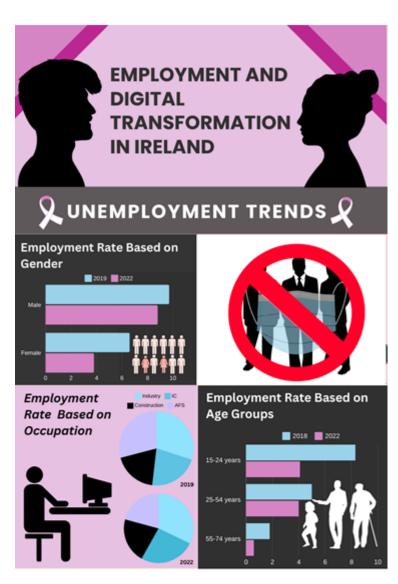
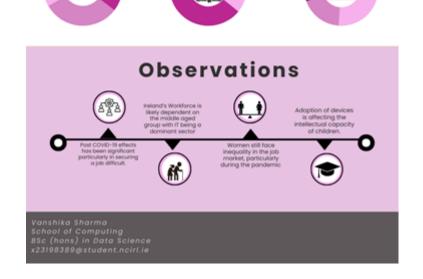
VANSHIKA SHARMA DATA VISUALIZATION

REPORT

O C T O B E R 2 0 2 4



Usage of Digital Devices



Employment and Digital Transformation in Ireland

Vanshika Sharma

School of Computing, National College of Ireland, Ireland x23198389@student.ncirl.ie

Abstract— This document explores digital transformation and employment trends in Ireland, analysing the impact of education, age, gender, and occupational roles. Higher education and professional occupations show greater digital engagement, while lower education levels and elementary jobs have less usage. Gender analysis indicates women face more mental health challenges due to increased phone use. Employment trends during COVID-19 highlight a sharper decline for females and younger workers, emphasizing the need for targeted strategies to improve digital literacy and access.

I. INTRODUCTION

This project presents a comprehensive analysis of the digital transformation and employment trends in Ireland, focusing on various demographic and economic segments. It focuses to explore the impact of digital device usage across different factors like, education levels, age groups, and gender categories. Additionally, the project examines the economic effects of the COVID-19 pandemic on employment rate in Ireland.

The analysis is conducted using publicly available datasets, which provide valuable insights into how digital engagement and employment have evolved across key segments of the Irish workforce. Visualizations, such as bar chart, tree map, and line graph, have been used throughout the project to illustrate key findings. An accompanying infographic provides a visual summary of the main insights, making the data more accessible and understandable.

II. DATA PREPARATION & TOOL SELECTION

The datasets have been downloaded from the official site of Central Statistics Office[1]. Two types of datasets were used: one containing multiple categorical fields, like, occupations and gender, and the other containing continuous numerical data, like year. All the datasets downloaded were easy to read as CSO provides multiple options to download it, csv file format was selected as it is easier to handle for data cleaning and works well with Tableau.

For data visualization, several tools were considered, but due to the complexity of the data, Tableau[2] was chosen. Tableau not only works effortlessly with csv files but also provides flexibility in visualizing complex datasets, offering multiple visualizations for a single dataset. This process was consistent for all the datasets used in the project. Tableau significantly streamlined the preprocessing phase. Instead of manually handling complex data cleaning tasks, the final data was ready by using filters directly to the relevant information within Tableau. This allowed for a focus on key insights, making the process efficient. With just a few steps, unnecessary data was filtered out, and the required visualizations were generated depending upon the nature of the data.

III. DATA ANALYSIS & VISUALIZATION

For the first three visualisations, the dataset categorized usage levels into four categories: None, Little, Some, and Half of the working time. However, these were simplified into three: "Don't use" (None), "Maybe" (Some), and "Yes, they do" (Half of the working time). The "Little" category was omitted, as it did not provide significant insights.

The first dataset[3] compares how men, women, and both sexes interact with digital technologies, and reveals a correlation with psychological well-being. A clustered bar chart was used to visualize because of its ability to compare multiple categories across gender. The x-axis represents digital device usage categories, and the y-axis shows the percentage of digital device usage. Different colours are used to distinguish gender groups. It has been observed that all the genders exhibit similar digital usage patterns, however, women tend to use digital devices slightly more than the others. This suggests that women may face greater mental health challenges related to digital device usage. This finding is supported by a research work done by Twenge[4] which indicates that the higher usage of digital devices has impacted women in terms of having lower psychological well-being, with mental health issues, being more prominent among women than men.

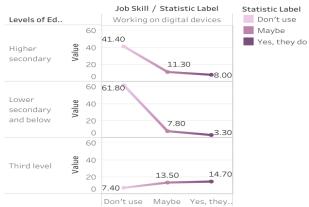
Usage of Digital Devices Based on Genders



Education level significantly influences an individual's knowledge base, shaping one's ability to acquire, understand, and apply information across various domains. In the second dataset[5], a line chart was used to visualize a relation between education levels (Higher Secondary, Lower Secondary, and Third Level) and digital device usage. It was used for its ability to effectively represent the trend of digital engagement and making it easy to interpret. The x-axis represents the degree of usage of digital devices amongst different education levels, and the y-axis represents different levels of engagement.

The chart highlights that individuals with lower secondary education and below have the highest percentage of non-users (61.80%), while those with third-level education show the highest engagement with digital devices (14.70%). A clear trend emerges, showing that as education levels increase, digital device usage rises, particularly in the "Yes, they do" category for those with higher education. To distinguish the education categories different colours were applied. The chart provides insights into how education level impacts digital adoption, with those having lower education levels exhibiting less digital engagement. This emphasizes the need to improve digital literacy to help bridge the digital divide. However, encouraging the adoption of digital devices can have negative impact as well. In a paper by Limniou[6], it was found that there's a need to reconsider teaching practices, or perhaps revert to traditional methods, to reduce distractions and enhance engagement, as the students using fewer applications during lectures performed better academically.





Occupational roles significantly impact the extent of digital device usage in daily work, with variations seen across different job categories. This analysis examines the engagement of digital devices across various occupations such as, Associate Professional, Caring and Leisure, and Sales and Customer Service roles. The data[7] reveals distinct differences, with higher digital engagement in roles like Administrative and Secretarial occupations, and lower engagement in roles such as Elementary Occupations. A heat map was used as it provides a clear, structured format and allows to compare multiple categories by visualizing these differences and displaying the intensity of digital device usage across various occupations. The x-axis represents digital engagement levels, while the y-axis represents the occupational categories. The colour intensity, ranging from light pink to deep purple, indicates the extent of digital device usage, with darker shades reflecting higher percentages of non-usage. The heat map reveals that Elementary occupations have the highest percentage of

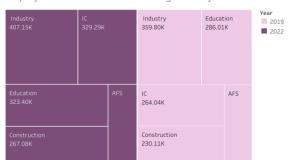
non-usage category, indicating a low level of digital engagement. In contrast, Professional occupations use digital devices the most, with 15.20% regularly using them. This analysis highlights the significant disparities between occupations, with certain roles, such as Administrative and Secretarial, showing higher levels of digital engagement, while others, like Elementary Occupations, demonstrate lower levels of digital usage. A paper by Lennon et el[8] provides an intuitive view of these differences, revealing which job categories are more digitally driven and which might benefit from increased digital integration in the workplace.

Digital Device Usage Based on Profession

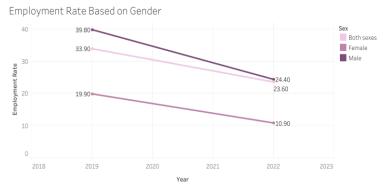
| | Statistic Label | | | Value | |
|--|-----------------|-------|--------------|-------|-------|
| Occupation | Don't use | Maybe | Yes, they do | | |
| Administrative and secretarial occupations | 2.20 | 5.10 | 11.30 | 2.20 | 64.70 |
| Elementary occupations | 64.70 | 7.60 | 3.60 | | |
| Professional occupations | 3.20 | 15.70 | 15.20 | | |
| Sales and customer service occupations | 34.40 | 13.80 | 8.10 | | |

In the second last dataset[9], the dataset consisted of salaries based annually, weekly, hourly, for various working sectors from the year 2010 to 2023. To adhere strictly to the objective to the current report, only the year 2019 and 2022 was chosen and a filter was applied to the occupation sector as well and the aliases were edited so that the visualization could be clearer and readable. The working sectors picked in the data are education, construction, industry, IC for Information and communication, and AFS for Accommodation and food service activities. A boxplot was chosen as it is easier to represent the relevant proportion of salaries within each industry, and majorly tells us which sector has the greatest number of employees. Moreover, the colour contrast chosen was a purple palette just to adhere to the uniformity of the other visualizations. From the visualization, Industry and Education seem to grow equally by approximately 13% each. It was observed that IC had the most prominent increase in salary pre and post COVID by 24.71%. In a research paper by Mukherjee[10], it was founded that the rise in IT jobs has been directly linked to the remote work practices post COVID.

Employment Rate Based on Working Industry



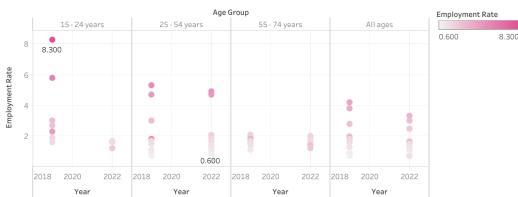
In the final dataset[11] analysed, two distinct visualizations were employed to examine employment rate trends from 2018 to 2022, providing detailed insights into unemployment rates and highlighting how demographic factors like gender and age groups have influenced these trends pre and post pandemic. Based on the complexity of the dataset, two visualizations, a slope graph and a dot plot have been employed to get a better understanding and illustrate the key findings effectively. The slope graph tracks employment rates for males, females, and both sexes over the period from 2018 to 2022. This visualization was chosen because it efficiently displays changes over time for multiple categories, making it easier to compare gender-specific employment trends before and after the COVID-19 pandemic. The graph reveals a consistent decline in the employment rate for both males and females, but it was prominent to see a significant drop in case of females (observed via negative slope). This significant gender gap highlights the disparate impact of the pandemic on men and women, with females facing more severe employment challenges.



As displayed above, the employment rate for males dropped from 9.7% in 2019 to 8.8% in 2022, showing only a slight decline. On the other hand, the employment rate for females decreased more dramatically, from 6.6% in 2019 to 3.8% in 2022. The overall employment rate for both sexes combined remained relatively stable. The slope graph efficiently illustrates these trends by connecting data points with lines, making the analysis quicker by demonstrating the upward or downward trends across different gender categories.

The use of distinct colours for each gender in the slope graph further enhances readability and allows for quick identification of each group's trends. In a paper by National Burau of Economic Research[12], during the pandemic crisis, there has been gender inequality which accounts for the disproportionate impact on women, particularly in balancing employment and caregiving responsibilities and this visualization serves as a critical tool in understanding how gender-specific employment trends evolved during and after the pandemic, potentially informing future policies aimed at closing the gender gap in employment.

In the second visualization, a dot plot, explores employment rate trends based on age groups. This plot provides a comprehensive view of how employment rates have varied across three key age groups: 15-24 years, 25-54 years, and 55-74 years, over the same years 2019 & 2022. Each panel in the dot plot corresponds to a specific age group, making it easier to observe and compare employment trends within each category over time. The dot plot was chosen as it helps to represent multiple categories over several years without cluttering the visualization. Dot plots excel at showing the distribution of data points across distinct groups, which makes them ideal for comparing age categories and their corresponding employment rates. Unlike line graphs, which are more suited for visualizing trends, dot plots offer a clearer view of individual data points and the relationship between them across different categories and time periods. In the dot plot, individual data points are plotted for each year and age group. The layout is organized into separate panels for each age group, allowing for an easy comparison of trends between the groups. The x-axis represents the years and y-axis represent the degree of the employment rate which is used across all panels to maintain clarity and uniformity.



Employment Rate Based on Age Group

A pink colour gradient is applied to represent the range of employment rates, with darker shades indicating higher rates and lighter shades representing lower rates. The dot plot reveals significant differences in employment rates across age groups. The 15-24 age group exhibited the highest employment rate in 2019 (8.3%), but this group also experiences a sharp decline by 2022. This trend is supported by a report by Moen et al[13], which reveals that in Ireland from 2020, there were significant job losses across all age groups, particularly among young adults in their 20s. The report also highlights that woman experienced the largest increases in unemployment and exits from full-time work due to the pandemic. In contrast, the 55-74 years age group consistently shows the lowest employment rates, with a minimum of 0.6% recorded in 2022. Nonetheless, for the middle-aged group, there doesn't seem too much difference in the employment rate even after the post effect of the pandemic.

IV. CONCLUSIONS

Various demographic and economic segments, such as education levels, gender, age groups, and occupational roles have highly influenced the digital transformation in Ireland's workforce. The study conducted reveals various observations, one being that men tend to use digital devices slightly more than women. Interestingly, however, women face more significant challenges related to mental health, which has been linked to their use of digital devices. Talking about the education industry, there's a serious need to reconsider traditional teaching practices. Occupations also demonstrate distinct differences in digital engagement, with professional roles exhibiting the highest usage of digital tools, while elementary occupations show the least. The employment trends analysis during the COVID-19 pandemic revealed a decline in both male and female employment rates, with females experiencing a sharper drop. Age-based analysis showed younger workers in their 20s faced greater fluctuations in employment rates than other age groups. The project highlights the role of digital adoption in education, occupational roles, and employment trends, indicating the need to improve the digital skills and accessibility to bridge gaps in the Irish workforce.

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[1]