPENDIX

TABLE A.1 ADDITIONAL SUMMARY STATS (EU POOLED)

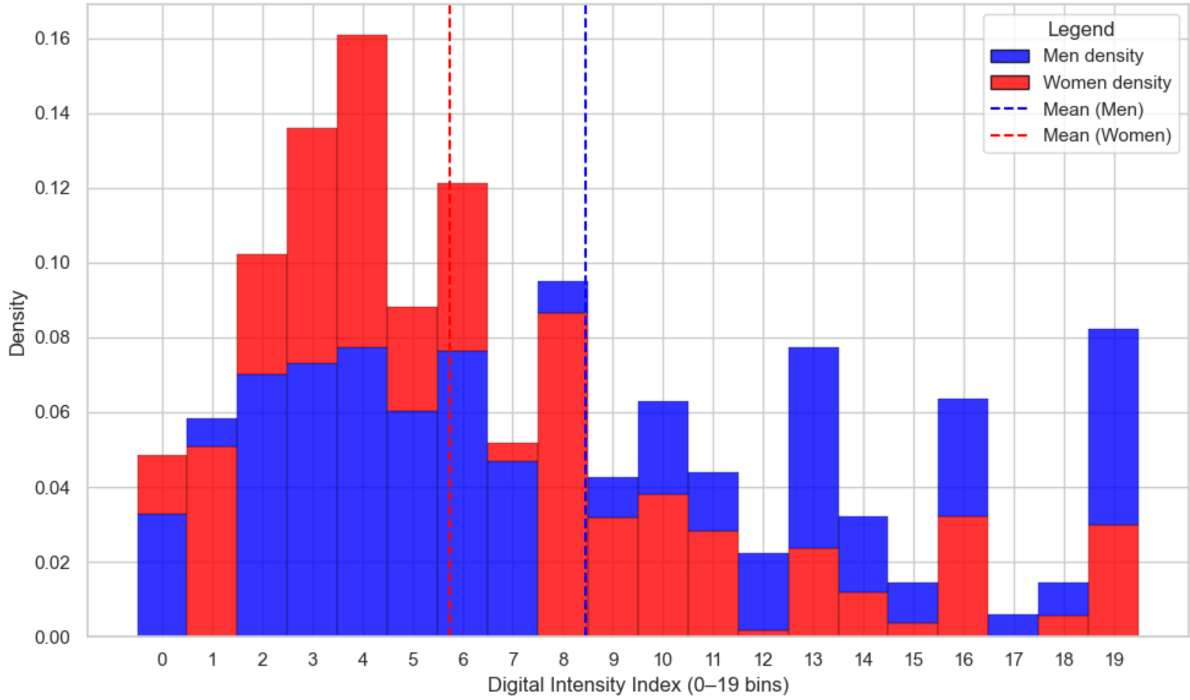
Variable	Observations	Overall Prevalence	Male Prevalence	Female Prevalence
Female	44,178	0.49	0	1
Tenure	43,665	9.9	10.07	9.74
Age	44,208	43.41	43.28	43.54
Part-time	44,208	0.21	0.13	0.29
Contract type				
Permanent	44,132	0.84	0.86	0.82
Temporary	44,132	0.13	0.12	0.15
No contract	44,132	0.02	0.02	0.03
Education level				
Low	44,122	0.11	0.13	0.09
Middle	44,122	0.46	0.5	0.41
High	44,122	0.43	0.37	0.49
Area of residence				
Rural	44,181	0.25	0.24	0.25
Small/medium town	44,181	0.37	0.37	0.37
City	44,181	0.38	0.39	0.37
Firm size				
1 to 10	43,908	0.21	0.2	0.23
11 to 49	43,908	0.28	0.27	0.29
50 to 249	43,908	0.26	0.26	0.25
250 or more	43,908	0.25	0.27	0.23
Sector				
Private	44,055	0.63	0.72	0.54
Public	44,055	0.29	0.21	0.37
Not-for-profit	44,055	0.03	0.02	0.03
Other	44,055	0.05	0.05	0.05
Education field				
Arts and humanities	27,409	0.07	0.03	0.1
Generic programmes	27,409	0.08	0.05	0.11
Education	27,409	0.1	0.11	0.09
Social sciences	27,409	0.04	0.03	0.05
Business, admin and law	27,409	0.18	0.14	0.22
Natural sciences, maths and stats	27,409	0.08	0.09	0.08
ICT	27,409	0.08	0.12	0.04
Engineering and construction	27,409	0.18	0.27	0.08
Agriculture	27,409	0.03	0.03	0.02
Health	27,409	0.08	0.04	0.13
Services	27,409	0.08	0.09	0.06

Occupation				
Commissioned armed forces officers	43,352	0.11	0.18	0.04
Non-commissioned armed forces officers	43,352	0.02	0.01	0.02
Armed forces occupations, other ranks	43,352	0.15	0.21	0.08
Chief executives, senior officials and legislators	43,352	0.86	0.98	0.73
Administrative and commercial managers	43,352	3.08	3.29	2.85
Production and specialised services managers	43,352	4	4.89	3.07
Hospitality, retail and other services	43,352	1.27	1.27	1.26
Science and engineering professionals	43,352	3.11	3.9	2.27
Health professionals	43,352	2.9	1.11	4.79
Teaching professionals	43,352	6	2.67	9.51
Business and administration professionals	43,352	4.4	3.39	5.47
Information and communications technology professionals	43,352	2.91	4.14	1.59
Legal, social and cultural professionals	43,352	2.61	1.76	3.5
Science and engineering associate professionals	43,352	2.68	3.91	1.39
Health associate professionals	43,352	1.85	0.96	2.79
Business and administration associate professionals	43,352	8.12	6.22	10.13
Legal, social, cultural and related assistants	43,352	1.41	1.22	1.61
Information and communications technicians	43,352	1.9	2.7	1.06
General and keyboard clerks	43,352	3.84	2.27	5.5
Customer services clerks	43,352	3.27	2.42	4.17
Numerical and material recording clerks	43,352	3.2	2.81	3.61
Other clerical support workers	43,352	1.33	0.93	1.76
Personal service workers	43,352	2.99	2.32	3.68
Sales workers	43,352	4.65	3.06	6.34
Personal care workers	43,352	3.75	1.03	6.62
Protective services workers	43,352	1.8	2.82	0.72
Market-oriented skilled agricultural workers	43,352	1.04	1.21	0.85
Market-oriented skilled forestry, fishery, hunting workers	43,352	0.23	0.36	0.09
Subsistence farmers, fishers, hunters	43,352	0.01	0.01	<1%
Building and related trades workers, excluding electricians	43,352	2.71	4.79	0.5
Metal, machinery and related trades workers	43,352	3.3	5.8	0.66
Handicraft and printing workers	43,352	0.81	1.14	0.47
Electrical and electronic trades worker	43,352	2.25	3.91	0.49
Food processing, wood working, garment manufacturers	43,352	2.16	2.36	1.96
Stationary plant and machine operators	43,352	2.31	3.16	1.41
Assemblers	43,352	1.23	1.75	0.68
Drivers and mobile plant operators	43,352	3.9	6.7	0.95
Cleaners and helpers	43,352	2.16	0.8	3.59
Agricultural, forestry and fishery labourers	43,352	0.48	0.61	0.34
Labourers in mining, construction, manufacturing	43,352	3.72	5.39	1.95
Food preparation assistants	43,352	0.77	0.51	1.04
Street and related sales and service workers	43,352	0.06	0.08	0.05

Refuse workers and other elementary workers	43,352	0.69	0.96	0.39
NACE-1 Industry				
Agriculture, forestry and fishing	43,434	0.02	0.02	0.01
Mining and quarrying	43,434	<1%	0.01	<1%
Manufacturing	43,434	0.18	0.25	0.11
Energy supply	43,434	0.02	0.02	0.01
Water and waste management	43,434	0.01	0.01	0.01
Construction	43,434	0.05	0.08	0.02
Wholesale and retail trade	43,434	0.09	0.09	0.1
Transportation and storage	43,434	0.06	0.09	0.03
Accommodation and food services	43,434	0.04	0.04	0.05
Information and communication	43,434	0.06	0.07	0.04
Finance and insurance	43,434	0.03	0.03	0.04
Real estate	43,434	0.01	0.01	0.01
Professional and technical services	43,434	0.06	0.05	0.07
Admin and support services	43,434	0.06	0.06	0.07
Public admin and defence	43,434	0.06	0.05	0.06
Education	43,434	0.09	0.04	0.15
Health and social work	43,434	0.11	0.04	0.18
Arts and recreation	43,434	0.02	0.01	0.02
Other services	43,434	0.02	0.01	0.02
Household activities	43,434	<1%	<1%	<1%
Extraterritorial organisations	43,434	<1%	<1%	<1%

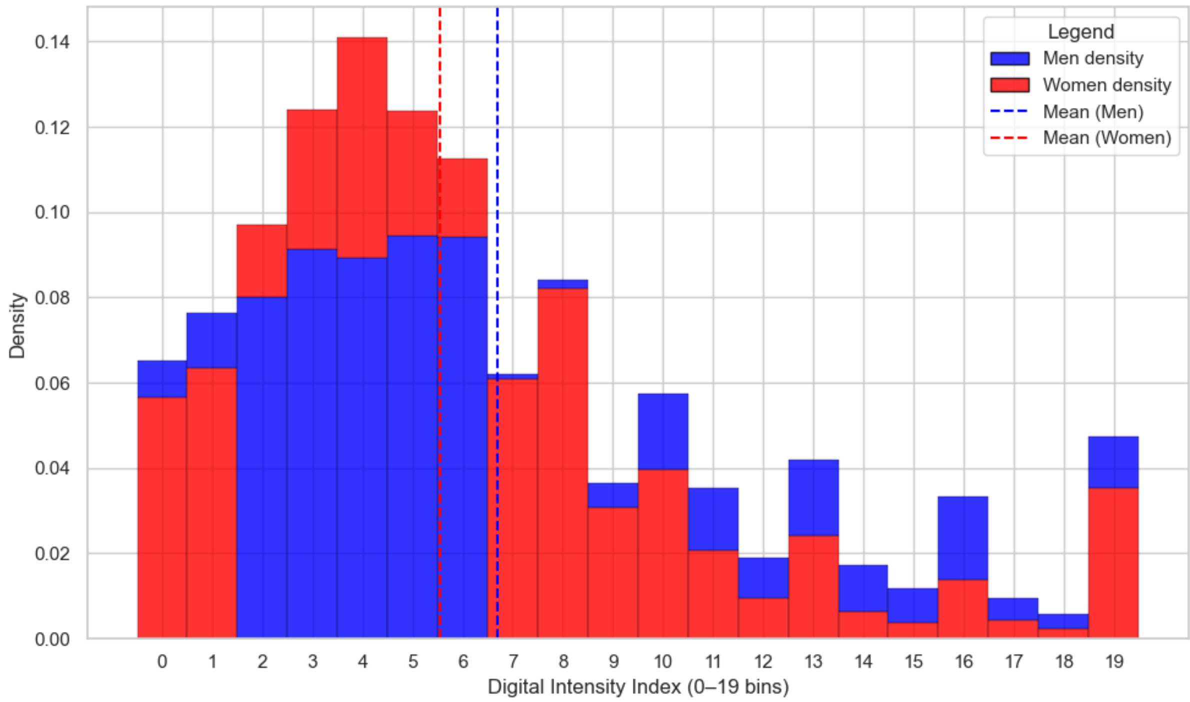
Source: ESJS2 (2021).
Note: Based on authors' own calculations. Weighted.

FIGURE A.1: RAW DISTRIBUTION OF JDII BY GENDER – IRELAND (NO RESCALING AND NO SMOOTHING 0–19)



Source: ESJS2 (2021).
Notes: Raw distribution of JDII (0–19 scale) for Ireland, unsmoothed. Weighted.

FIGURE A.2: RAW DISTRIBUTION OF JDII BY GENDER – REST OF EUROPE (NO RESCALING AND NO SMOOTHING 0–19)



Source: ESJS2 (2021).
Notes: Raw distribution of JDII (0–19 scale) for rest of Europe, unsmoothed. Weighted.

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