DEFENCE DATA RESEARCH CENTRE

AI, data analytics, and digital technology use: A survey of the UK workforce

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Executive Summary: AI, Data Analytics, and Digital Technology in the UK Workforce

Introduction

This report details a national-level survey exploring workforce experiences, knowledge, and perceptions of artificial intelligence (AI), data analytics, and digital technologies within the UK. Unlike previous studies focusing on the general public's attitudes to AI in the UK or other international contexts, this report examines the UK workforce. The report provides specific insights across various sectors, roles, and demographic groups. The survey builds on prior research by Yates and Lockley (2021) on workplace digital transformation and data literacy, aiming to provide a baseline for future studies and to inform strategic priorities, including the UK Ministry of Defence's (MOD) AI adoption goals.

Study Design and Methodology

The survey was developed by the DDRC team at the University of Liverpool and undertaken by Critical Research. The survey covered 5,201 participants selected to be representative of the UK working population. Key demographic variables such as age, gender, sector of employment, and employment type were accounted for in the sampling process. The study collected quantitative data on workers' awareness, confidence, and attitudes toward AI, data analytics, and digital technologies.

The survey design included testing phases to ensure readability, logic flow, and clarity. Questions covered topics such as AI and data analytics knowledge, workplace adoption and barriers, ethical concerns, and organisational readiness. Latent Class Analysis (LCA) were employed to categorize participants into user types based on their digital behaviours. Multivariate analyses were undertaken to identify key factors influencing workforce attitudes.

Key Findings

Awareness and Knowledge of AI and Data Analytics

The survey revealed notable disparities in awareness and understanding of AI and data analytics across sectors and roles:

- **Awareness Levels**: 73.9% of respondents were aware of at least one technology (AI or data analytics) in the workplace, with 53.9% aware of both.
- **Sectoral Variations**: Awareness was highest in IT and finance, where over 69% of participants were aware of both AI and data analytics. Sectors such as education and hospitality lagged behind.

- **Knowledge Gaps**: Only 10% of participants demonstrated full knowledge of AI systems, and 24% for data analytics. Confidence often outpaced actual knowledge, highlighting a need for targeted training.

Organisational Readiness for AI and Data Analytics

Perceptions of organisational readiness varied significantly:

- **AI Readiness**: Among respondents unaware of AI use in their workplace, only 25.1% believed their organisation was ready to adopt AI solutions.
- **Data Analytics Readiness**: Similar trends were observed, with 39.7% of participants unaware of data analytics use in their workplace, agreeing their organisations were ready to adopt data analytics solutions.
- **Barriers to AI Adoption**: Commonly cited barriers included financial pressures, lack of training, and integration challenges with legacy systems. Over 45% agreed that financial constraints hindered AI investments.

Perceptions of Workplace AI and Data Analytics

Participants with workplace exposure to AI and data analytics expressed mixed views:

- **Perceived Benefits**: The most cited benefits included increased productivity (57.8% for AI, 56.5% for data analytics) and process automation (52.3% for AI, 41.7% for data analytics).
- **Challenges**: A significant portion of respondents felt their organisations lacked a clear vision or adequate training for AI and data analytics.
- **Training Effectiveness**: Less than half of respondents reported receiving training, with satisfaction levels varying across sectors. IT professionals rated their training adequacy higher than other sectors.

Broader Attitudes Toward Digital Transformation

The survey also explored general attitudes toward digital technologies:

- **Adoption Drivers**: Respondents perceived cost-cutting, productivity improvement, and automation as primary drivers of digital transformation.
- **Ethical Considerations**: Concerns about data privacy, transparency, and bias emerged, particularly among respondents with higher data literacy.
- **Digital Skills Worry**: A sizable proportion of the workforce (46.2%) expressed concerns about their ability to adapt to evolving digital tools and processes.

Implications for Defence and National Strategy

The survey's findings have the potential to guide responses to the UK government's strategic priorities outlined in the AI for Defence policy (2022). This emphasizes becoming AI-ready and shaping global AI development. Key implications include:

- **Barriers to AI Readiness**: The UK workforce's limited knowledge and confidence in AI technologies pose a challenge to achieving national data analytics and AI readiness.

- **Training and Communication**: Effective training programs and clear communication of the benefits of AI and data analytics are critical for fostering adoption.
- **Sector-Specific Strategies**: Tailored interventions are needed for sectors lagging in AI and data analytics awareness.

Recommendations

1. **Enhance Workforce Training**: Develop sector-specific training programs to address knowledge gaps and build confidence in AI and data analytics.
2. **Foster Organisational Readiness**: Provide resources and support for organisations to integrate AI and data analytics effectively.
3. **Promote Ethical AI Practices**: Increase awareness of ethical considerations and establish frameworks for transparent and responsible AI use.
4. **Strengthen Cross-Sector Collaboration**: Encourage partnerships between public, private, and academic institutions to drive innovation and knowledge sharing.
5. **Address Digital Skills Gaps**: Consider the possibility of national initiatives to improve digital literacy and ensure equitable access to digital tools and training.

Conclusion

This survey underscores the UK workforce's uneven preparedness for AI, data analytics, and digital transformation. While significant progress has been made in some sectors, widespread knowledge gaps, organisational barriers, and ethical concerns remain. Addressing these challenges through targeted interventions and strategic investments will be crucial for realizing the UK's vision of becoming a global leader in AI and digital innovation.

1. Introduction

At the time of writing, there has not been a UK-based survey of workforce experience and attitudes to workplace use of AI and data analytics (DA). There have been some prior surveys of public attitudes to AI in general and the use of AI in security contexts (see, for example, UK Centre for Data Ethics and Innovation, 2023). We collated the questions from publicly available UK, USA, and European surveys into a single database and assessed their topics. We note the following three key points. First, none of these prior surveys have focused on workforce and workplace use. Second, given what we know about UK citizens' digital and data literacy, many of these surveys were overly complex and assumed high levels of knowledge about AI that respondents were unlikely to hold. Third, the studies closest to the one reported here were undertaken in the US and Germany.

In the US, Redmiles, Kross, & Mazurek (2016) conducted representative survey that found evidence that those with higher digital skill levels, higher socioeconomic status, and/or those who handle sensitive data at work were far more likely to have better cybersecurity skills. In Germany, Kozyreva et al., (2020) undertook a nationally representative survey to explore the use of AI in online environments by gauging public opinions. They found that public awareness was relatively high and that there should be clear ethical boundaries to using AI online. Similarly, Riebe et al. (2022) conducted a nationally representative survey of attitudes toward Open-Source Intelligence (OSINT) in Germany, finding that higher OSINT awareness was linked with OSINT acceptance, while lower knowledge levels were more concerned with the use of OSINT.

The survey reported here builds on our prior work on citizens' and workers' attitudes to digital technologies. Yates and Lockley (2021) examined workforce attitudes to digital transformations in the workplace through a national survey (n = 3040). They found that many members of the UK workforce do not see the benefits of digital solutions and hold negative attitudes toward digital innovation within their organisations. However, we also identified that good training and organisational communication drive successful digital innovations in the workplace. We also assessed UK citizen's data literacy (see Yates et al., 2021 for research findings and Yates and Carmi, 2022, for a discussion of data and digital literacy definitions) based on broader criteria of data uses, how data is understood, and how citizens use data to participate in broader society. This research found the overall level of data literacy in the UK to be low for much of the population.

2. Study Design, Method and Data Analysis

2.1 Overview

This survey was designed to gather information on attitudes to data analytics and AI in the workforce at the national level, in part building on several existing nationally representative studies (both in the UK and overseas), as outlined above, that investigated individual attitudes across the UK workforce. The study did not intend to test any specific hypotheses about attitudes toward AI and data analytics. Instead, it provides baseline data to underpin further studies that may test interventions or compare cases. Participants were asked to highlight their comfort level with different data analytics and AI types. Most measures were recorded using ordinal Likert scales or simple nominal categorisations.

2.2 Methodological Approach

The survey collected anonymous quantitative feedback on how data analytics and AI are used and understood. Its purpose was to understand the sociotechnical challenges of data and AI use in organisations from the perspective of individual workers. The survey also assessed broad quantitative patterns across sectors and work roles. This provided an understanding of the key challenges to data and AI use in public and private organisations and their relevance to Ministry of Defence (MOD) strategy.

We commissioned a national-level UK survey conducted by Critical Research (https://www.critical.co.uk). Critical is an experienced survey company that works with several sectors, including the public sector, education, healthcare, finance, charity, and beyond. Critical has led the majority of Ofcom's (media regulator) national Digital Media Literacy and Technology Tracker surveys for the last decade. The survey conducted by Critical was an online panel survey designed to represent the general UK adult working population (16+) by gender, age, region, and ethnicity (n = 5201).

Once data collection was completed, overall responses were weighted by variables such as employment sector, organisational size (in terms of the number of employees), and employment status (full-time, part-time, or self-employed) to align with the overall profile of the UK adult working population.

The questionnaire covered workforce understandings and attitudes to the following topics: - Understandings of 'data' as an organisational resource - Understanding of AI - Data analytics and AI use in the workplace - Data and AI ethics - Perceptions of organisational issues - Broader social understandings of the benefits and hazards of digitalisation, data, and AI use.

2.3 Survey testing

The survey underwent three levels of testing. First, the survey was tested by a set of project research staff for readability and clarity. Second, Critical tested the survey for readability, logic flow, timings, and usability as part of the final scripting process for upload into the survey platform. Third, Critical collected an initial set of data (150 to 200 cases). Critical and the University of Liverpool reviewed the responses to ensure the script was working as it should, assessed the response level to particular questions, sense-checked the data, and reviewed any feedback left by panellists about the survey.

2.4 Survey administration

Participants are routed through the survey based on their answers with the following sub-sections in the questionnaire:

- General demographics (Measures competencies and knowledge and is to be completed by all participants)
- AI in their organisation (Part 2, routing dictated by answers, only taken by those who are aware of AI in their organisation)
- Data analytics in their organisation (Part 2, routing dictated by answers, only taken by those who are aware of data analytics in their organisation)
- Digital Solutions in their organisation (Part 2, routing dictated by answers, only taken by those who are aware of digital solutions in their organisation)
- AI Barriers & Issues (Part 3, routing dictated by answers - those using AI within their organisation)

- Data analytics Barriers & Issues (Part 3, routing dictated by answers - those using DA within their organisation)
- Digital Solutions Barriers & Issues (Part 3, routing dictated by answers - those using digital solutions in their organisation)
- Data/AI in Society / Attitudinal questions (Completed by all participants, including those who do not use AI, DA, or digital solutions at all).

Examples of data analytics given to participants in the survey include:

- Use of ('Big') data for customer analytics (which can be used for product innovation)
- Use of ('Big') data for targeted advertising (e.g., Netflix recommendations)
- Use of ('Big') data analytics for risk management
- Data analytics for innovation (e.g., Amazon's data-driven logistics)
- Data analytics for supply chain management
- Data analytics for performance assessment (of people, products, or processes)
- Analysis of media content (e.g., social media analysis).

Examples of Artificial Intelligence (AI) technologies given to participants in the survey of AI in the workplace include, but are not limited to, the kinds of things listed below – (there may be other examples):

- Spam filters used by your email provider
- Use of chatbots including ChatGPT, Bard, Bing Chat
- Smart personal assistants, such as Siri, Cortana and Google Now
- Use of automated filtering systems by HR or other departments to select candidates for hiring processes
- AI-based Augmented Reality used for training (including education, aerospace, military, and fitness)
- Voice-to-text AI such as OtterAI
- AI Voice generators such as Speechify
- Product recommendations and purchase predictions
- Fraud detection and prevention for any suspicious online transactions through an organisation's website or app
- Automated responders and online customer support
- Robotics on factory floor, in warehouses, or in laboratories.

2.5 Data Preparation and Analysis

Data Preparation: Critical provided an SPSS format data file. Any additional data preparation was undertaken in R. The following stages of analysis have been undertaken:

1. Variable Descriptive Analysis: A complete descriptive analysis of all variables was undertaken as a final verification check (see the separate Basic Exploratory Data Analysis Report).

2. User-types assessment: Following similar methods used to assess data and digital literacy (see Yates et al., (2021)), we used basic internet behaviours to classify respondents using Latent Class Analysis (poLCA package in R). Yates et al. (2021) use this method to group citizens by their

range of internet behaviours. This will also allow us in future reports to compare responses from the identified groups with findings from prior studies that explored the key demographics, data and digital literacies, and digital attitudes.

3. Comparative Descriptive Analysis: User types, AI and Data analytic knowledge, job role, and work sector were cross-tabulated with responses about workplace technology use. This provides a descriptive analysis of the correlation and correspondence of findings with key demographics, such as knowledge of AI in the workplace and industrial sector or role type.

4. Multivariate analyses: Several general linear models have been undertaken. First, they predict the likelihood of being aware of AI and/or data analytics according to role and sector. Second, they explore predictors of workforce confidence in organisations' effective use of AI, data analytics, or digital technology in general.

5. Visualisation: Results have been visualised using the ggplot2 package in R to create appropriate graphs and charts for a more straightforward representation.

3. Purpose and Benefit for Defence

This survey has tangible benefits to defence and national security in the United Kingdom. It responds to the strategic priorities for the UK government in the AI for defence policy (2022), which outlines the need for the UK:

- to become 'AI-ready'
- to adopt and scale AI at pace
- to strengthen the UK's security through AI
- shape global AI development, and promote democratic values

Overall, the strategy envisions the UK becoming a global leader in AI, focusing on effectiveness, efficiency, trustworthiness, and influence. It highlights the importance of AI excellence for national security and emphasises its potential to transform various aspects of society. The strategy addresses the need to adapt to rapid technological changes and stresses the role of AI in decision-making.

The strategy outlines plans for cultural, skill, and policy transformations, promoting AI adoption across defence and civilian life. This survey will provide baseline data to help address this goal. The strategy also emphasises collaboration with allies, fostering the AI ecosystem, and shaping global AI developments to align with democratic values and security goals. Our research will specifically address the objectives of the defence strategy by assessing civilian barriers to AI adoption, which might prevent the UK from becoming 'AI-ready'. Consequently, we focus on attitudes to data, AI, and analytics in the broader population.

The objectives of this survey are therefore:

- to explore attitudes to data within the wider UK public workforce
- to provide a quantitative overview of attitudes to data and AI
- to assess AI awareness
- to assess AI scepticism nationally.

Studying attitudes to data and digital innovation in the workplace is vital for several reasons, including:

- Data Availability (Helps understand sources of data in the workplace and highlights issues around data practices; may also illuminate whether organisations can improve working processes and support future AI innovation)
- Data Governance (Relating to the ethical and responsible use of data; further the understanding of areas for improvement)
- Data Literacy (Assessing employee levels of understanding; their ability to analyse and interpret data; their comfort working with data in the workplace, and their willingness to embrace digital approaches)
- Data Ethics (Exploring awareness and concerns of bias within data and the importance of understanding and improving public perceptions of transparency and fairness)
- Change Management (The future implementation of AI will involve key organisational challenges. By studying public attitudes to data and AI within the wider UK workforce, factors affecting resistance to change and organisational readiness for AI may be identified).

This work will benefit MOD as it can support internal decision-making and inform MOD of broader public attitudes to using data and AI in sectors of specific interest to MOD's complex supply chain, logistics, and private partners. It reflects and builds upon the prior work described in the references.

4. Survey population

This section provides a brief overview of the survey population. The survey was an online panel selected to be representative of the UK working population. The basic demographics of the population are detailed in Tables 1 to 6 below. We knew that those in very senior positions and those completely offline at home and work would not likely be well represented in an online panel. However, these groups are a very small proportion of the UK workforce. The survey company (Critical) provided a basic weighting linked to employment area and type. All tables in the report make use of the provided weighting unless otherwise stated. Where we quote approximate numbers of the UK workforce in specific categories, we are using the September 2024 UK workforce estimate of 33.31M workers.

4.1 Age

	Freq	%
16-17 years	62.3	1.2
18-24 years	524.7	10.1
25-34 years	1199.0	23.1
35-44 years	1185.0	22.8
45-49 years	528.7	10.2
50-54 years	550.7	10.6
55-64 years	914.4	17.6
65-74 years	196.6	3.8
75 years or over	26.3	0.5
Total	5187.7	100.0

Table 1: Age breakdown of sample

4.2 Gender

	Freq	%
Man	2593.5	50.0
Woman	2570.2	49.5
Non-binary/Other	28.3	0.5
Total	5192.0	100.0

Table 2: Gender breakdown of sample

4.3 Education level

The table below details a basic breakdown of education level in the sample. For the full details of educational levels and types, please see the separate Basic Exploratory Data Analysis Report.

	Freq	%
No declared education	53.8	1.0
Pre-18 or vocational education	2767.1	53.3
Post-18 HE education	2371.2	45.7
Total	5192.0	100.0

Table 3: Education breakdown of sample

4.4 Employment types and sector

The following tables detail the sample's full-time, part-time, and self-employment levels (see Table 4). The main sectors respondents worked in (see Table 5) and their level of employment (see Table 6) were also included.

4.4.1 Type of employment

	Freq	%
In full-time employment	3521.7	67.8
In part-time employment	1126.9	21.7
Self employed	543.4	10.5
Total	5192.0	100.0

Table 4: Employment breakdown of sample

4.4.2 Sector of employment

	Freq	%
IT and Communication	519.6	10.0
Finance and Insurance	363.2	7.0
Manufacturing	391.5	7.5
Primary sector	50.7	1.0
Construction	309.5	6.0
Business and Professional Services	505.1	9.7
Transport	311.3	6.0
Health and Social Work	652.4	12.6
Wholesale/Retail	681.3	13.1
Charity/Third Sector	68.5	1.3
Leisure/Hospitality/Arts/Entertainment	481.5	9.3
Utilities	62.0	1.2
Education	519.8	10.0
Other public service	247.1	4.8
Other	28.6	0.6
Total	5192.0	100.0

Table 5: Sector breakdown of sample

4.4.3 Size of organisation

	Freq	%
0 to 4 employees	525.0	10.5
5 to 9 employees	273.9	5.5
10 to 49 employees	797.9	15.9
50 to 249 employees	1079.7	21.5
250 or more employees	2343.5	46.7
Total	5020.0	100.0

Table 6: Organisation size breakdown of sample

4.4.4 Level or grade of employment

The following table (see Table 7) breaks down the proportions of respondents in different employment grades in line with NS-SEC[1] categorisations of socio-economic status.

	Freq	%
Manager, Director or Senior Officials (e.g. Finance Directors/ managers, marketing and sales directors/ managers, etc.)	996.6	19.2
Professional occupations (e.g. Civic/ mechanical/ electronic engineers, IT and software, dentists, vets, pharmacists, etc.)	915.9	17.6
Associate professional and technical occupations (e.g. lab technician, building inspectors, IT technicians, nurses, …	502.5	9.7
Administrative and secretarial occupations (e.g. civil service admin, credit controllers, bookkeepers, insurance clerks, etc.)	944.9	18.2
Skilled trades occupations (e.g. farmers, welders, tool makers, motor mechanics, electricians, telecoms engineers, etc.)	537.4	10.4
Caring, leisure and other service occupations (e.g. childminders, school assistants, travel agents, hairdressers, etc.)	203.1	3.9
Sales and customer services occupations (e.g. shop workers, retail assistants, market traders, call centre workers etc.)	381.2	7.3
Process, plant and machine operatives (e.g. crane/ forklift drivers, taxi drivers, driving instructors, van drivers, etc.)	38.5	0.7
Semi-skilled or unskilled manual work/ other (e.g. farm, construction workers, labourers in process and plant operatives, etc.)	591.9	11.4
Don't know	30.2	0.6
Prefer not to say	49.8	1.0
Total	5192	100

Table 7: Grade of employment breakdown of sample

[1] https://www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticssocioeconomicclassificationnssecrebasedonsoc2010

4.5 Technology access

The survey gathered basic data on access to digital devices. We have categorised respondents into those with no devices, those with access to smart devices (e.g., phones and tablets), those with access to laptops and desktops only, and those with access to multiple types of devices (see Table 8).

	Freq	%
No device	19.8	0.4
Smart device only	1115.2	21.5
Large screen device only	343.5	6.6
Smart and large screen devices	3713.5	71.5
Total	5192.0	100.0

Table 8: Technology access breakdown of sample

4.6 User types

We have used the methodology utilised by Yates et al. (2021) in various studies to categorise digital technology users into a range from extensive to limited users using Latent Class Analysis (LCA). LCA is a subset of structural equation modelling used to find groups or sub-types of cases in multivariate categorical data. A latent class is distinguished by a pattern of conditional probabilities indicating each variable's chance to take on specific values. LCA, therefore, looks to generate a set of 'classes' that best predict the probability that categorical measures appear together. Table 9 details the proportions of the respondents falling into the identified latent classes or 'user-types'.

	Freq	%
Extensive political users	849.7	16.4
Extensive users	401.5	7.7
General users	2442.1	47.0
Social media focused users	1040.8	20.0
Limited users	282.9	5.4
Very Limited users	174.9	3.4
Nonusers	0.0	0.0
Total	5192.0	100.0

Table 9: User-types breakdown of sample

5. Knowledge of workplace AI and data analytics

As a first step, we will look at awareness of AI and data analytics in the workplace.

5.1 Awareness and confidence around AI and data analytics

The survey asked respondents about their awareness of AI and data analytics. We can see that 26.1% of the UK workforce is unaware of either AI or data analytics in their workplace, and conversely, 73.9% are aware of at least one of these technologies (see Table 10). However, 53.8% have an awareness of both. These levels of awareness align with other general findings on digital skills in the workforce. Analysis by Future Dot Now based on Lloyds Bank's Consumer Digital index points out that 54% of the UK labour force (c.21.7m people) cannot complete all twenty tasks that the UK industry, government and experts assess as essential for work. However, nearly half of those lacking the core skills (c.11m) are only missing three or fewer of these skills.

		n	%
Aware of AI	Not aware	1753	33.8
	Aware	3439	66.2
Aware of Data Analytics	Not aware	1997	38.5
	Aware	3195	61.5
Aware of Either/None	Aware of none	1355	26.1
	Aware of at least one	3837	73.9
Aware of Both	Not aware of both	2395	46.1
	Aware of both	2797	53.9

Table 10: Knowledge of AI and data analytics

5.1.1 Awareness by education

Looking at AI and data analytics awareness through education, we find that those with a higher education are more likely to be aware of at least one or both of these technologies (see Table 11, Table 12, and Figure 1).

Education	**Aware of none**	**Aware of at least one**	**Total**
No declared education	22.8 (42.4%)	31.0 (57.6%)	53.8 (100.0%)
Pre-18 or vocational education	921.5 (33.3%)	1845.5 (66.7%)	2767.1 (100.0%)
Post-18 HE education	417.3 (17.6%)	1953.9 (82.4%)	2371.2 (100.0%)
Total	1361.6 (26.2%)	3830.4 (73.8%)	5192.0 (100.0%)

Table 11: Either AI and DA awareness by education

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 183.53, p < .001; Adjusted Cramer's v = 0.19, 95% CI [0.16, 1.00])

Education	Not aware of both	Aware of both	Total
No declared education	26.9 (50.1%)	26.8 (49.9%)	53.8 (100.0%)
Pre-18 or vocational education	1515.2 (54.8%)	1251.9 (45.2%)	2767.1 (100.0%)
Post-18 HE education	876.2 (37.0%)	1495.0 (63.0%)	2371.2 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 12: Both AI and DA awareness by education

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 174.03, p < .001; Adjusted Cramer's v = 0.18, 95% CI [0.16, 1.00])

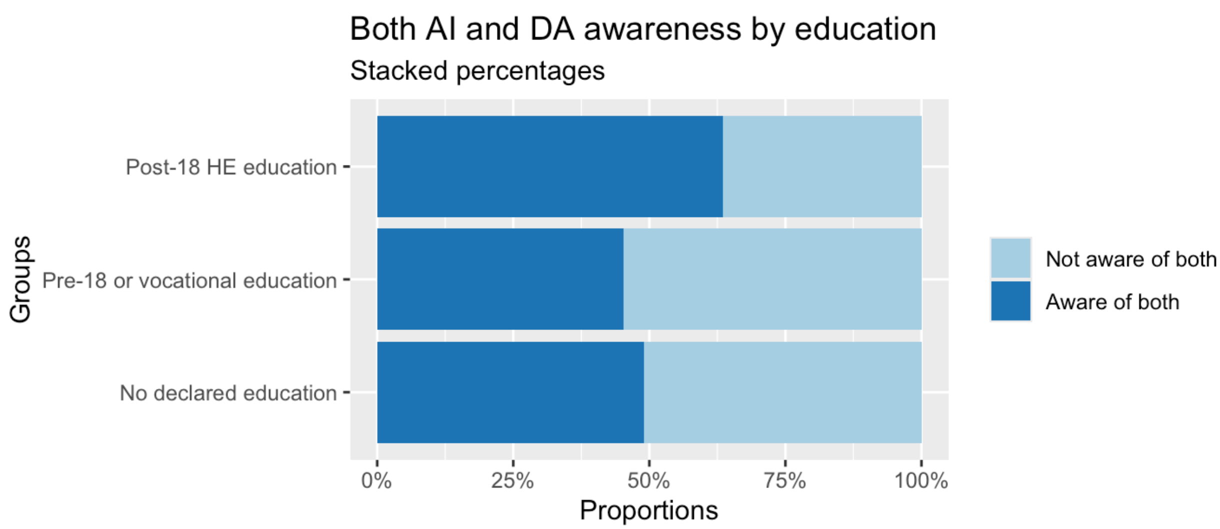


Figure 1: Both AI and DA awareness by education

5.1.2 Awareness by industry sector, business size, and role

If we also look by work sector, we also see a clear pattern, with Manufacturing, Finance and Insurance, IT and Communication being the sectors with the greatest awareness (see Table 13). Similarly, both being in a larger business (see Table 14) and having a more senior role are (see Table 15) are indicators of being more likely to be aware of both AI and Data Analytics in the organisation.

Sector	Not aware of both	Aware of both	Total
IT and Communication	123.5 (23.8%)	396.2 (76.2%)	519.6 (100.0%)
Finance and Insurance	112.1 (30.9%)	251.1 (69.1%)	363.2 (100.0%)
Manufacturing	160.9 (41.1%)	230.6 (58.9%)	391.5 (100.0%)
Primary sector	21.8 (43.1%)	28.9 (56.9%)	50.7 (100.0%)
Construction	142.6 (46.1%)	166.9 (53.9%)	309.5 (100.0%)
Business and Professional Services	241.6 (47.8%)	263.5 (52.2%)	505.1 (100.0%)
Transport	155.2 (49.9%)	156.1 (50.1%)	311.3 (100.0%)
Health and Social Work	329.1 (50.4%)	323.3 (49.6%)	652.4 (100.0%)
Wholesale/Retail	355.5 (52.2%)	325.8 (47.8%)	681.3 (100.0%)
Charity/Third Sector	36.3 (53.1%)	32.1 (46.9%)	68.5 (100.0%)
Leisure/Hospitality/Arts/Entertainment	257.6 (53.5%)	223.8 (46.5%)	481.5 (100.0%)
Utilities	34.2 (55.2%)	27.8 (44.8%)	62.0 (100.0%)
Education	287.2 (55.3%)	232.5 (44.7%)	519.8 (100.0%)
Other public service	142.2 (57.6%)	104.8 (42.4%)	247.1 (100.0%)
Other	18.3 (64.2%)	10.2 (35.8%)	28.6 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 13: Both AI and DA awareness by sector

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 216.94, p < .001; Adjusted Cramer's v = 0.20, 95% CI [0.17, 1.00])

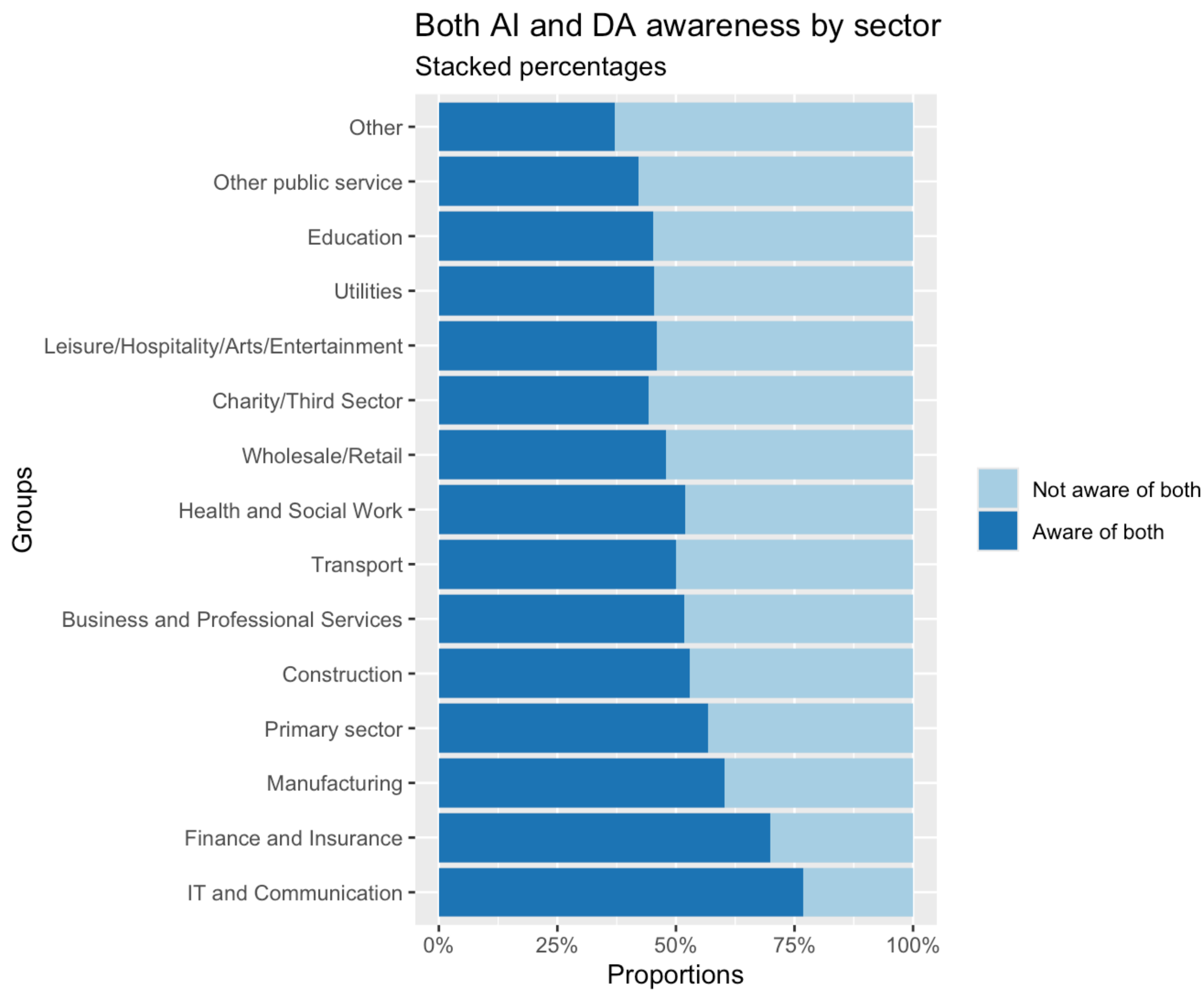


Figure 2: Both AI and DA awareness by sector

Size	Not aware of both	Aware of both	Total
0 to 4 employees	346.1 (65.9%)	178.9 (34.1%)	525.0 (100.0%)
5 to 9 employees	139.6 (51.0%)	134.3 (49.0%)	273.9 (100.0%)
10 to 49 employees	392.8 (49.2%)	405.2 (50.8%)	797.9 (100.0%)
50 to 249 employees	449.5 (41.6%)	630.2 (58.4%)	1079.7 (100.0%)
250 or more employees	981.1 (41.9%)	1362.4 (58.1%)	2343.5 (100.0%)
Total	2309.0 (46.0%)	2711.0 (54.0%)	5020.0 (100.0%)

Table 14: Both AI and DA awareness by size

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 127.79, p < .001; Adjusted Cramer's v = 0.16, 95% CI [0.13, 1.00])

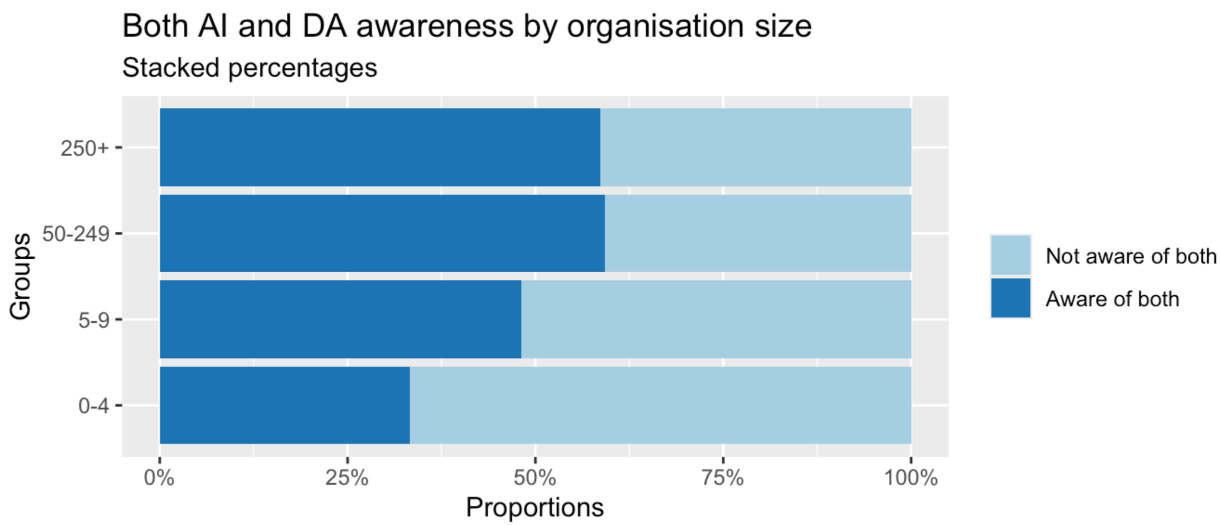


Figure 3: Both AI and DA awareness by organisation size

Grade	Not aware of both	Aware of both	Total
Manager, Director or Senior Officials (e.g. Finance Directors/ managers, marketing and sales directors/ managers, etc.)	228.7 (23.0%)	767.9 (77.0%)	996.6 (100.0%)
Professional occupations (e.g. Civic/ mechanical/ electronic engineers, IT and software, dentists, vets, pharmacists, etc.)	353.1 (38.5%)	562.9 (61.5%)	915.9 (100.0%)
Associate professional and technical occupations (e.g. lab technician, building inspectors, IT technicians, nurses, …	222.4 (44.3%)	280.1 (55.7%)	502.5 (100.0%)
Administrative and secretarial occupations (e.g. civil service admin, credit controllers, bookkeepers, insurance clerks, etc.)	510.0 (54.0%)	434.8 (46.0%)	944.9 (100.0%)
Skilled trades occupations (e.g. farmers, welders, tool makers, motor mechanics, electricians, telecoms engineers, etc.)	274.5 (51.1%)	262.9 (48.9%)	537.4 (100.0%)
Caring, leisure and other service occupations (e.g. childminders, school assistants, travel agents, hairdressers, etc.)	137.0 (67.4%)	66.1 (32.6%)	203.1 (100.0%)
Sales and customer services occupations (e.g. shop workers, retail assistants, market traders, call centre workers etc.)	232.1 (60.9%)	149.1 (39.1%)	381.2 (100.0%)
Process, plant and machine operatives (e.g. crane/ forklift drivers, taxi drivers, driving instructors, van drivers, etc.)	25.2 (65.4%)	13.3 (34.6%)	38.5 (100.0%)
Semi-skilled or unskilled manual work/ other (e.g. farm, construction workers, labourers in process and plant operatives, etc.)	380.4 (64.3%)	211.5 (35.7%)	591.9 (100.0%)
Don’t know	21.4 (71.0%)	8.8 (29.0%)	30.2 (100.0%)
Prefer not to say	33.5 (67.2%)	16.3 (32.8%)	49.8 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 15: Both AI and DA awareness by grade

The Pearson’s Chi-squared test of independence between and suggests that the effect is statistically significant, and medium (chi2 = 423.08, p < .001; Adjusted Cramer’s v = 0.28, 95% CI [0.26, 1.00])

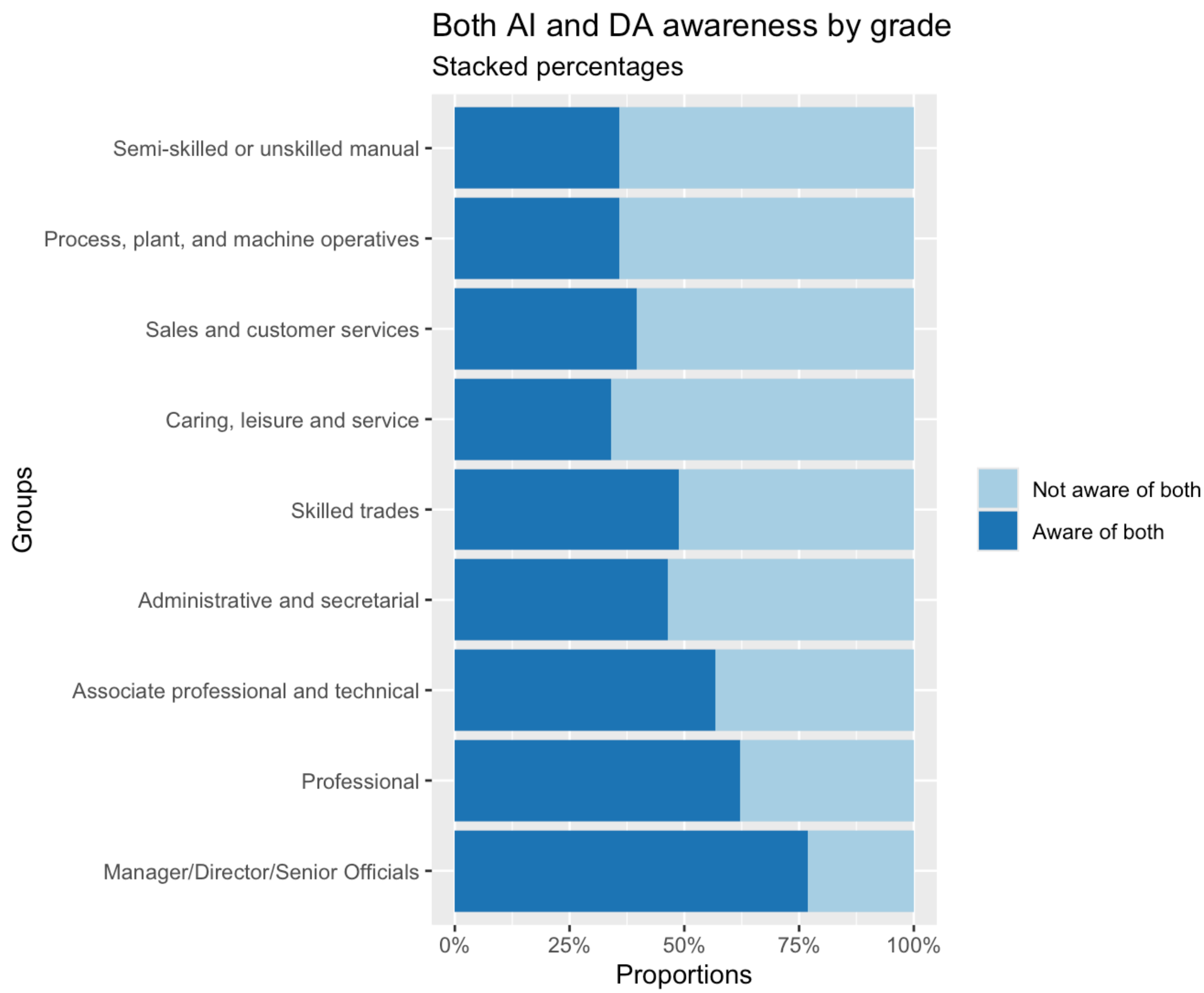


Figure 4: Both AI and DA awareness by grade

5.1.3 Awareness by digital technology use at work

Similarly we be find that those who use digital technologies at work are, quite obviously, far more likely to be aware of AI and data analytics (see Table 16 and Figure 5). A similar result holds if we look at levels of digital technology use on a daily basis in the workplace (see Table 17 and Figure 6).

DT use	Not aware of AI or DA	Aware of both	Total
Yes	1920.4 (41.6%)	2691.0 (58.4%)	4611.4 (100.0%)
No	497.8 (85.8%)	82.7 (14.2%)	580.6 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 16: AI and DA awareness by levels of technology use at work

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and medium (chi2 = 433.64, p < .001; Adjusted Cramer's v = 0.29, 95% CI [0.27, 1.00])

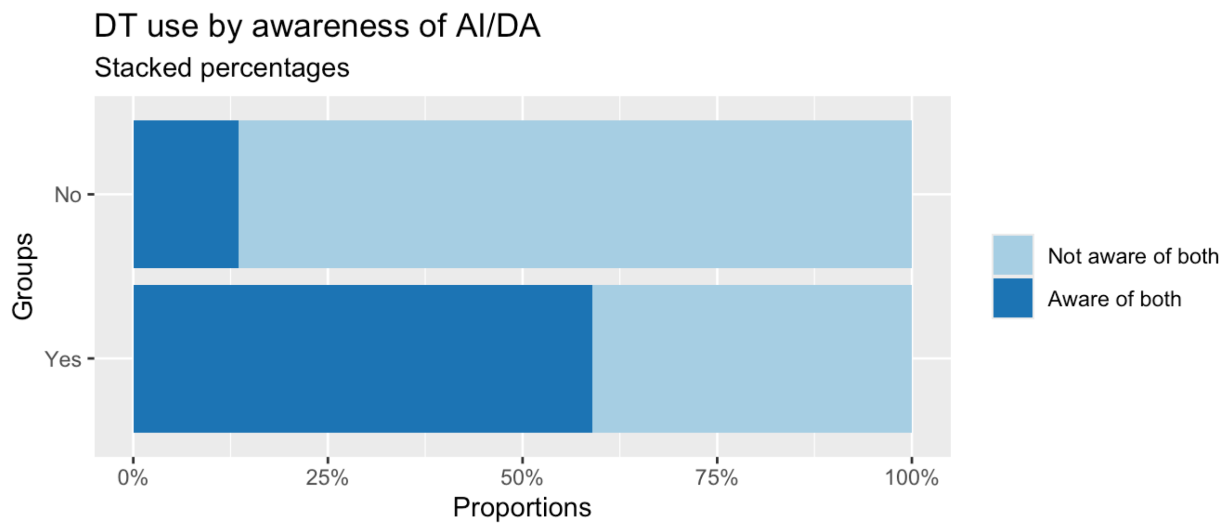


Figure 5: DT use by awareness of AI/DA

DT use	Not aware of both	Aware of both	Total
1-20%	440.6 (64.3%)	244.2 (35.7%)	684.8 (100.0%)
21-40%	357.6 (40.3%)	529.0 (59.7%)	886.6 (100.0%)
41-60%	371.6 (36.8%)	638.1 (63.2%)	1009.8 (100.0%)
61-80%	287.9 (31.4%)	629.4 (68.6%)	917.3 (100.0%)
81-100%	427.0 (40.1%)	638.4 (59.9%)	1065.4 (100.0%)
No use	533.5 (84.9%)	94.5 (15.1%)	628.0 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 17: AI and DA awareness by levels of technology use at work

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and large (chi2 = 671.36, p < .001; Adjusted Cramer's v = 0.36, 95% CI [0.33, 1.00])

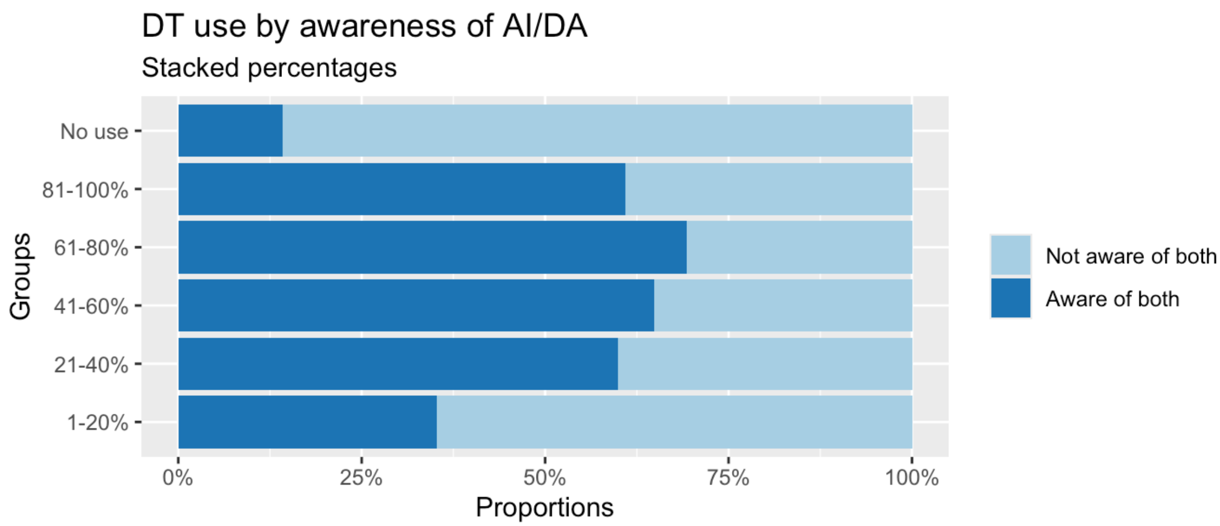


Figure 6: DT use by awareness of AI/DA

5.1.4 Awareness by domestic technology use and user types

Again, as maybe expected awareness of both AI and data analytics in their organisation corresponds with having more technology in the home and being a more extensive digital user.

Technology	Not aware of both	Aware of both	Total
No device	13.9 (70.0%)	6.0 (30.0%)	19.8 (100.0%)
Smart device only	626.7 (56.2%)	488.5 (43.8%)	1115.2 (100.0%)
Large screen device only	185.4 (54.0%)	158.1 (46.0%)	343.5 (100.0%)
Smart and large screen devices	1592.3 (42.9%)	2121.2 (57.1%)	3713.5 (100.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 18: Both AI and DA awareness by domestic technology

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 76.14, p < .001; Adjusted Cramer's v = 0.12, 95% CI [0.09, 1.00])

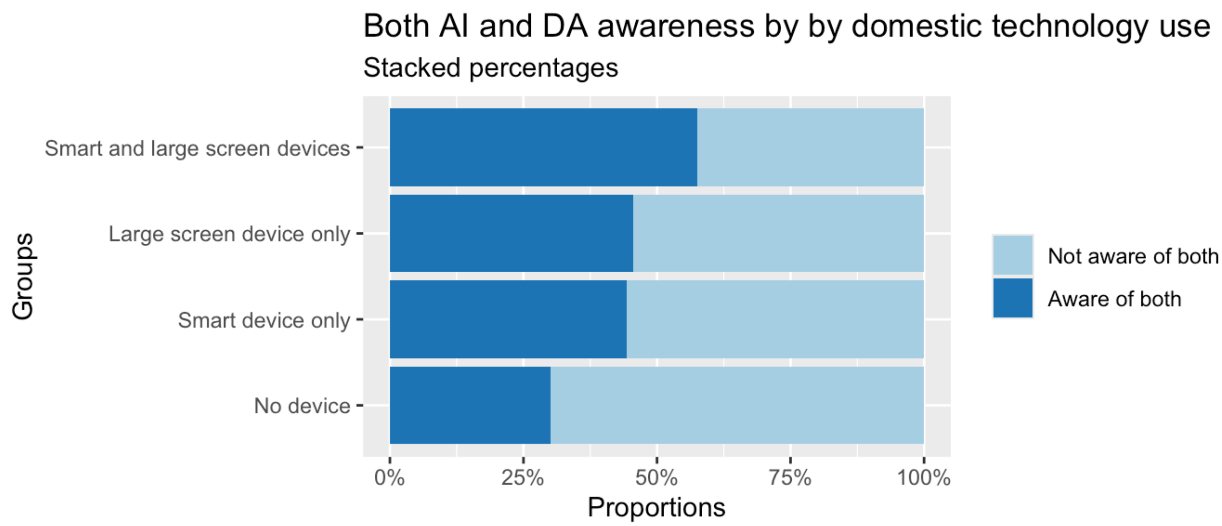


Figure 7: Both AI and DA awareness by domestic technology

User type	Not aware of both	Aware of both	Total
Extensive Political	195.6 (23.0%)	654.1 (77.0%)	849.7 (100.0%)
Extensive	175.9 (43.8%)	225.6 (56.2%)	401.5 (100.0%)
General	1085.5 (44.5%)	1356.5 (55.5%)	2442.1 (100.0%)
Social media	687.3 (66.0%)	353.5 (34.0%)	1040.8 (100.0%)
Limited	143.6 (50.7%)	139.4 (49.3%)	282.9 (100.0%)
Very limited	130.3 (74.5%)	44.6 (25.5%)	174.9 (100.0%)
Non-user	0.0 (0.0%)	0.0 (0.0%)	0.0 (0.0%)
Total	2418.3 (46.6%)	2773.7 (53.4%)	5192.0 (100.0%)

Table 19: Both AI and DA awareness by user type

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and medium (chi2 = 420.29, p < .001; Adjusted Cramer's v = 0.28, 95% CI [0.26, 1.00])

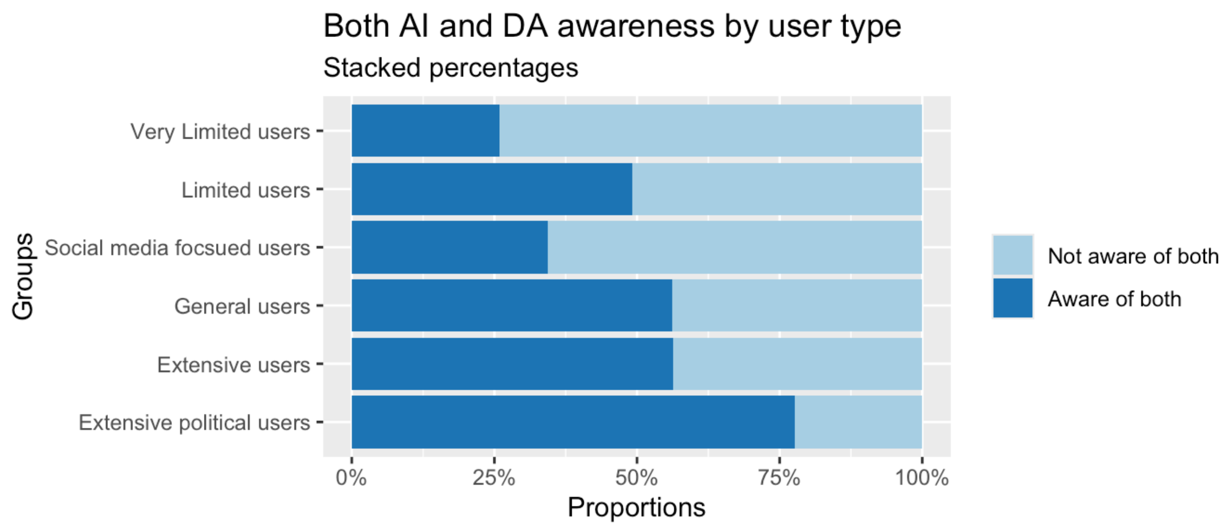


Figure 8: Both AI and DA awareness by user type

5.2 Modelling AI and DA awareness by work role, sector, and user types

We have modelled the likelihood of having awareness of both AI and DA in the workplace against the following variables:

- Age
- Sector
- Employment type
- Grade and type of role
- User types
- Digital devices

Age was measured on an ordinal scale, while all other variables were factors, with the following serving as the baseline reference category:

- Sector: IT
- Employment: Full-time
- Grade and type: Manager/Director/Senior Officials
- User types: Extensive political
- Digital devices: No devices

Taking all these factors into account, younger workers are statistically significantly more likely to be aware of AI and DA in the workplace. IT and Communications workers are the most likely to be aware, and following are statistically significantly less likely than IT workers:

- Business and Professional Services
- Utilities
- Education
- Other public services

Predictor	**B**	**SE**	**t**	**p**
Intercept	2.79	0.621	4.49	<0.001
Age	-0.17	0.017	-10.22	<0.001
Pre-18 or vocational education	-0.10	0.302	-0.32	0.752
Post-18 HE education	0.17	0.304	0.55	0.584
Finance and Insurance	-0.14	0.169	-0.80	0.423
Manufacturing	-0.18	0.162	-1.14	0.253
Primary sector	-0.41	0.329	-1.26	0.209
Construction	-0.48	0.173	-2.77	0.006
Business and Professional Services	-0.60	0.149	-3.99	<0.001
Transport	-0.29	0.172	-1.69	0.090
Health and Social Work	-0.52	0.142	-3.68	<0.001
Wholesale/Retail	-0.38	0.150	-2.52	0.012
Charity/Third Sector	-0.77	0.284	-2.71	0.007
Leisure/Hospitality/Arts/Entertainment	-0.57	0.155	-3.64	<0.001
Utilities	-0.94	0.291	-3.23	0.001
Education	-0.85	0.152	-5.61	<0.001
Other public service	-0.76	0.181	-4.17	<0.001
Other	-1.16	0.450	-2.57	0.010
In part-time employment	-0.43	0.079	-5.37	<0.001
Self employed	-0.42	0.106	-4.01	<0.001
Professional	-0.48	0.112	-4.29	<0.001
Associate professional and technical	-0.77	0.127	-6.05	<0.001
Administrative and secretarial	-1.00	0.111	-9.00	<0.001
Skilled trades	-0.90	0.128	-6.98	<0.001
Caring and leisure and services	-1.28	0.183	-6.99	<0.001
Sales and customer services	-1.20	0.151	-7.94	<0.001
Process plant and machine operatives	-1.39	0.365	-3.81	<0.001
Semi-skilled or unskilled manual	-1.26	0.125	-10.05	<0.001
Extensive	-0.72	0.142	-5.08	<0.001
General	-0.77	0.098	-7.79	<0.001
Social media	-1.49	0.113	-13.19	<0.001
Limited	-0.84	0.155	-5.40	<0.001
Very Limited	-1.71	0.203	-8.42	<0.001
Smart device only	0.22	0.540	0.41	0.681
Large screen device only	0.29	0.549	0.52	0.602
Smart and large screen devices	0.40	0.538	0.75	0.456

Coefficient-Level Estimates for a Model Fitted to Estimate Awareness of AI and DA.

Table 20: Both AI and DA awareness by key variables

Both part-time and self-employed workers are statistically **less** likely to be aware of AI and DA in the workplace. There is an almost linear drop in awareness by grade and role, with all grades being statistically less likely than the Manager/Director/Senior Officials grade. A similar pattern holds for user types, with 'Extensive political being statistically most likely and Limited/Non-users the least likely. Effects plots can be found in Section 11.1.

5.3 Knowledge of AI and data analytics

We asked the respondents to identify consumer and health technologies with embedded AI or Data Analytics. The overall results show a very poor understanding. We categorized the results into three classifications:

- Fully incorrect or don't know: where respondents had ticked only incorrect answers or don't know
- Partially correct: where respondents had ticked the right answer but also wrong ones
- Fully correct: where respondents had only ticked the correct answers.

As the following tables show most respondents were partially or fully incorrect in their answers.

		n	%
AI knowledge test	Fully incorrect or don't know	1842	35.5
	Partially correct	2832	54.5
	Fully correct	518	9.98
DA knowledge test	Fully incorrect or don't know	1400	27
	Partially correct	2555	49.2
	Fully correct	1237	23.8

Table 21: Knowledge of AI and data analytics

We also asked about confidence in understanding and talking about digital technologies at work. Again, strong confidence is not high (see Table 22). We found that 14% of respondents strongly agreed that they understand the underlying AI and DA technologies, and 19% strongly agreed they are confident in using technical terminology. Combining 'Strong' and 'Slightly' confidence, we find that 51.4% are confident about AI technologies, 50.4% are confident about data analytics, and 59.0% are confident in digital technologies in general. Again, these fit the pattern identified by Future Dot Now.

	Freq	**%**
Strongly agree	703.3	13.9
Slightly agree	1904.1	37.5
Neither agree nor disagree	1110.5	21.9
Slightly disagree	838.7	16.5
Strongly disagree	519.3	10.2
Total	5076.1	100.0

Table 22: Confidence in understanding core AI technologies

	Freq	%
Strongly agree	706.2	13.9
Slightly agree	1852.3	36.5
Neither agree nor disagree	1210.4	23.8
Slightly disagree	815.7	16.1
Strongly disagree	492.8	9.7
Total	5077.4	100.0

Table 23: Confidence in understanding core DA technologies

	Freq	%
Strongly agree	889.9	19.0
Slightly agree	1872.0	40.0
Neither agree nor disagree	990.9	21.2
Slightly disagree	654.4	14.0
Strongly disagree	273.6	5.8
Total	4680.8	100.0

Table 24: Confidence with digital terminology

However, we must note that most respondents wrongly identified AI and Data Analytic apps and systems, as indicated in Table 21. Comparing confidence with correct answers to our question to identify AI and DA apps (see Table 25, Figure 9, Table 26, and Figure 10), unsurprisingly, those who get questions wholly wrong are likelier to be less confident. However, the pattern is not that different across those getting things entirely correct; in fact, the partially correct have greater confidence in their knowledge of AI and DA. We conclude from this that actual knowledge and confidence levels are not high nor strongly correspond. This result should not be surprising as these technologies are still relatively new to organisations, combined with the reasonably low workforce digital skills noted earlier (Section 5.1).

AI score	*AI confidence* Strongly agree	Slightly agree	Neither agree nor disagree	Slightly disagree	Strongly disagree	Total
Fully incorrect or don't know	176.2 (10.0%)	560.1 (31.8%)	477.2 (27.1%)	287.7 (16.3%)	261.6 (14.8%)	1762.8 (100.0%)
Partially correct	450.0 (16.1%)	1146.7 (41.1%)	512.0 (18.4%)	466.3 (16.7%)	211.9 (7.6%)	2786.8 (100.0%)
Fully correct	77.1 (14.6%)	197.4 (37.5%)	121.4 (23.1%)	84.8 (16.1%)	45.8 (8.7%)	526.5 (100.0%)
Total	703.3 (13.9%)	1904.1 (37.5%)	1110.5 (21.9%)	838.7 (16.5%)	519.3 (10.2%)	5076.1 (100.0%)

Table 25: AI score by confidence

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 145.69, p < .001; Adjusted Cramer's v = 0.12, 95% CI [0.10, 1.00])

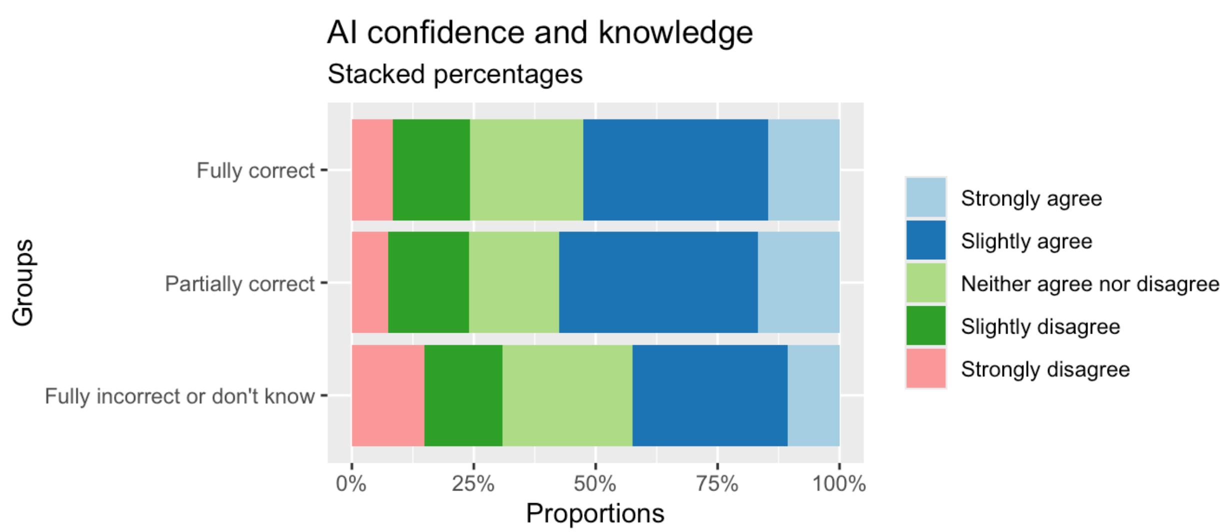


Figure 9: Confidence and knowledge: AI

DA score	*DA confidence* **Strongly agree**	**Slightly agree**	**Neither agree nor disagree**	**Slightly disagree**	**Strongly disagree**	**Total**
Fully incorrect or don't know	172.1 (13.0%)	393.8 (29.8%)	360.4 (27.2%)	206.2 (15.6%)	190.3 (14.4%)	1322.7 (100.0%)
Partially correct	424.6 (17.1%)	1015.2 (40.8%)	539.9 (21.7%)	344.4 (13.8%)	163.2 (6.6%)	2487.3 (100.0%)
Fully correct	109.5 (8.6%)	443.3 (35.0%)	310.1 (24.5%)	265.1 (20.9%)	139.3 (11.0%)	1267.4 (100.0%)
Total	706.2 (13.9%)	1852.3 (36.5%)	1210.4 (23.8%)	815.7 (16.1%)	492.8 (9.7%)	5077.4 (100.0%)

Table 26: DA score by confidence

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 181.35, p < .001; Adjusted Cramer's v = 0.13, 95% CI [0.11, 1.00])

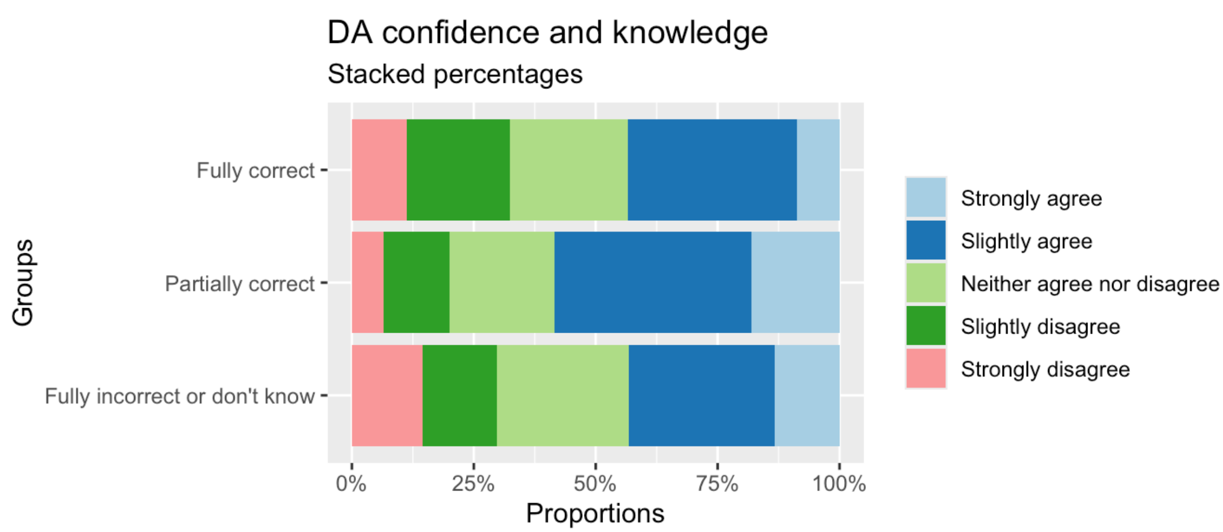


Figure 10: Confidence and knowledge: DA

6. AI in the workplace

This section considers workforce perceptions of AI use and implementation in organisations. Unless otherwise stated, these results are based on respondents' perceptions of AI use in their own organisation.

6.1 Perceptions of organisational readiness for AI

However, we start with 33.8% of respondents who were unaware of using AI in their organisation. They were asked if they agreed with the statement:

- Though they don't currently use them, I think my workplace or organisation is ready to embrace artificial intelligence (AI) solutions.

As Table 27 highlights, only 4.4% strongly agreed, and 25.1% strongly or slightly agreed. This leaves 74.9% of this group (equal to 25.3% of the UK workforce) who do not believe their organisation is ready for AI solutions. Looking at this by sector (Figure 11), we can note some key variations. With primary (e.g. mining, minerals), business and professional services, and leisure standing out as being perceived as **least** ready. However, we need to note that this is the perception of those parts of the workforce who are unaware of AI use in their organisations.

	Freq	%
Strongly agree	68.5	4.4
Slightly agree	463.1	29.7
Neither agree nor disagree	534.9	34.3
Slightly disagree	270.7	17.3
Strongly disagree	224.2	14.4
Total	1561.3	100.0

Table 27: Readiness to embrace AI

	Freq	%

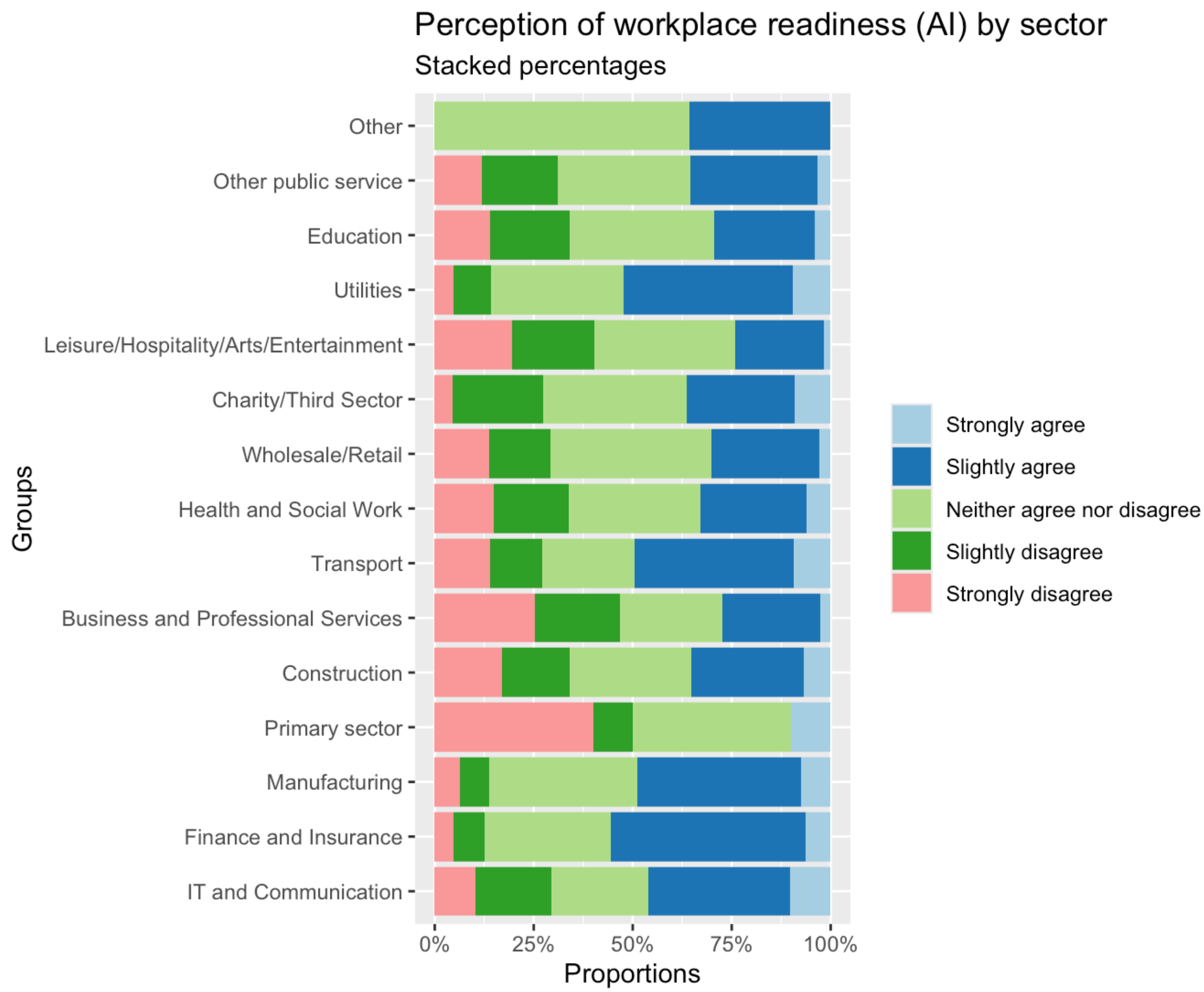


Figure 11: Workplace readiness: AI

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 120.88, p < .001; Adjusted Cramer's v = 0.10, 95% CI [0.00, 1.00])

6.2 Perceived reasons for uptake of AI in the workplace

We now look at those respondents who are aware of AI in their organisation. When asked what they believe are the three main reasons organisations are making use of AI, the most common answers given were (see Table 28):

- To improve productivity (57.8%)
- To automate processes (52.3%)
- To cut costs (49.7%)

The response ‘To gather data to aid business intelligence’ appears fourth at 32.7%. These results are comparable to prior studies on digital technology implementation, with the workforce perceiving digital transformations as driven by cost cutting and productivity goals (see Yates and Lockley, 2020a). However, 25.7% saw one of the reasons for implementing AI solutions being to directly “automate jobs and reduce the workforce”.

Workforce perception of reasons for AI introduction	Percent of all responses
To cut costs	49.7
To automate processes	52.3
To improve productivity	57.8
To make the business more competitive	25.2
To improve the customer experience	27.5
To help meet regulatory requirements	14.4
To gather data to aid business intelligence	32.7
To automate jobs and reduce the workforce	25.7
Something else	>1
I don't think that companies and organisations are using more AI technologies	>1
Don't know	1.1

Table 28: Reasons for introducing AI

6.3 Perceptions of AI organisational factors

We asked those with awareness of AI to rate both personal and workplace aspects of AI use in their organisation:

- Personal aspects
    - How effectively you personally make use of AI in your workplace?
    - A lack of AI technologies in my organisation hinders my job effectiveness.
    - I understand how good AI technologies can support ethical data practices.
    - I have access to all the AI technologies I need to do my job effectively.
    - AI technologies have made a positive impact on the way I operate at work.
- Workplace
    - Potential benefits of AI are clearly communicated to you by your organisation?
    - Financial pressures are preventing investment in AI in my organisation.
    - AI in my organisation easily connects with the older systems we have in place.
    - My organisation has AI but we haven’t had the training to make use of them.
    - My organisation provides support and training AI solutions are rolled out.
    - The organisation has a clear vision for AI.
    - Only some of my colleagues use the AI technologies available to us.
    - My organisation’s management understands the importance of AI.

Across these questions the results are not highly "positive", with a range from 60-40 to 50-50 splits between those giving positive responses (Very, Highly, or Slightly Agree/Confident/Effective) and those not (see Table 29). This implies that many in the workforce are neither feeling supported nor informed about AI developments in their workplaces. It is significant that this is the group with some awareness of ongoing workplace AI developments.

		n	%
Perceived effective use by organisation	Confident	2278	66.2
	Not Confident	1164	33.8
Potential benefits of AI communicated clearly	Clearly	2053	59.6
	Not Clearly	1389	40.4
Personal effective use	Effective	2035	59.1
	Not Effective	1407	40.9
Financial pressures prevent investment	Agree	1575	45.8
	Disagree	1867	54.2
Easy connection of AI to older systems	Agree	1751	50.9
	Disagree	1691	49.1
Lack of training in using available AI	Agree	1647	47.9
	Disagree	1795	52.1
Support and training provided for AI	Agree	1888	54.9
	Disagree	1554	45.1
Clear vision for AI	Agree	1864	54.2
	Disagree	1578	45.8
Lack of AI hinders job effectiveness	Agree	1201	34.9
	Disagree	2241	65.1
Only some colleagues use available AI tools	Agree	1900	55.2
	Disagree	1542	44.8
Understands ethical AI practices	Agree	2254	65.5
	Disagree	1188	34.5
Have the AI tools needed	Agree	1916	55.7
	Disagree	1526	44.3
Management understands importance of AI	Agree	2138	62.1
	Disagree	1304	37.9
Positive impact on my own work	Agree	1908	55.4
	Disagree	1534	44.6

Table 29: Key organisational factors and AI use

Therefore, we modelled how these perceptions might predict views on management and the organisation's implementation of AI. We asked the respondents:

- How confident are you that the management team at your organisation is able to implement artificial intelligence (AI) technologies successfully and effectively?

Taking Likert scale responses to this question as the dependent variable, we modelled how personal and workplace perceptions act as predictors. Data in Table 30 and the effects plots in Section 11.2 indicate the main predictors of management and organisations being successful and effective with AI implementations are:

- Personal:
    - Feeling effective in personal use
    - Positive impact on work tasks
- Organisational:
    - Communicating AI benefits clearly
    - Easy connection with legacy systems
    - Provision of support and training
    - Having a clear vision for AI in the organisation
    - Management understanding importance of AI

Predictor	**B**	**SE**	**t**	**p**
Intercept	0.64	0.071	9.00	<0.001
Potential benefits of AI communicated clearly	0.21	0.017	12.38	<0.001
Personal effective use	0.12	0.017	6.87	<0.001
Financial pressures prevent investment	-.03	0.012	-2.33	0.020
Easy connection of AI to older systems	0.07	0.014	5.39	<0.001
Lack of training in using available AI	0.00	0.012	0.03	0.975
Support and training provided for AI	0.10	0.015	6.73	<0.001
Clear vision for AI	0.14	0.016	8.76	<0.001
Lack of AI hinders job effectiveness	-.02	0.011	-2.03	0.042
Only some colleagues use available AI tools	0.02	0.012	1.39	0.163
Understands ethical AI practices	0.02	0.016	1.01	0.311
Have the AI tools needed	0.05	0.015	3.00	0.003
Management understands importance of AI	0.13	0.017	7.66	<0.001
Positive impact on my own work	0.07	0.017	4.04	<0.001

Coefficient-Level Estimates for a Model Fitted to perceived effective use of AI.

Table 30: AI effectiveness of use by key variables

Such results fit with prior studies (Yates and Lockley, 2020a) and with technology acceptance models (TAM) (Davis, 1989; Ventakesh, 2000; Ventakesh et al., 2003). TAMs have tended to focus on two areas:

- Perceived usefulness – the extent to which a worker or home user believes that using a technology would enhance the task they are engaged in
- Perceived ease-of-use—the extent to which a worker or home user believes that using a technology would be free from substantive effort.

These two issues have been measured in various ways in various studies (Adams, et al., 1992; Segers & Grover, 1993; Szajna, 1994). Many of these studies have a very individualistic focus. They look solely at the motivations and rational behaviours of individual users. Users' organisational or personal situation is taken as a 'backdrop' context in which they engage with the technology. More recent research by Ventakesh and Davis (2003) has identified four factors to explore:

- Performance expectancy, parallel to perceived usefulness, is the degree to which an individual believes that using the system will help him or her improve his or her job performance.
- Effort expectancy, parallel to perceived ease of use, is the degree of ease associated with using the system.
- Social influence is the degree to which an individual perceives that significant others believe he or she should use the new system.
- Facilitating conditions are the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system (Ventakesh & Davis, 2003).

As we can see from our data, organisations perceived to have successfully and effectively implemented AI are those where workforce experience fits with TAM. Respondents who feel AI systems are personally useful and effective, as well as having supportive social contexts and facilitating conditions, are more likely to view AI implementations as successful and effective.

6.4 AI training

We find that just under half (47.9%) of respondents who are aware of AI in the workplace have had some form of training involving AI. The presence of training varies across sectors (see Figure 12), with, as might be expected, the IT sector offering more training (73.8%). The lowest levels of training were in the Charity (27.9%), Other Public Sectors (35.5%), Education (36.9%), and Leisure (38.4%). These are of course only figures for those aware of AI. Assuming anyone with training would be aware of AI, these figures indicate that 31.7% of the workforce have had some form of training in AI. However, satisfaction with training was relatively high across all sectors with 39.7% deeming the training *very* or *fairly* adequate. There was a very small statistically significant difference across sectors driven by slightly higher adequacy rating among IT workers (see Figure 13).

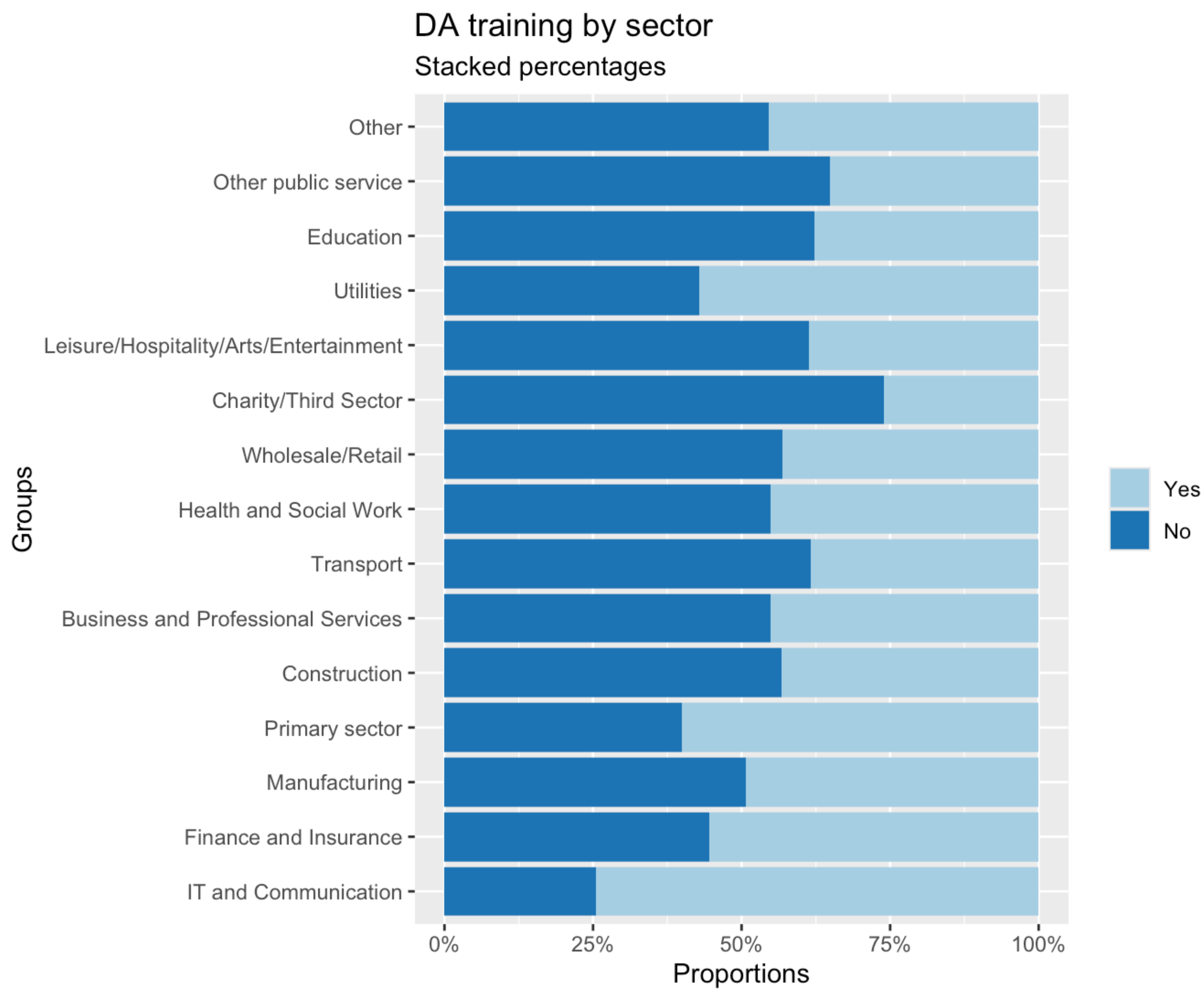


Figure 12: Have taken AI training

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 122.89, p < .001; Adjusted Cramer's v = 0.18, 95% CI [0.14, 1.00])

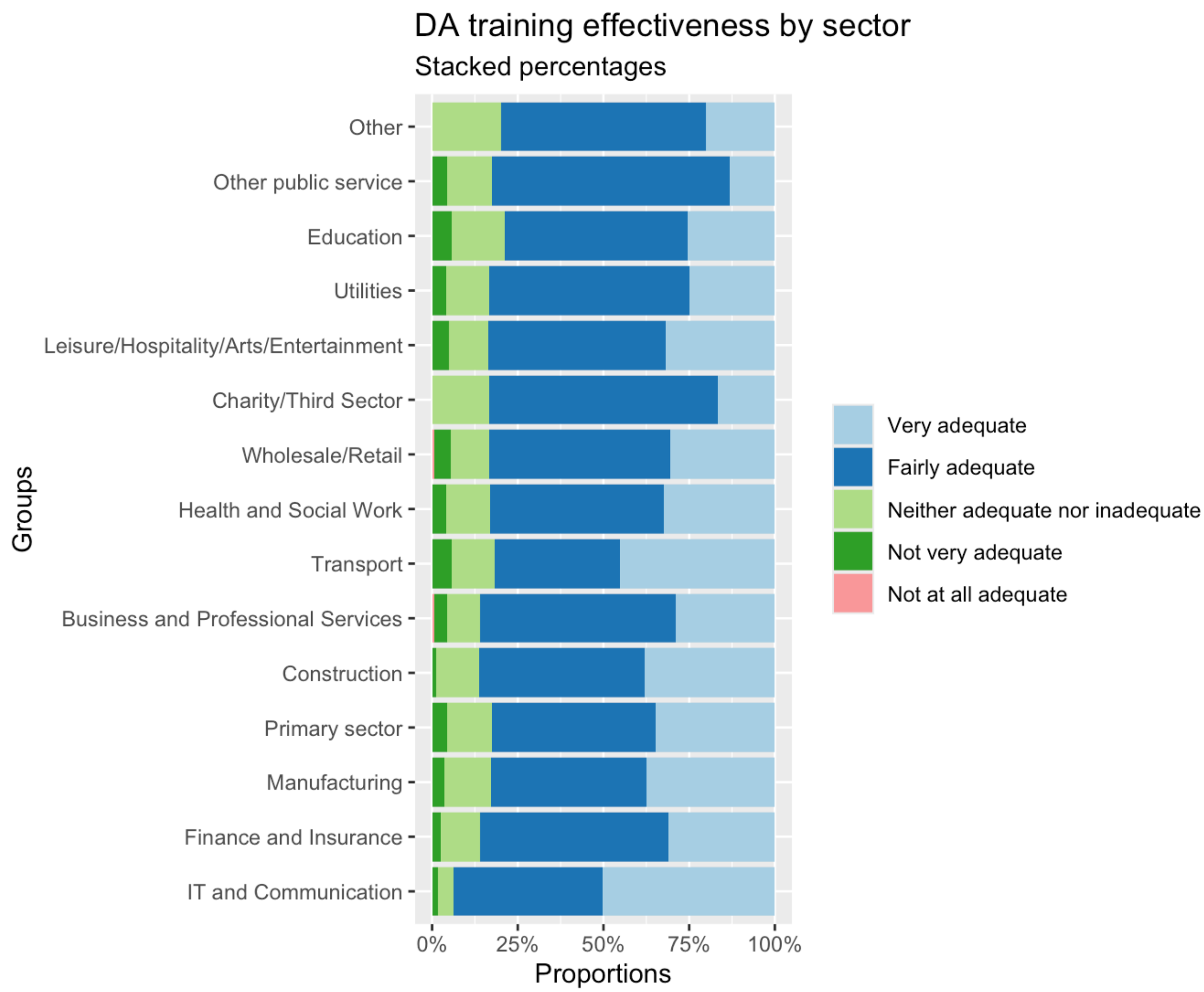


Figure 13: Effectiveness of AI training

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and very small (chi2 = 89.22, p = 0.042; Adjusted Cramer's v = 0.07, 95% CI [0.00, 1.00])

6.5 How AI had a positive impact on work activity

Of those who were aware of AI, we found that 55.4% thought that AI has had a positive impact on the way they operate at work. This implies conversely that 44.6% did not think that AI had a positive impact on how they operate at work. The two most common positive impacts were:

- It made my job easier to do.
- It made it quicker to do my job.

Other positive impacts were only noted by 23.7% to 36.9% of respondents (see Table 31). Therefore, we can't conclude that respondents are gaining a wide range of benefits to their work from AI use.

How AI has improved work activity	Percent of all responses
It made my job easier to do	51.0
It made it quicker to do my job	56.7
It streamlined internal processes	36.9
It helped me reprioritise tasks	36.6
It allowed me greater flexibility in how I do my job	38.9
It allowed me greater flexibility in where I do my job	32.0
It helped me connect with other employees	23.7
It helped the company better meet their regulatory requirements	32.3
It opened up additional opportunities in my role	27.4
Something else	>1.0

Table 31: How AI has improved work activity

7. Data analytics in the workplace

In this section, we consider the perceptions of Data Analytics use and implementation in organisations. Unless otherwise stated, these results are based on the perceptions of respondents who are aware of Data Analytics use in their organisation.

7.1 Perceptions of organisational readiness for DA

However, we start with 38.5% of respondents who were not aware of the use of Data Analytics in their organisation. They were asked if they agreed with the statement:

- Though they don't currently use them, I think my workplace or organisation is ready to embrace Data Analytics (DA) solutions.

As Table 32 highlights, only 8.2% strongly agreed, and 39.7% strongly or slightly agreed. This leaves 71.7% of this group (equal to 27.6% of the UK workforce) who do not believe their organisation is ready for AI solutions. Looking at this by sector (Figure 14), we can note some key variations. Primary industries (e.g. mining, minerals), business and professional services, leisure, education, and other public services stand out as being perceived as **least** ready. However, we need to note that this is the perception of those parts of the workforce who are not yet aware of Data Analytics use in their organisations.

	Freq	%
Strongly agree	140.0	8.2
Slightly agree	538.6	31.5
Neither agree nor disagree	598.7	35.0
Slightly disagree	237.6	13.9
Strongly disagree	195.2	11.4
Total	1710.0	100.0

Table 32: Readiness to embrace DA

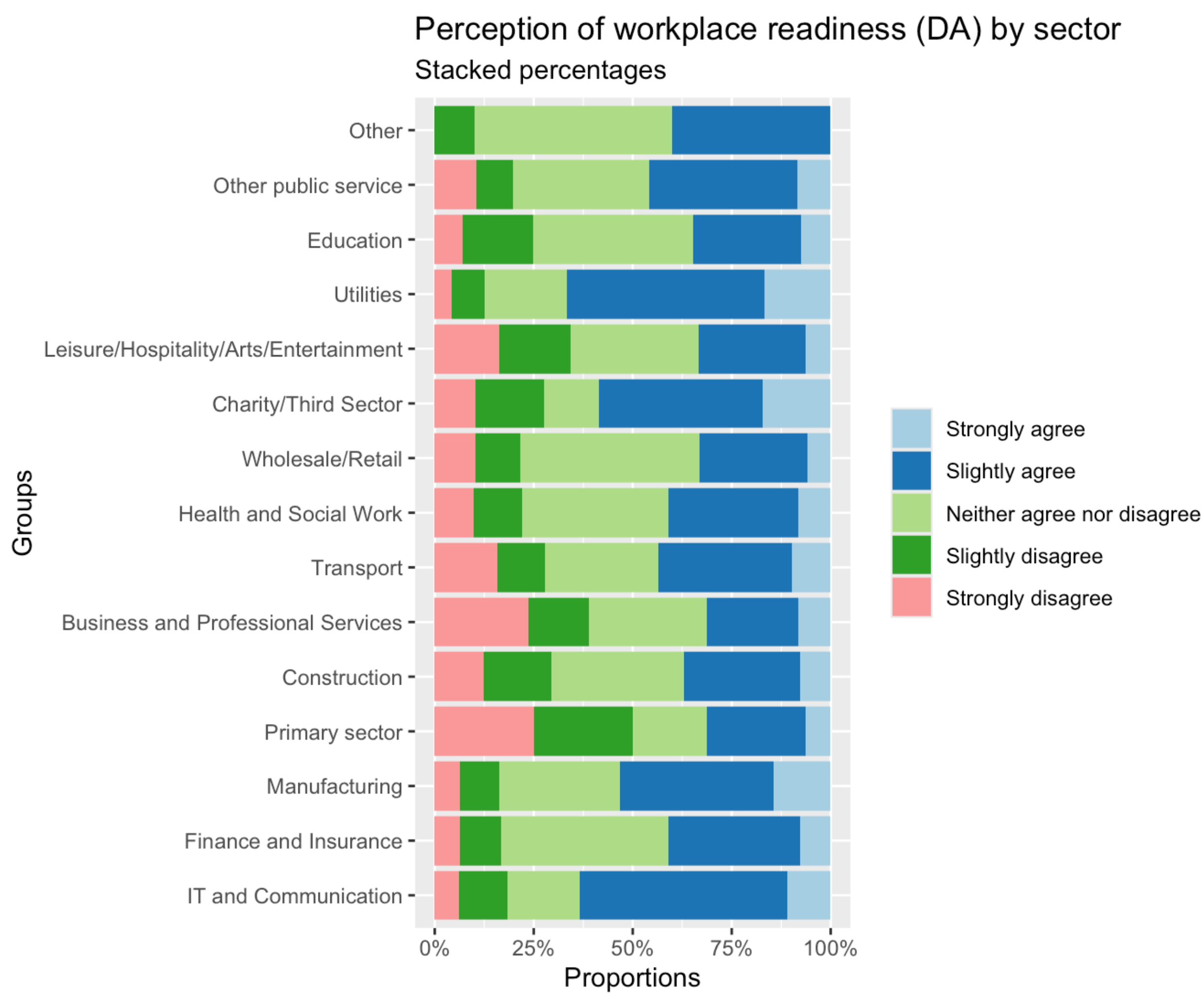


Figure 14: Workplace readiness: DA

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 126.63, p < .001; Adjusted Cramer's v = 0.10, 95% CI [0.00, 1.00])

7.2 Perceived reasons for uptake of data analytics in the workplace

We now look at those respondents who are aware of Data Analytics in their organisation. When asked what they believe are the three main reasons organisations are making use of data analytics, the most common answers given were:

- To improve productivity (56.5%)
- To automate processes (41.7%)
- To cut costs (41.0%)

These are the same as with AI (see Section 6.2), although at slightly lower percentages. Again, these results are comparable to prior studies, with the workforce perceiving digital transformations as driven by cost cutting and productivity goals (see Yates and Lockley, 2020a). However, the following three reasons were more highly scored for Data Analytics than for AI:

- To gather data to aid business intelligence (39.6%)
- To make the business more competitive (33.0%)
- To improve the customer experience (32.0%).

These results imply that the workforce has different perceptions of the uses of AI and Data Analytics within organisations. In this case, 19.8% saw one of the **reasons** for implementing Data Analytics solutions being to directly “automate jobs and reduce the workforce”.

Workforce perception of reasons for DA introduction	Percent of all responses
To cut costs	41.0
To automate processes	41.7
To improve productivity	56.5
To make the business more competitive	33.0
To improve the customer experience	32.0
To help meet regulatory requirements	19.5
To gather data to aid business intelligence	39.6
To automate jobs and reduce the workforce	19.8
Something else	>1.0
I don't think that companies and organisations are using more data analytics technologies	>1.0
Don't know	1.72

Table 33: Reasons for introducing AI

7.3 Perceptions of data analytics organisational factors

As with AI, we asked those with awareness of Data Analytics to rate both personal and workplace aspects of Data Analytics use in their organisation:

- Personal aspects

- How effectively you personally make use of data analytics in your workplace?
  - A lack of data analytics technologies in my organisation hinders my job effectiveness.
  - I understand how good data analytics technologies can support ethical data practices.
  - I have access to all the data analytics technologies I need to do my job effectively.
  - Data analytics technologies have made a positive impact on the way I operate at work.
- Workplace
  - Potential benefits of data analytics are clearly communicated to you by your organisation?
  - Financial pressures are preventing investment in data analytics in my organisation.
  - Data analytics in my organisation easily connects with the older systems we have in place.
  - My organisation has data analytics but we haven't had the training to make use of them.
  - My organisation provides support and training data analytics solutions are rolled out.
  - The organisation has a clear vision for data analytics.
  - Only some of my colleagues use the data analytics technologies available to us.
  - My organisation's management understands the importance of data analytics.

As with AI, the results are not highly "positive" across these Data Analytic questions. Again, there is a range from 60-40 to 50-50 splits between those giving positive responses (Very, Highly, or Slightly Agree/Confident/Effective) and those who do not (see Table 34). This implies that many in the workforce feel neither supported nor informed about AI developments in their workplaces. It is important to remember that this is the group with some awareness of ongoing workplace AI developments.

		n	%
Perceived effective use by organisation	Confident	2258	70.6
	Not Confident	941	29.4
Potential benefits of DA communicated clearly	Clearly	2008	62.8
	Not Clearly	1191	37.2
Personal effective use	Effective	2004	62.6
	Not Effective	1195	37.4
Financial pressures prevent investment	Agree	1506	47.1
	Disagree	1693	52.9
Easy connection of DA to older systems	Agree	1833	57.3
	Disagree	1366	42.7
Lack of training in using available DA	Agree	1732	54.1
	Disagree	1467	45.9
Support and training provided for DA	Agree	1926	60.2
	Disagree	1273	39.8
Clear vision for DA	Agree	2024	63.3
	Disagree	1175	36.7
Lack of DA hinders job effectiveness	Agree	1304	40.8

	Disagree	1895	59.2
Only some colleagues use available DA tools	Agree	1904	59.5
	Disagree	1295	40.5
Understands ethical DA practices	Agree	2271	71
	Disagree	928	29
Have the DA tools needed	Agree	1958	61.2
	Disagree	1241	38.8
Management understands importance of DA	Agree	2170	67.8
	Disagree	1029	32.2
Positive impact on my own work	Agree	1914	59.8
	Disagree	1285	40.2

Table 34: Workplace perceptions of data analytics technologies

We therefore modelled how these perceptions might predict perceptions of management and the organisations implementation of data analytics. We asked the respondents:

- How confident are you that the management team at your organisation is able to implement Data Analytic (DA) technologies successfully and effectively?

Taking Likert scale responses to this question as the dependent variable, we again modelled how personal and workplace perceptions act as predictors. Table 35 and the effects plots in Section 11.3 indicate similar predictors for this question as we found for the AI equivalent. However, the impact on respondents' work is not statistically significant, and financial constraints are perceived as important.

- Personal:
    - Feeling effective in personal use
- Organisational:
    - Communicating AI benefits clearly
    - Easy connection with legacy systems
    - Financial pressures are **not** perceived to impact investment
    - Provision of support and training
    - Having a clear vision for AI in the organisation
    - Management understanding importance of AI.

As with the AI results, these fit well with a TAM-based interpretation. However, including the financial element and the loss of the impact on one's work implies that the practical workplace context—the facilitating conditions—is of higher importance in relation to perceptions of data analytics implementations.

Predictor	B	SE	t	p
Intercept	0.49	0.070	6.95	<0.001
Potential benefits of DA communicated clearly	0.23	0.017	13.40	<0.001
Personal effective use	0.15	0.017	8.84	<0.001
Financial pressures prevent investment	-0.05	0.012	-4.08	<0.001
Easy connection of DA to older systems	0.08	0.014	6.04	<0.001
Lack of training in using available DA	0.02	0.012	1.53	0.125
Support and training provided for DA	0.07	0.015	4.68	<0.001
Clear vision for DA	0.17	0.016	10.27	<0.001
Lack of DA hinders job effectiveness	0.00	0.011	-0.24	0.812
Only some colleagues use available DA tools	0.01	0.012	0.81	0.418
Understands ethical DA practices	0.04	0.016	2.63	0.009
Have the DA tools needed	0.01	0.015	0.77	0.440
Management understands importance of DA	0.13	0.017	8.03	<0.001
Positive impact on my own work	0.04	0.017	2.18	0.029

Coefficient-Level Estimates for a Model Fitted to perceived effective use of AI.

Table 35: Data analytics effectiveness of implementation by key variables

7.4 Data analytics training

We find that just under half (54.3%) of respondents aware of Data Analytics in the workplace have had some form of training in Data Analytics. The presence of training varies across sectors (see Figure 15). As might be expected, the technology sectors offer more training (75.2%). The lowest levels of training were in the Other (37.2%), Charity (43.3%), and Transport (43.5%) sectors. These are, of course, only figures for those aware of Data Analytics, though overall training levels were higher than for AI. Assuming anyone with training would be aware of Data Analytics, these figures indicate that 31.6% of the workforce have had some form of training in AI. Satisfaction with training was relatively high across all sectors, with 44.4% deeming the training very or fairly adequate. There was a small statistically significant difference across sectors driven by higher adequacy rating among IT sector workers and lower adequacy ratings among charity sector workers (see Figure 16).

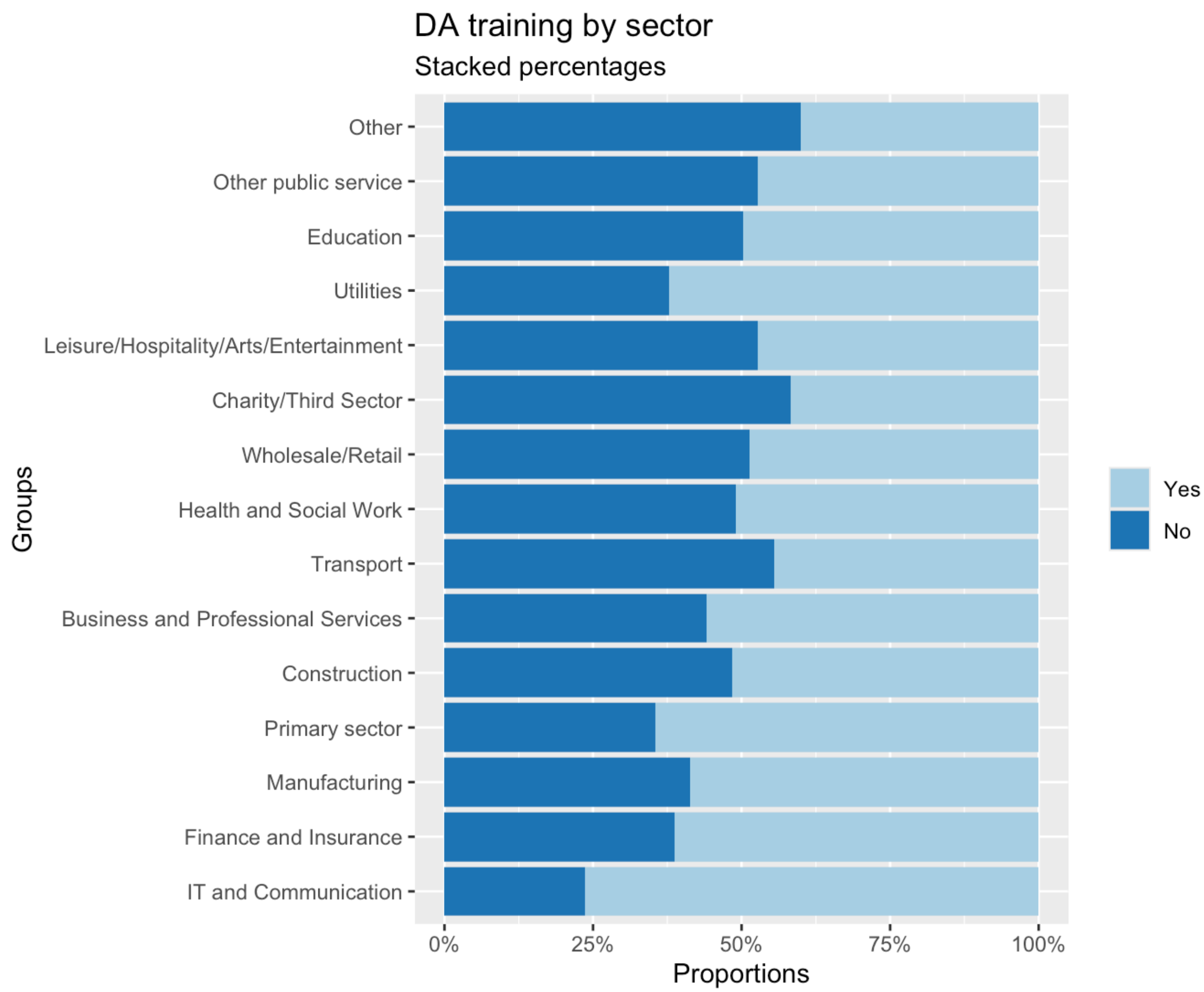


Figure 15: Have taken data analytics training

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and small (chi2 = 122.89, p < .001; Adjusted Cramer's v = 0.18, 95% CI [0.14, 1.00])

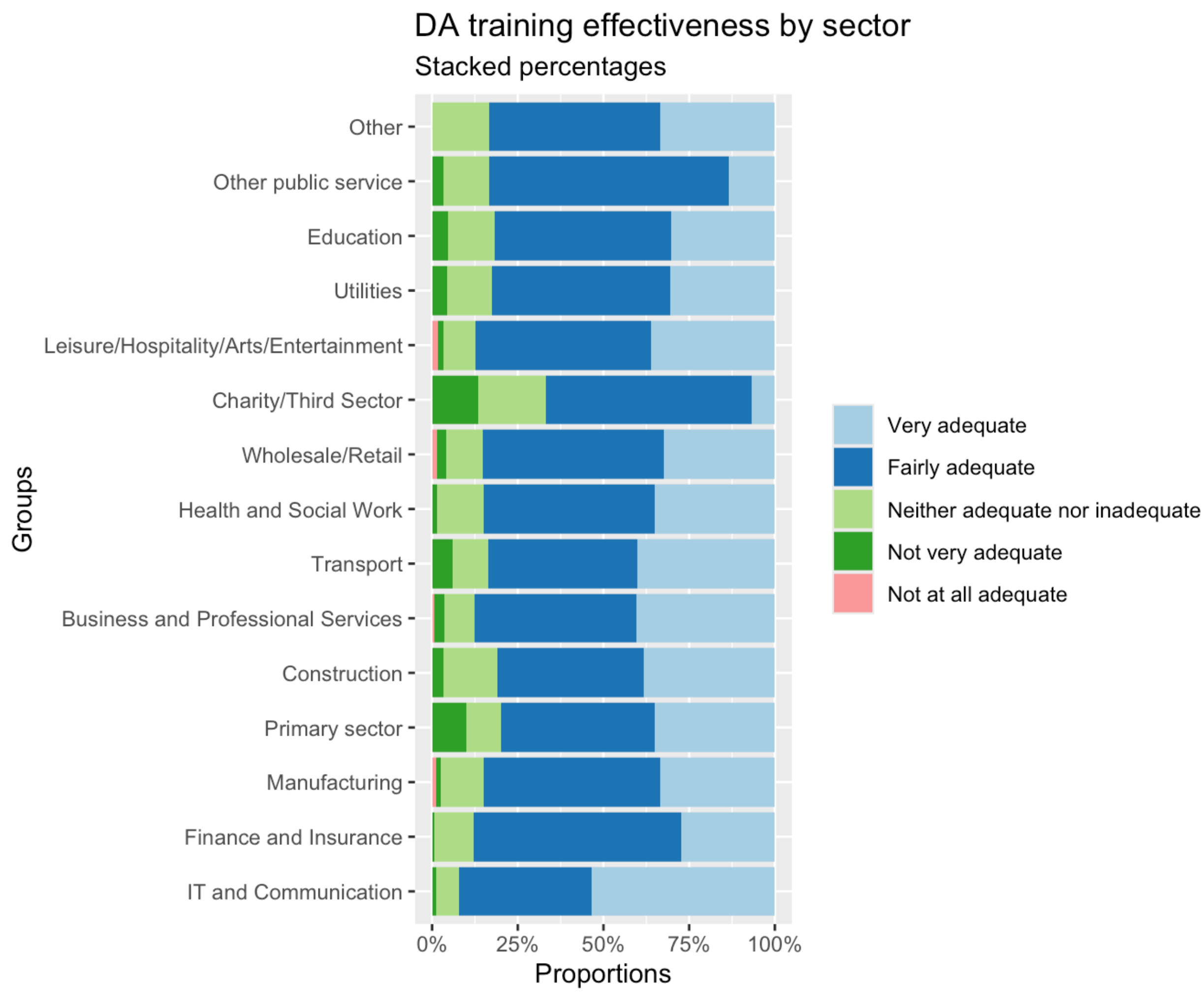


Figure 16: Effectiveness of DA training

The Pearson's Chi-squared test with simulated p-value (based on 2000 replicates) of independence between and suggests that the effect is statistically significant, and very small (chi2 = 122.28, p < .001; Adjusted Cramer's v = 0.10, 95% CI [0.00, 1.00])

7.5 How data analytics had a positive impact on work activity

Of those who are aware of data analytics, just over half, 59.8%, believed that data analytics had a positive impact on their work operations. Conversely, 40.2% did not feel that data analytics positively influenced their work operations. The two most common positive impacts were:

- It made my job easier to do.
- It made it quicker to do my job.

However, none of the positive impacts was noted by more than 50% of the respondents, with results ranging from 23.0% to 47.1% of respondents (see Table 36). Therefore, we can question whether these respondents saw themselves as gaining a wide range of benefits from data analytics use in their work.

How Data Analytics have improved work activity	Percent of all responses
It made my job easier to do	47.1
It made it quicker to do my job	48.1
It streamlined internal processes	37.9
It helped me reprioritise tasks	38.6
It allowed me greater flexibility in how I do my job	37.4
It allowed me greater flexibility in where I do my job	31.2
It helped me connect with other employees	23.0
It helped the company better meet their regulatory requirements	32.9
It opened up additional opportunities in my role	28.4
Something else	>1.0

Table 36: How data analytics have improved work activity

8. Digital technologies in the workplace

In this section, we consider respondents' perceptions of Digital Technologies. These respondents were unaware of AI or data analytics but used digital tools at work. These could, in fact, be AI or data analysis-based technologies. However, respondents do not recognise them as such

8.1 Perceived reasons for uptake of digital technologies in the workplace

The most common reasons respondents perceive as to why organisations are making use of digital technologies are:

- To cut costs (48.1%)
- To improve productivity (45.6%)
- To automate processes (34.4%)

However, these were less clearly demarcated than the other reasons compared to AI and data analytics. Once again, around a quarter (25.1%) of respondents thought automating jobs to reduce the workforce was a key reason.

Workforce perception of reasons for DT introduction	Percent of all responses
To cut costs	48.1
To automate processes	34.4
To improve productivity	45.6
To make the business more competitive	28.3
To improve the customer experience	25.7
To help meet regulatory requirements	14.5
To gather data to aid business intelligence	28.8
To automate jobs and reduce the workforce	25.1
Something else	>1.0
I don't think that companies and organisations are using more digital technologies	2.28
Don't know	10.6

Table 37: Reasons for introducing Digital Technologies

8.2 Perceptions of digital technology organisational factors

Again, we asked those with no awareness of AI or data analytics to rate both personal and workplace issues but this time about digital technology (DT) use in general:

- Personal aspects
  - How effectively you personally make use of DT in your workplace?
  - A lack of DT technologies in my organisation hinders my job effectiveness.
  - I understand how good DT technologies can support ethical data practices.
  - I have access to all the DT technologies I need to do my job effectively.
  - DT technologies have made a positive impact on the way I operate at work.
- Workplace
  - Potential benefits of DT are clearly communicated to you by your organisation?
  - Financial pressures are preventing investment in DT in my organisation.
  - DT in my organisation easily connects with the older systems we have in place.
  - My organisation has DT but we haven’t had the training to make use of them.
  - My organisation provides support and training DT solutions are rolled out.
  - The organisation has a clear vision for DT.
  - Only some of my colleagues use the DT technologies available to us.
  - My organisation’s management understands the importance of DT.

The results across these questions are very negative, ranging from 40-60 to 25-75 splits between those giving positive responses (Very, Highly, or Slightly Agree/Confident/Effective) and those not (see Table 38). This implies that many in the workforce do not feel supported or informed about digital technology developments in their workplaces. Remember that this group is unaware of ongoing workplace AI or data analytics developments.

		n	%
Potential benefits of DT communicated clearly	Clearly	294	21.6
	Not Clearly	1066	78.4
Personal effective use	Effective	477	35.1
	Not Effective	883	64.9
Financial pressures prevent investment	Agree	368	27.1
	Disagree	992	72.9
Easy connection of DT to older systems	Agree	321	23.6
	Disagree	1039	76.4
Lack of training in using available DT	Agree	338	24.9
	Disagree	1022	75.1
Support and training provided for DT	Agree	440	32.4
	Disagree	920	67.6
Clear vision for DT	Agree	331	24.3
	Disagree	1029	75.7
Lack of DT hinders job effectiveness	Agree	225	16.5
	Disagree	1135	83.5
Only some colleagues use available DT tools	Agree	429	31.5
	Disagree	931	68.5
Understands ethical DT practices	Agree	440	32.4
	Disagree	920	67.6
Have the DA tools needed	Agree	600	44.1
	Disagree	760	55.9
Management understands importance of DT	Agree	519	38.2
	Disagree	841	61.8
Positive impact on my own work	Agree	454	33.4
	Disagree	906	66.6

Table 38: Workplace perceptions of Digital Technologies

We again modelled how these perceptions might predict perceptions of management and the organisations implementation of Digital Technologies. We asked the respondents:

- How confident are you that the management team at your organisation is able to implement Digital Technologies (DT) successfully and effectively?

Taking Likert scale responses to this question as the dependent variable we again modelled how the personal and workplace perceptions act as predictors. As Table 39 and the effects plots in Section 11.4 indicate the results are notably different from the AI and data analytics aware respondents. There are no personal factors acting as predictors only organisational ones:

- Organisational:
    - Communicating benefits of digital technology clearly
    - Easy connection with legacy systems
    - Provision of support and training
    - Having a clear vision for digital technology in the organisation
    - Management understanding importance of digital technology.

These results fit less well with standard TAM-based interpretation as personal usefulness and effectiveness are not statistically significant. However, we should note that these are responses from those who are not aware of AI or data analytics in their workplace. We know from Section 5 that these respondents are :

- More likely to be older
- More likely to not work in an IT facing sector
- More likely to be part-time or self-employed
- More likely to be of a lower grade/role in their organisation
- More likely to be Limited or non-users of domestic digital technologies
- Less likely to use Digital Technologies at all or extensively in work.

As a result, this group represents the section of the workforce that is less likely to be engaged with digital technologies in work on a regular basis - either because of the type of work they do or their workplace context.

Predictor	**B**	**SE**	**t**	**p**
Intercept	0.67	0.181	3.70	<0.001
Potential benefits of DT communicated clearly	0.12	0.035	3.34	<0.001
Personal effective use	0.09	0.035	2.67	0.008
Financial pressures prevent investment	-0.06	0.028	-2.28	0.023
Easy connection of DT to older systems	0.11	0.033	3.39	<0.001
Lack of training in using available DT	-0.05	0.029	-1.80	0.073
Support and training provided for DT	0.18	0.036	5.17	<0.001
Clear vision for DT	0.16	0.036	4.45	<0.001
Lack of DT hinders job effectiveness	-0.05	0.027	-1.67	0.095
Only some colleagues use available DT tools	0.04	0.027	1.62	0.105
Understands ethical DA practices	-0.04	0.035	-1.21	0.229
Have the DT tools needed	0.10	0.034	2.97	0.003
Management understands importance of DT	0.19	0.039	4.72	<0.001
Positive impact on my own work	0.01	0.035	0.34	0.731

Coefficient-Level Estimates for a Model Fitted to perceived effective use of DT.

Table 39: Digital technologies effectiveness of implementation by key variables

8.3 How Digital Technologies had a positive impact on work activity

Of those unaware of AI or Data Analytics, we found that 33.4% thought that AI has positively impacted how they operate at work. Conversely, 66.6% did not believe that digital technologies positively impacted their work operations. The two most common positive impacts were:

- It made my job easier to do.
- It made it quicker to do my job.

However, all other positive impacts were also noted by 9.5% to 31.7% of respondents (see Table 40). More clearly evidenced, as against AI and data analytics, we can conclude that these respondents did not see themselves as gaining many benefits from AI use.

How Digital Technologies have improved work activity	Percent of all responses
It made my job easier to do	58.4
It made it quicker to do my job	53.7
It streamlined internal processes	24.4
It helped me reprioritise tasks	20.9
It allowed me greater flexibility in how I do my job	31.7
It allowed me greater flexibility in where I do my job	29.1
It helped me connect with other employees	25.1
It helped the company better meet their regulatory requirements	18.1
It opened up additional opportunities in my role	9.47
Something else	1.1
Total cases	454

Table 40: How Digital Technologies have improved work activity

9. Digital tool use in general: Workplace issues

We asked all respondents a set of questions about the workplace use of digital tools of any kind. These covered:

- My organisation's management makes digital technology solutions a priority.
- My organisation's management understands the significance of adopting a more digital way of working.
- My organisation's management is trying to push through new digital ways of working, but the wider business isn't interested in changing the way things are already done.
- It is easy to get access to the digital technologies I need to do my job well.
- How often, if at all, do you worry that you lack the digital technology skills needed to do your job?

Taking each of these in turn, we get a mixed picture.

9.1 Prioritising digital technologies and solutions

As with many prior results, just over 50% of respondents agree that their organisations prioritise digital solutions (see Table 41). Again, there is variation by sector, with IT, Finance, Manufacturing, and Utilities, with more than 50% of respondents in these sectors agreeing (strongly or slightly) that their organisation prioritises digital solutions (see Figure 17). This implies that 48.3% of respondents do **not** think their organisation prioritises digital solutions.

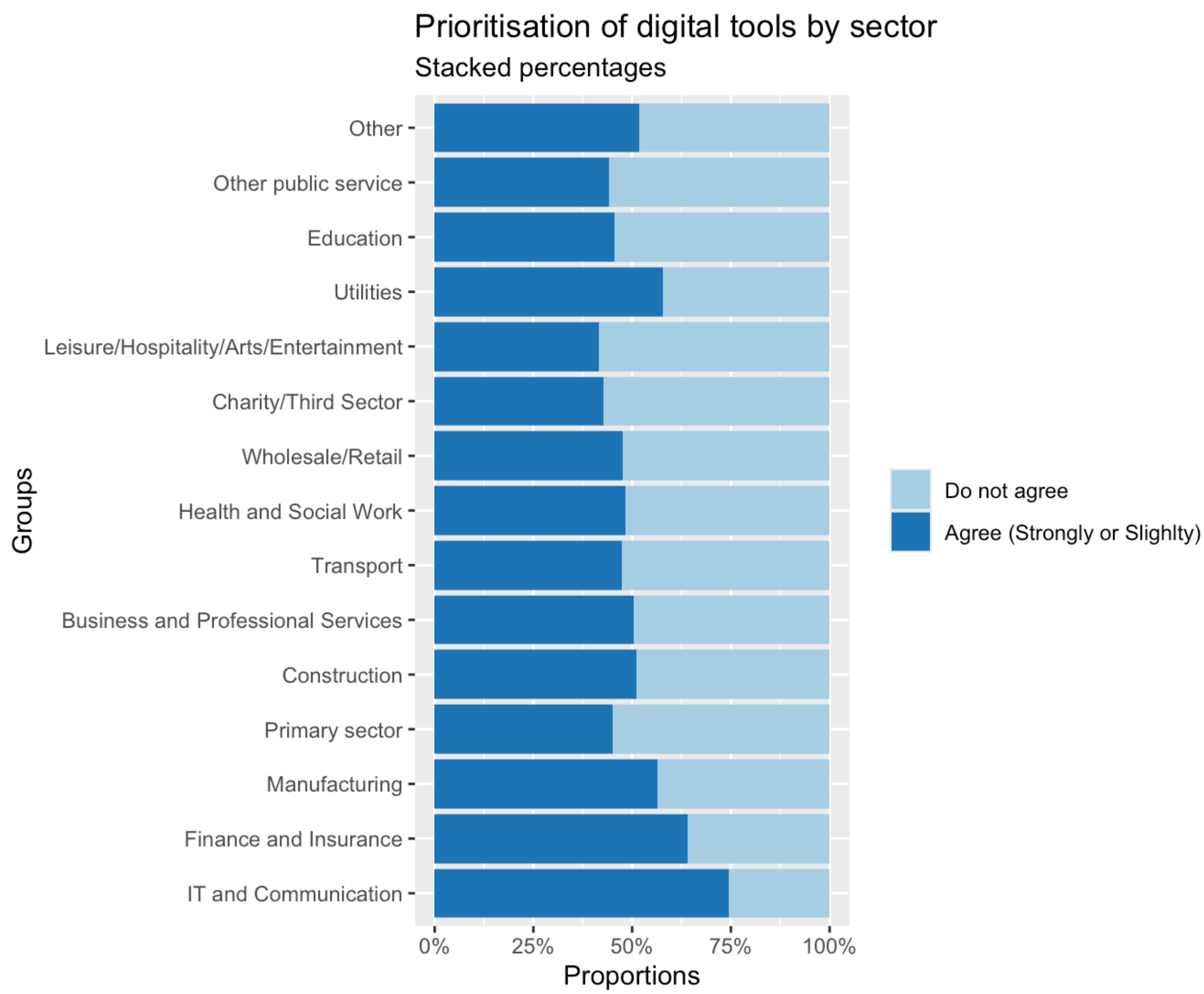


Figure 17: Prioritisation of digital tools by sector

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 181.17, p < .001; Adjusted Cramer's v = 0.18, 95% CI [0.15, 1.00])

	Freq	%
Strongly agree	1047.2	20.2
Slightly agree	1614.9	31.1
Neither agree nor disagree	1218.3	23.5
Slightly disagree	633.8	12.2
Strongly disagree	363.8	7.0
Don't know	314.1	6.0
Total	5192.0	100.0

Table 41: Prioritising digital solutions

9.2 Significance of adopting a more digital way of working

In this case, 63.8% of respondents agree to some extent that their organisations are aware of the significance of adopting more digital solutions (see Table 42). Again, there is variation by sector, but at least 50% of respondents in all sectors agree (strongly or slightly) that their organisation prioritises digital solutions (see Figure 18). However, overall 36.2% do **not** think that that their organisation understands the significance of adopting more digital solutions.

	Freq	%
Strongly agree	1311.9	25.3
Slightly agree	1988.8	38.3
Neither agree nor disagree	1030.3	19.8
Slightly disagree	349.1	6.7
Strongly disagree	231.8	4.5
Don't know	280.1	5.4
Total	5192.0	100.0

Table 42: Prioritising digital solutions

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 122.83, p < .001; Adjusted Cramer's v = 0.14, 95% CI [0.11, 1.00])

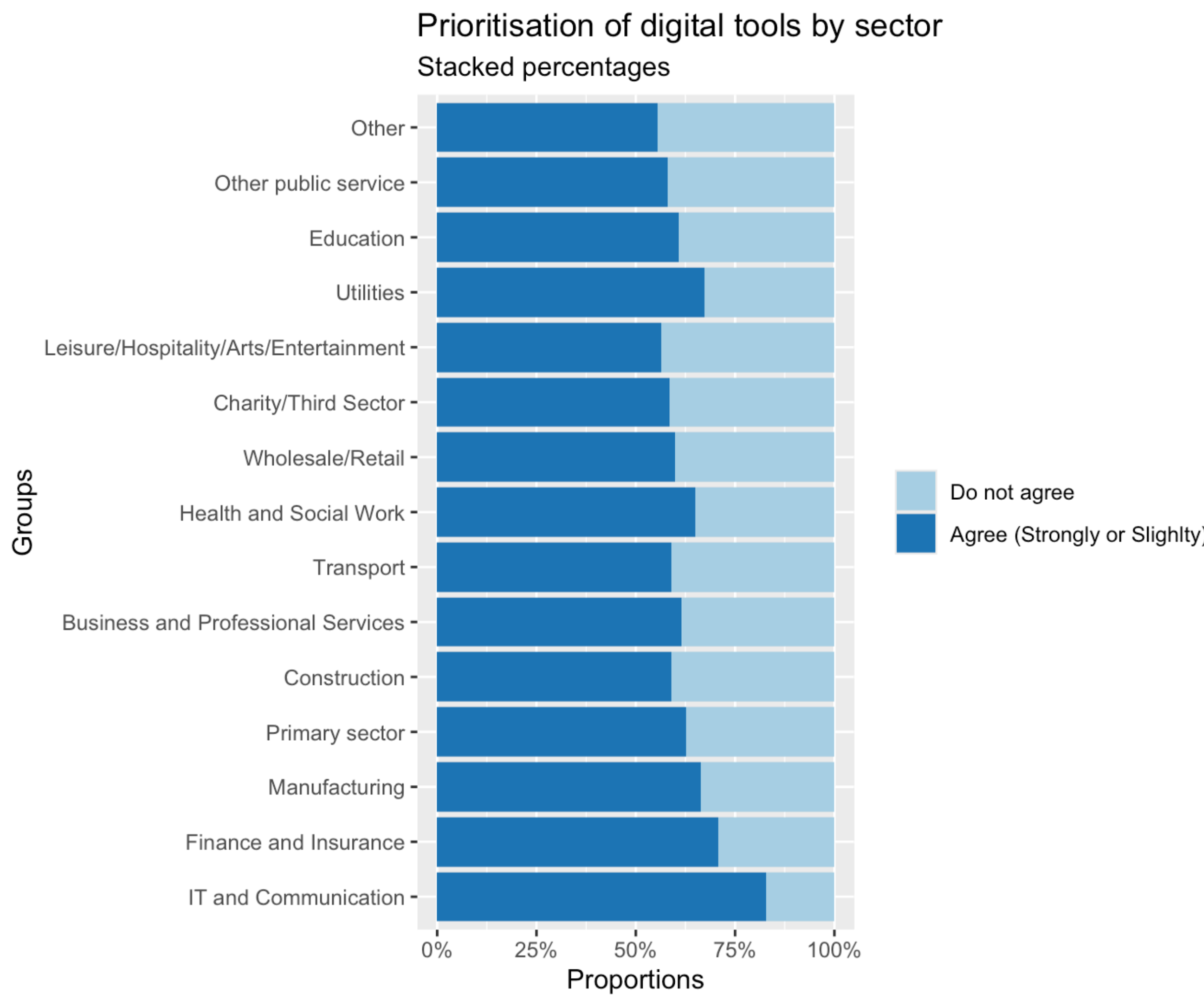


Figure 18: Significance of adopting digital tools by sector

9.3 Organisational resistance to digital transformation

Here we find that 41.4% of respondents agree to some extent that parts of their organisation are resistant to management attempts to bring in digital solutions (see Table 43). Again, there is variation by sector with only the IT sector going over 50% agreeing that parts of their organisation are resistant to management attempts to bring in digital solutions (see Figure 19).

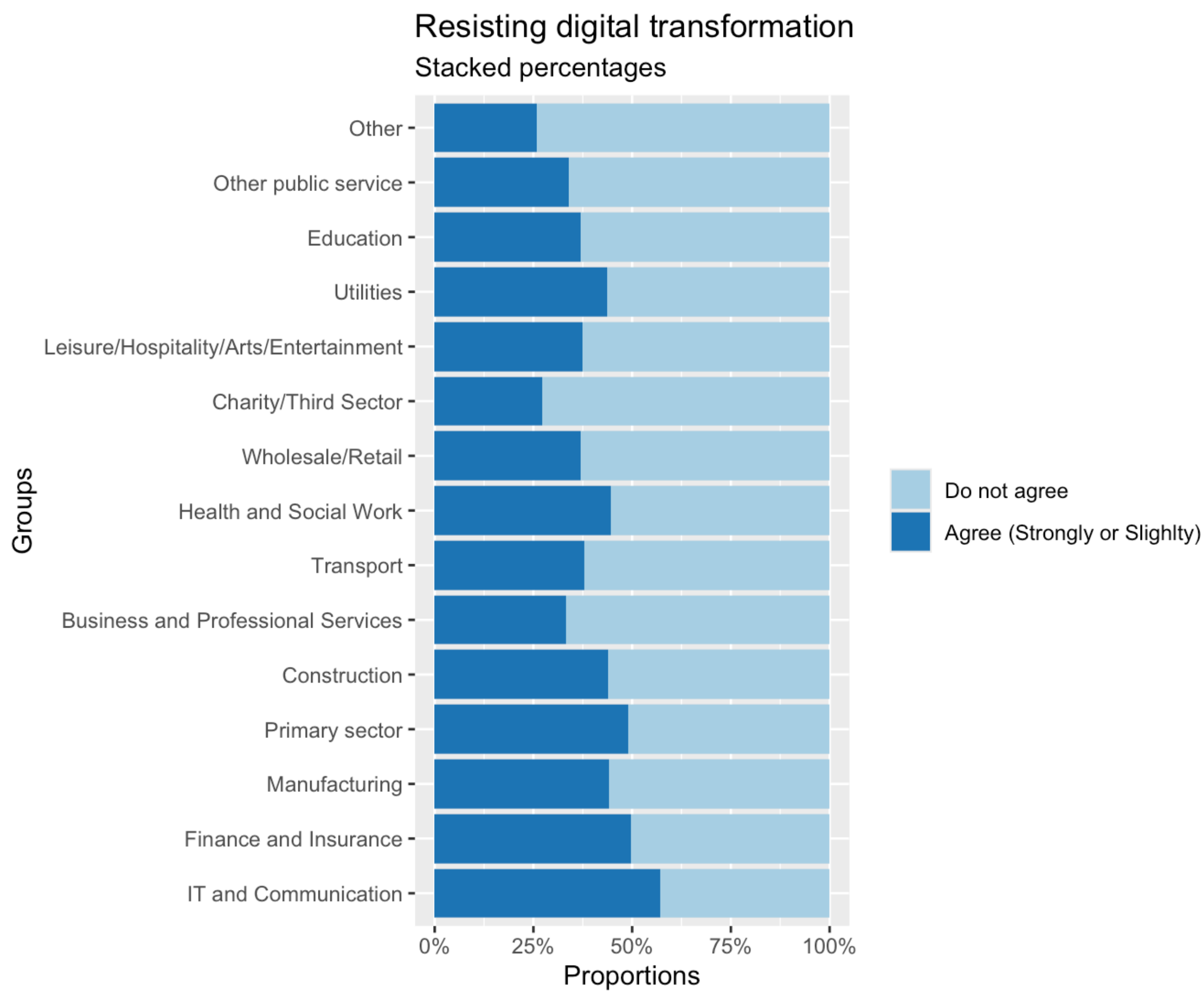


Figure 19: Resisting digital transformation

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 112.41, p < .001; Adjusted Cramer's v = 0.14, 95% CI [0.10, 1.00])

	Freq	%
Strongly agree	785.9	15.1
Slightly agree	1354.2	26.1
Neither agree nor disagree	1279.7	24.6
Slightly disagree	843.3	16.2
Strongly disagree	566.5	10.9
Don't know	362.4	7.0
Total	5192.0	100.0

Table 43: Resisting digital solutions

9.4 Easy access to digital technologies

In this case, 60.9% of respondents agree to some extent that they have easy access to the digital technologies needed for their jobs (see Table 44). Again, there is variation by sector, but at least 50% of respondents in all sectors agree (strongly or slightly) that they have easy access to these technologies (see Figure 20). However, overall, 39.1% do not think that their organisation understands the significance of adopting more digital solutions.

	Freq	%
Strongly agree	1213.0	23.4
Slightly agree	1945.0	37.5
Neither agree nor disagree	1061.2	20.4
Slightly disagree	520.9	10.0
Strongly disagree	267.4	5.2
Don't know	184.5	3.6
Total	5192.0	100.0

Table 44: Easy access digital solutions

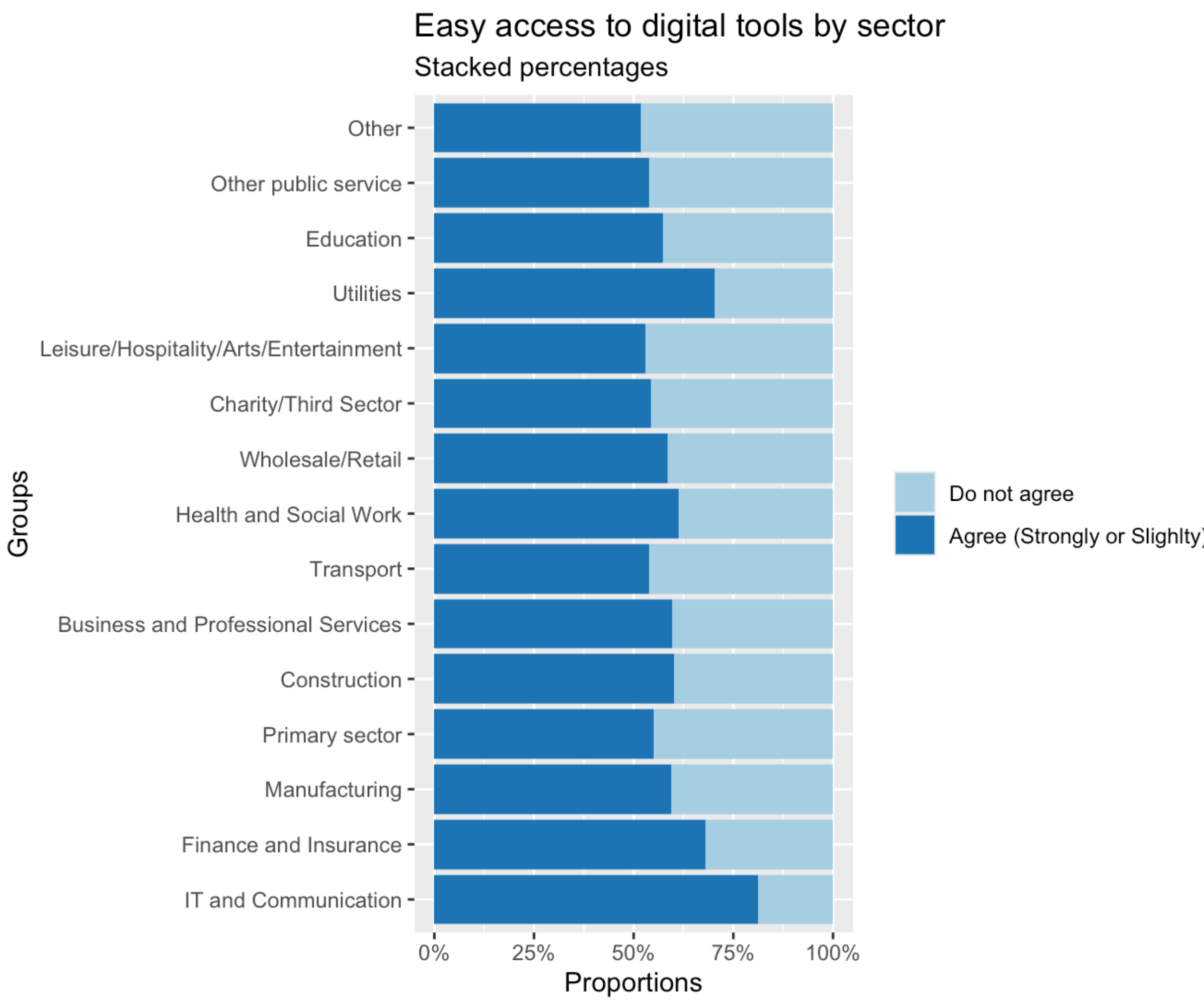


Figure 20: Easy access to digital tools by sector

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 133.75, p < .001; Adjusted Cramer's v = 0.15, 95% CI [0.12, 1.00])

9.5 Worry about digital skills

In this case, 66.5% of respondents do not worry about their own digital skills (see Table 45). Again, there is variation by sector, with IT, Finance, Primary (Mining/Minerals), Utilities, and Others having the greatest levels of worry (see Table 46 and Figure 21).

	Freq	%
Very often	495.6	9.5
Fairly often	1244.7	24.0
Neither often nor not often	916.9	17.7
Not very often	1184.3	22.8
Not at all often	587.8	11.3
Not applicable – I don't worry about lacking the digital technology skills needed to do my job	681.8	13.1
Don't know	80.9	1.6
Total	5192.0	100.0

Table 45: Worry about digital skills

Sector	Do not worry often	Worry very or fairly often	Total
IT and Communication	276.4 (53.2%)	243.2 (46.8%)	519.6 (100.0%)
Finance and Insurance	212.2 (58.4%)	151.0 (41.6%)	363.2 (100.0%)
Manufacturing	250.6 (64.0%)	140.9 (36.0%)	391.5 (100.0%)
Primary sector	29.0 (57.2%)	21.7 (42.8%)	50.7 (100.0%)
Construction	185.7 (60.0%)	123.8 (40.0%)	309.5 (100.0%)
Business and Professional Services	376.9 (74.6%)	128.2 (25.4%)	505.1 (100.0%)
Transport	211.1 (67.8%)	100.2 (32.2%)	311.3 (100.0%)
Health and Social Work	432.9 (66.4%)	219.4 (33.6%)	652.4 (100.0%)
Wholesale/Retail	471.6 (69.2%)	209.7 (30.8%)	681.3 (100.0%)
Charity/Third Sector	50.3 (73.5%)	18.1 (26.5%)	68.5 (100.0%)
Leisure/Hospitality/Arts/Entertainment	348.5 (72.4%)	133.0 (27.6%)	481.5 (100.0%)
Utilities	36.3 (58.6%)	25.7 (41.4%)	62.0 (100.0%)
Education	379.7 (73.1%)	140.1 (26.9%)	519.8 (100.0%)
Other public service	173.1 (70.1%)	73.9 (29.9%)	247.1 (100.0%)
Other	17.3 (60.7%)	11.2 (39.3%)	28.6 (100.0%)
Total	3451.7 (66.5%)	1740.3 (33.5%)	5192.0 (100.0%)

Table 46: Worry about digital skills by sector

The Pearson's Chi-squared test of independence between and suggests that the effect is statistically significant, and small (chi2 = 95.47, p < .001; Adjusted Cramer's v = 0.13, 95% CI [0.09, 1.00])

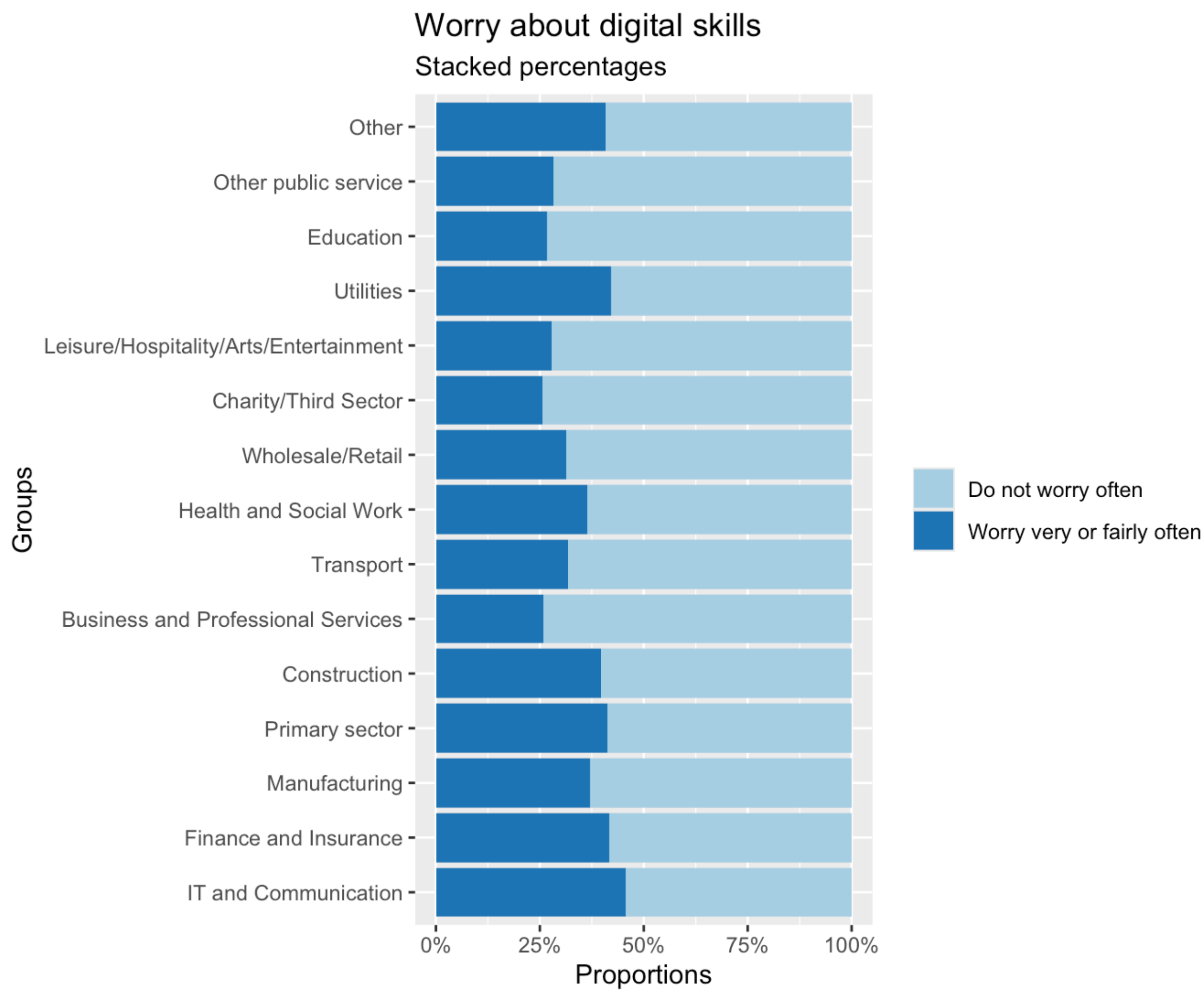


Figure 21: Easy access to digital tools by sector

10. Conclusions

The survey provides an overview of workforce attitudes, awareness, and perceptions of artificial intelligence (AI), data analytics (DA), and digital technologies across the UK workforce. Key findings and implications include:

- **AI and DA Awareness**: Over half of respondents (53.4%) demonstrated awareness of both AI and DA, with higher education levels and roles in IT, finance, and manufacturing corresponding with greater familiarity.

- **Training Gaps**: Despite awareness, only 47.9% of respondents had access to AI training, and 54.3% to DA training. This and the other findings around Technology Acceptance and perceptions of management vision highlighting a significant need for skill-building programs, and organisational communication of plans and strategies, particularly in non-technology sectors like charities and public services.

- **Organisational Perceptions**: Workers expressed mixed confidence in their organisations' readiness to adopt AI and DA, with financial constraints and lack of training being recurring barriers.
- **Perceived Benefits**: Respondents recognized productivity and process improvements as the primary drivers for AI and DA adoption but emphasized the importance of clear communication, support, and integration with legacy systems.
- **Broader Impacts**: The results also identify a need for strategic interventions to address digital literacy, ethical considerations, and resistance to change in the workforce.

These findings, along with further detailed analysis for particular sectors, and their integration with qualitative findings from the broader DDRC project could be used to shape policy and organisational strategies for both MoD and to enhance the UK workforce's readiness for digital transformation.

11. References

Adams, D. A., Nelson, R. R., & Todd, P. A., (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS Quarterly*, 16(2), 227–247.

Carmi, E, Yates, S.J., (2020), "What do digital inclusion and data literacy mean today?", *Internet Policy Review,* Vol 9, Issue 2, (DOI: 10.14763/2020.2.1474) (ISSN: 2197-6775).

Carmi, E., Yates, S.J., Lockley, E., Pawluczuk, A., (2020), "Data citizenship: rethinking data literacy in the age of disinformation, misinformation, and malinformation". Internet Policy Review, Vol. 9, Issue 2. (DOI: 10.14763/2020.2.1481) (ISSN: 2197-6775).

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R., (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003.

Segars, A. H. & Grover, V., (1993). Re-examining perceived ease of use and usefulness: A confirmatory factor analysis. *MIS Quarterly*, 17(4), 517–525.

Szajna, B., (1994). Software evaluation and choice: Predictive validation of the technology acceptance instrument. *MIS Quarterly*, 18(3), 319–324.

Venkatesh, V., (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, 11(4), 342–365.

Venkatesh, V. & Davis, F. D., (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D., (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.

Yates, S.J., Carmi, E, Lockley, E., Pawluczuk, A., French, T., Vincent, S., (2020), "Who are the limited users of digital systems and media? An examination of UK evidence". *First Monday*, Vol. 25, No. 7. (ISSN:1396-0466).

Yates, S.J., Kirby, J., Lockley, E., (2015), "Digital media use: differences and inequalities in relation to class and age", *Sociological Research Online,* Vol. 20, Issue 4, (ISSN: 1360-7804) (DOI: 10.5153/sro.3751) (http://www.socresonline.org.uk/20/4/12.html)

Yates, S.J., Lockley, E., (2018), "Social media and social class", *American Behavioural Scientist,* Vol. 62, Issue 9, pp.1291-1316 (ISSN: 0002-7642/1552-3381)

Yates, S.J., Lockley, E., (2020a), "Digital Culture at Work and the Uptake of Digital Solutions: Personal and Organisational Factors" in Yates, S.J., Rice, R., (eds.), *The Oxford Handbook of Digital Technology and Society,* Oxford: Oxford University Press (ISBN: 9780190932596).

Yates, S.J., Lockley, E., (2020b), "Digital Engagement and Class: Economic, Social, and Cultural Capital in a Digital Age" in Yates, S.J., Rice, R., (eds.), *The Oxford Handbook of Digital Technology and Society,* Oxford: Oxford University Press (ISBN: 9780190932596).

12. Appendix: Effects plots from regression analyses

For details of levels in each variable please see the separate Basic Exploratory Data Analysis Report.

12.1 Effects plots knowledge of AI and DA implementation

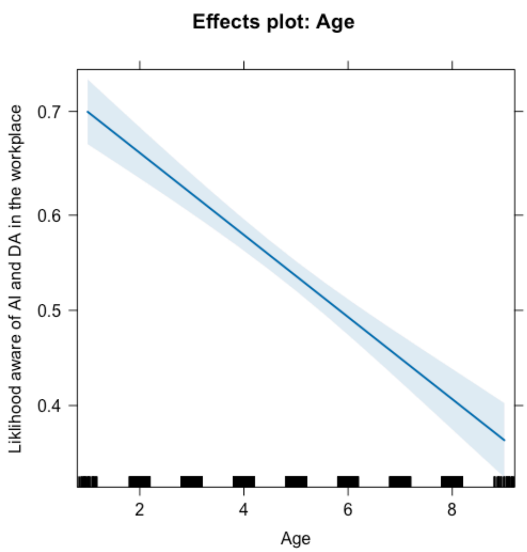


Figure 22: Effects plot: Age categories

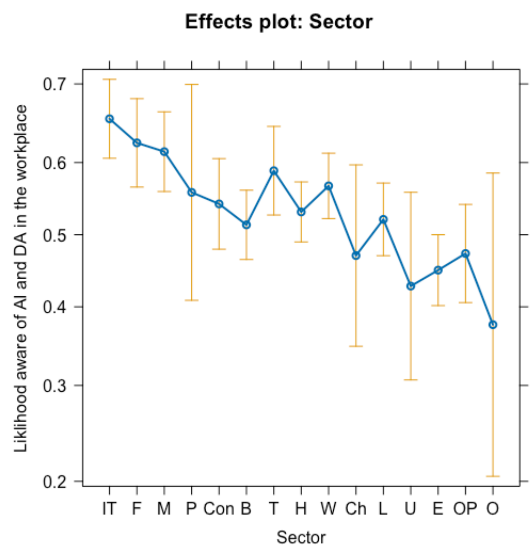


Figure 23: Effects plot: Sector

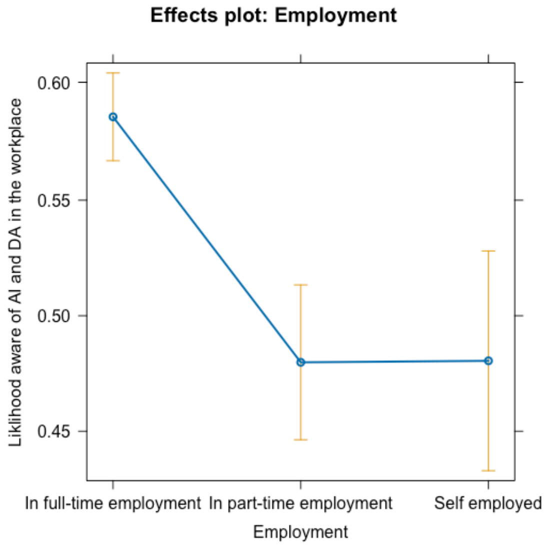


Figure 24: Effects plot: Employment

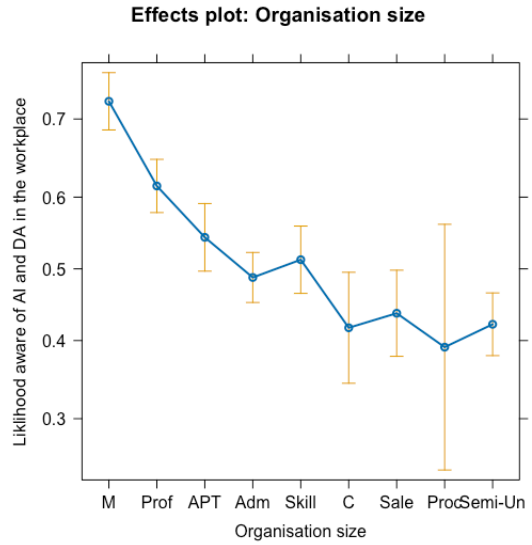


Figure 25: Effects plot: Grade

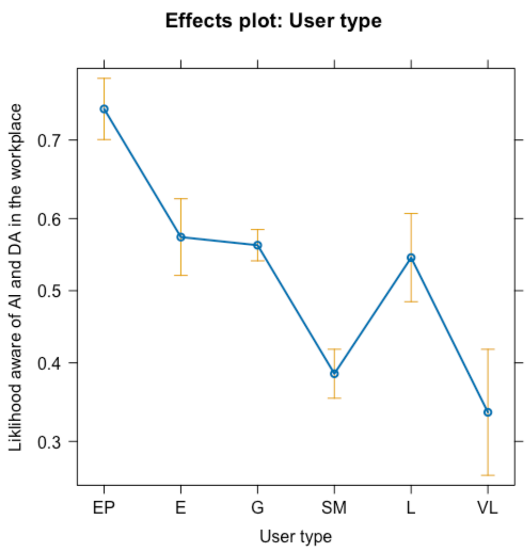


Figure 26: Effects plot: User type

12.2 Effects plots perceptions of effective AI implementation

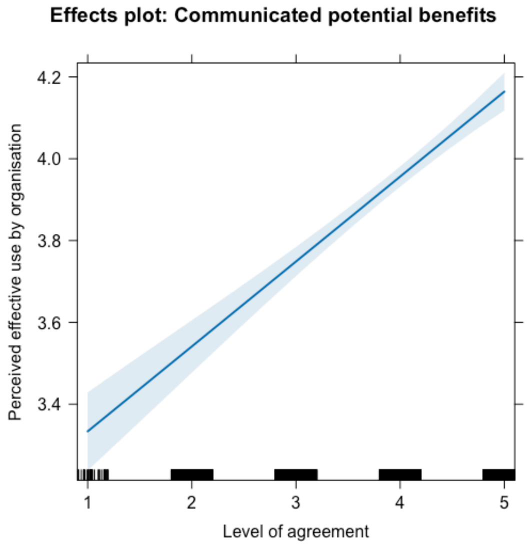


Figure 27: Effects plot: Communicated potential benefits

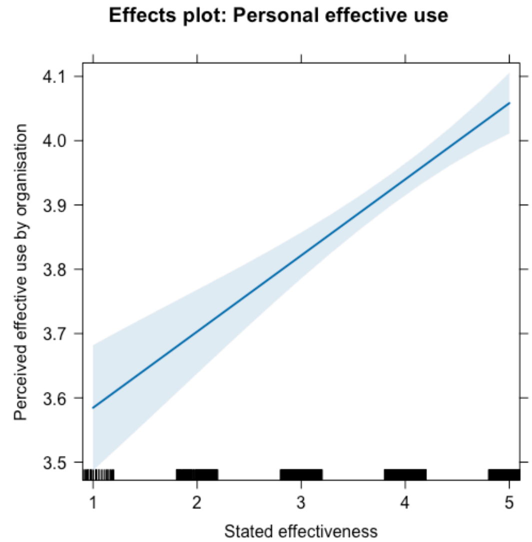


Figure 28: Effects plot: Personal effective use

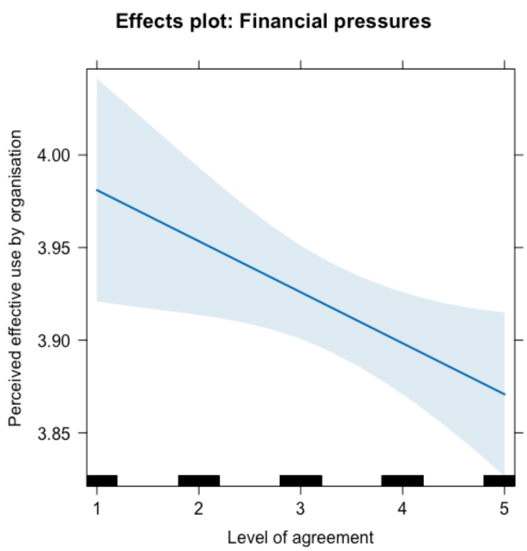


Figure 29: Effects plot: Financial pressures

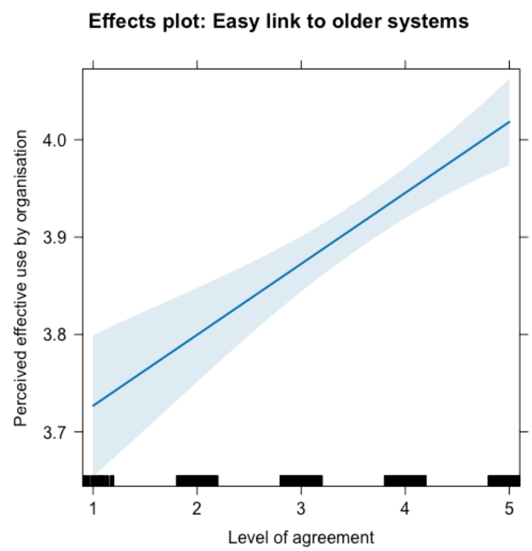


Figure 30: Effects plot: Easy link to older systems

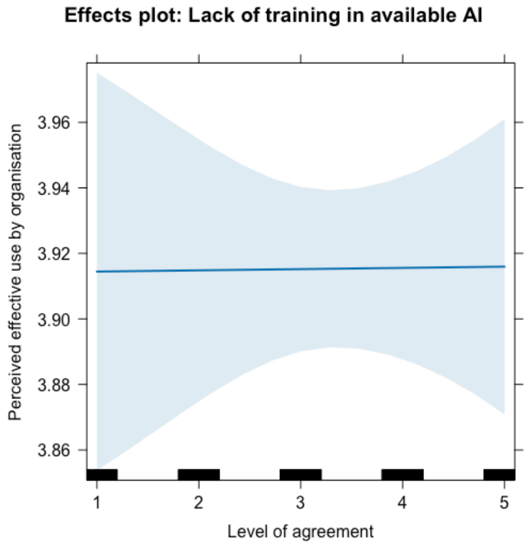


Figure 31: Effects plot: Lack of training in available AI

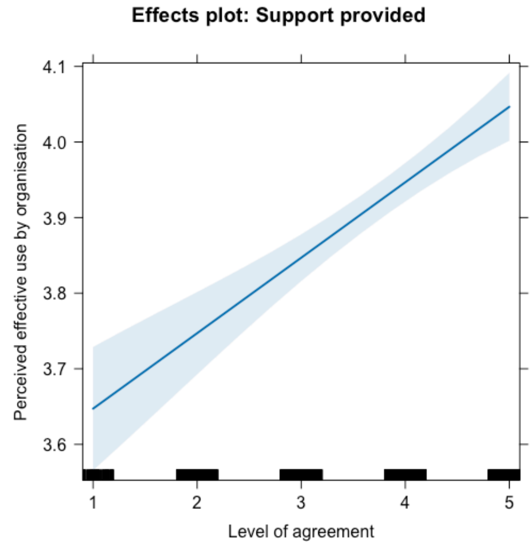


Figure 32: Effects plot: Support provided

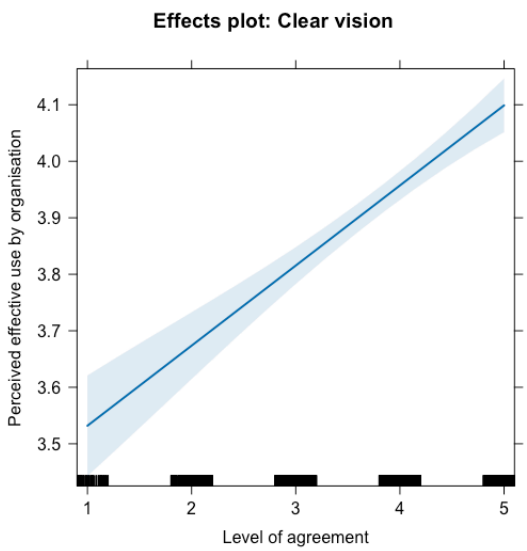


Figure 33: Effects plot: Clear vision

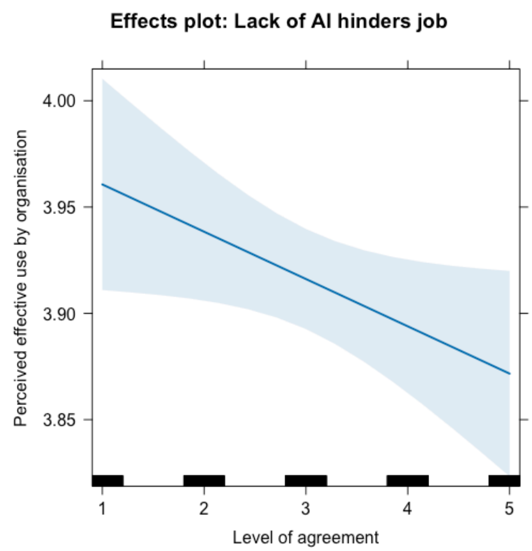
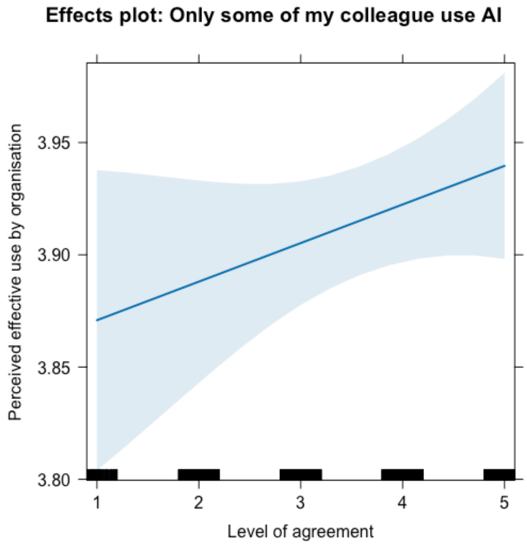


Figure 34: Effects plot: Lack of AI hinders job



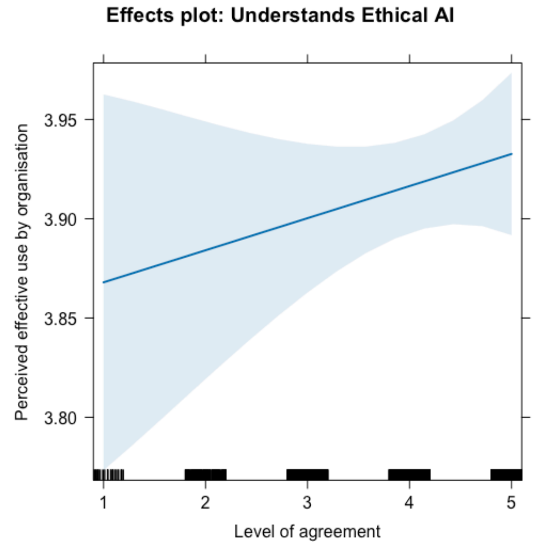


Figure 35: Effects plot: Only some colleagues

Figure 36: Effects plot: Understands ethical AI

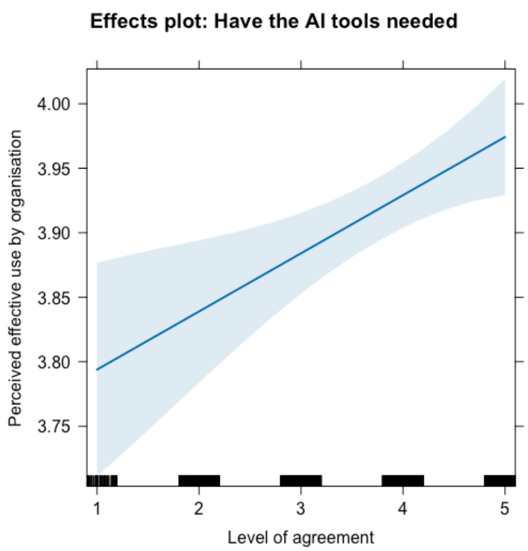


Figure 37: Effects plot: Have the AI tools needed

Figure 38: Effects plot: Management understands

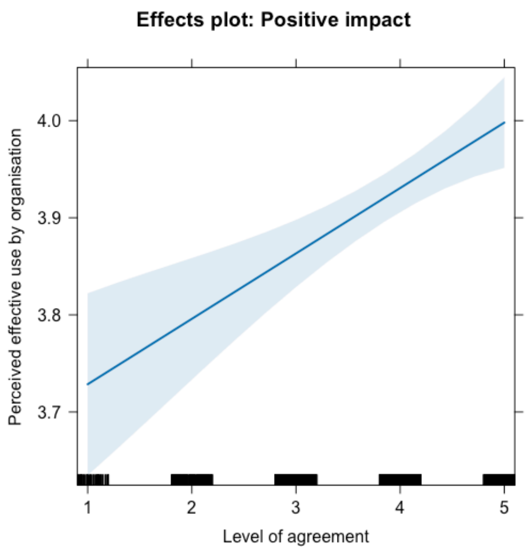


Figure 39: Effects plot: Positive impact

12.3 Effects plots perceptions of effective DA implementation

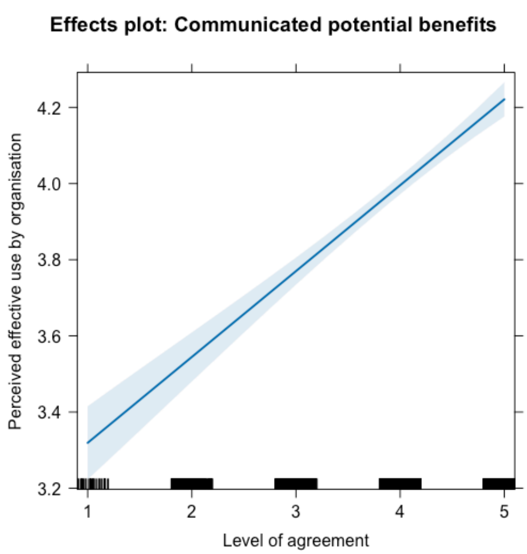


Figure 40: Effects plot: Communicated potential benefits

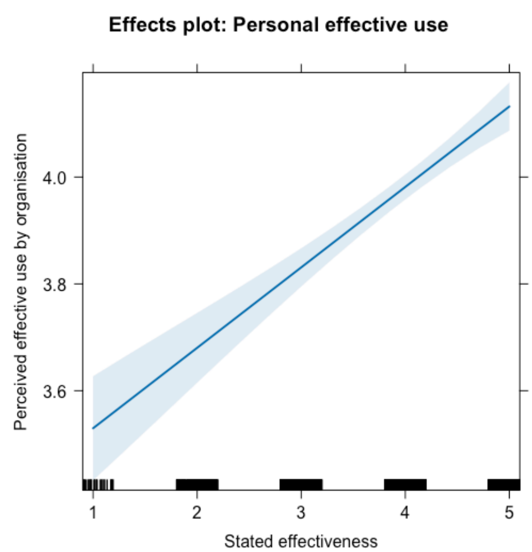


Figure 41: Effects plot: Personal effective use

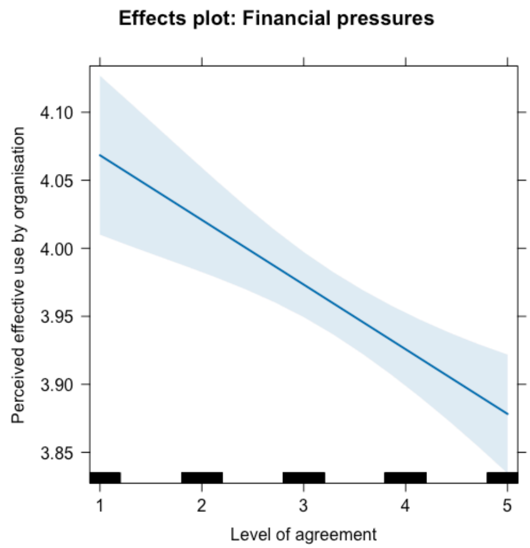


Figure 42: Effects plot: Financial pressures

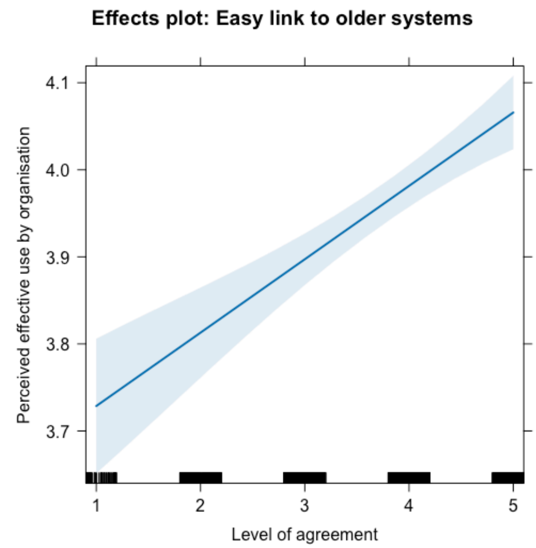


Figure 43: Effects plot: Easy link to older systems

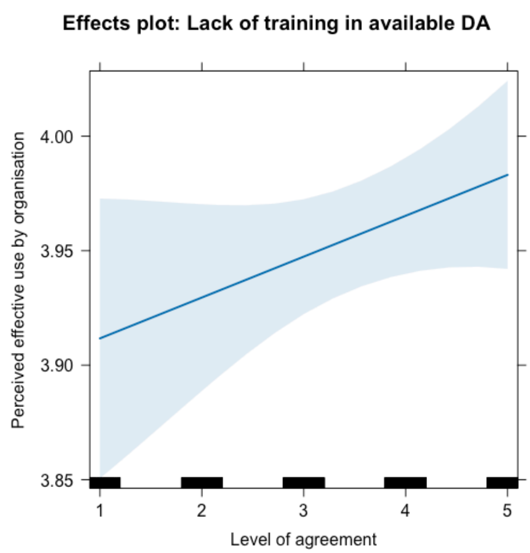


Figure 44: Effects plot: Lack of training in available DA

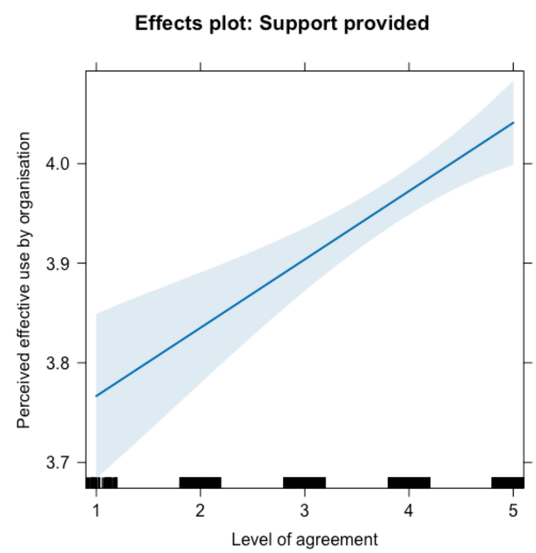


Figure 45: Effects plot: Support provided

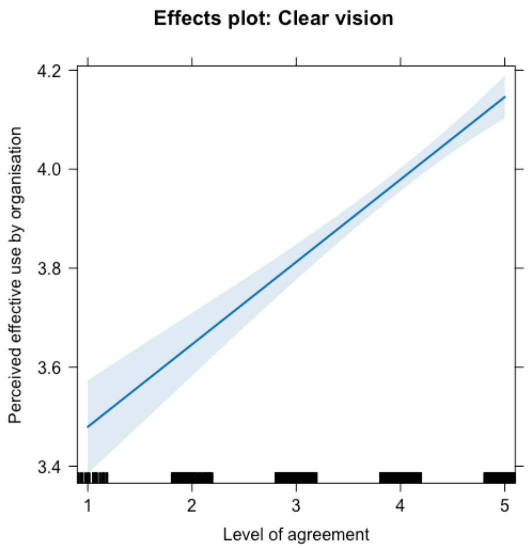


Figure 46: Effects plot: Clear vision

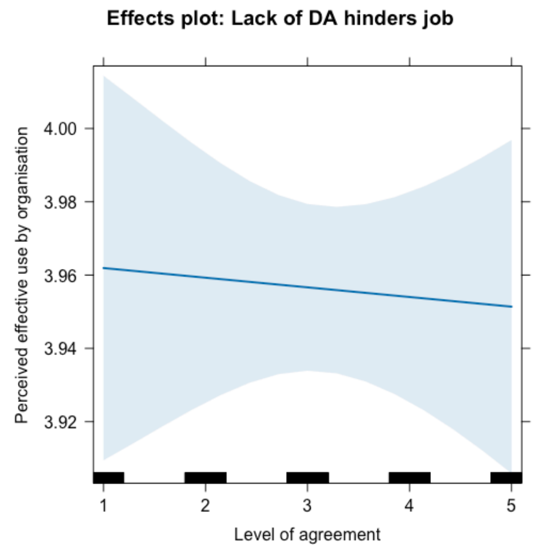


Figure 47: Effects plot: Lack of DA hinders job

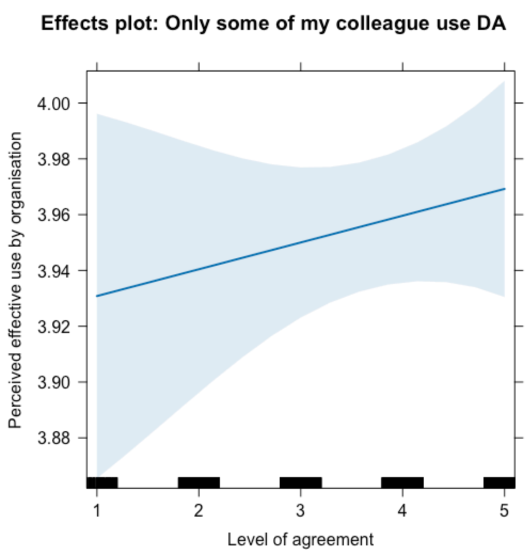


Figure 48: Effects plot: Only some colleagues

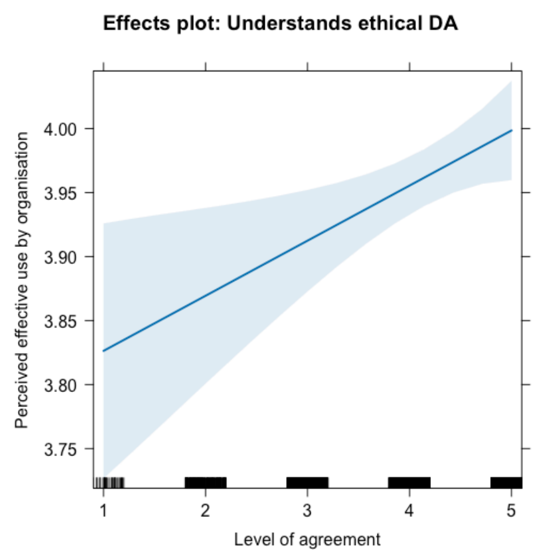


Figure 49: Effects plot: Understands ethical DA

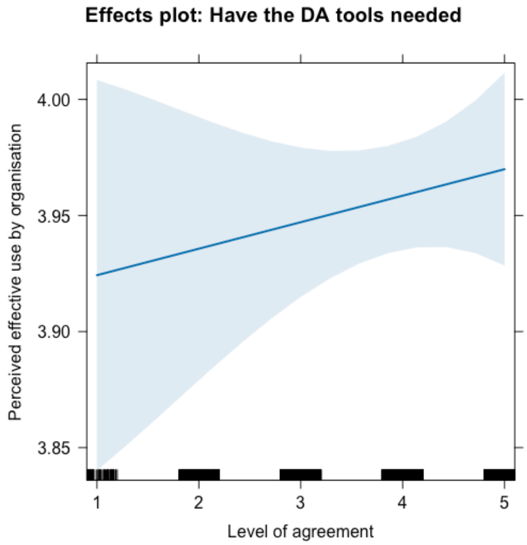


Figure 50: Effects plot: Have the DA tools needed

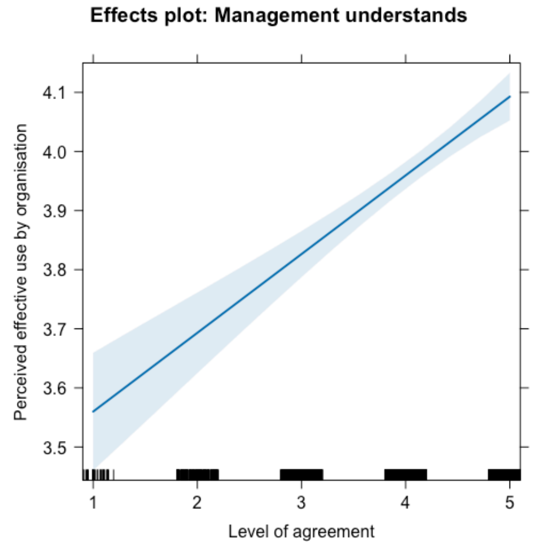


Figure 51: Effects plot: Management understands

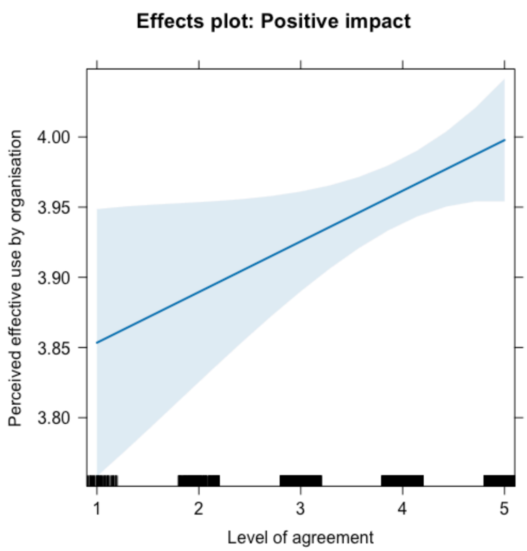


Figure 52: Effects plot: Positive impact

11.4 Effects plots perceptions of effective digital technology implementation

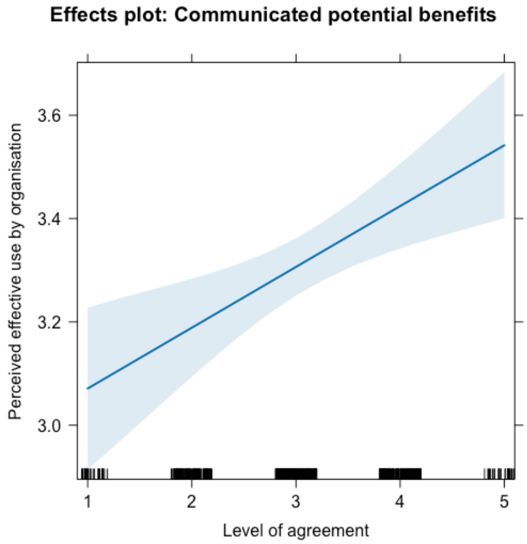


Figure 53: Effects plot: Communicated potential benefits

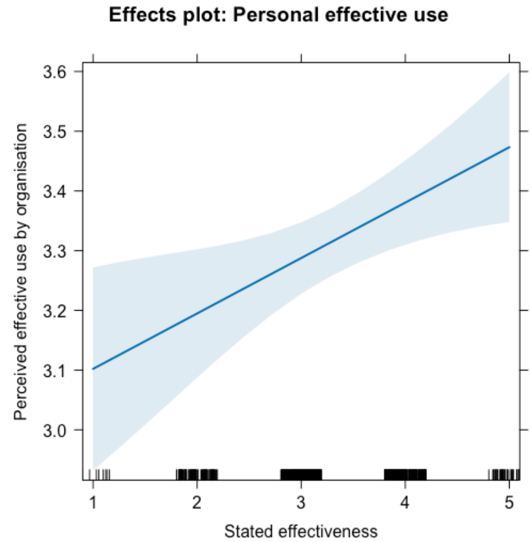


Figure 54: Effects plot: Personal effective use

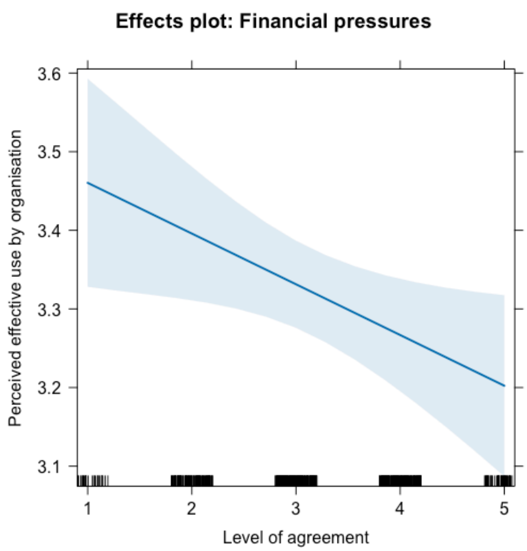


Figure 55: Effects plot: Financial pressures

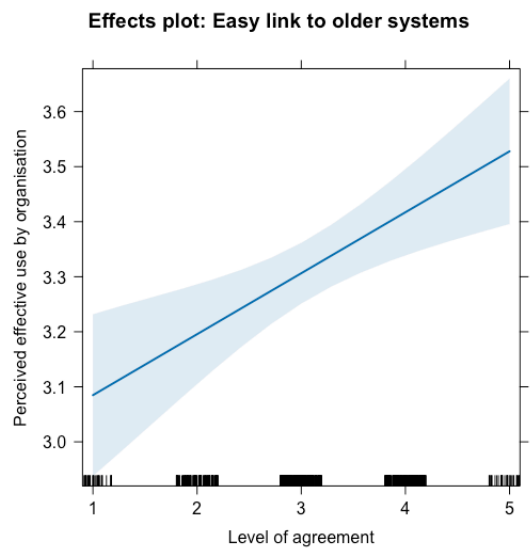


Figure 56: Effects plot: Easy link to older systems

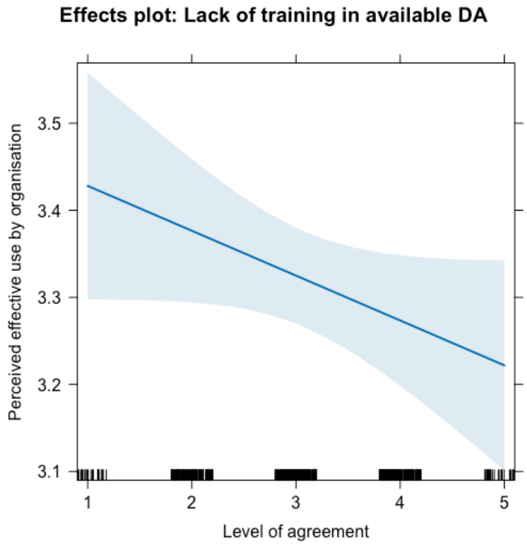


Figure 57: Effects plot: Lack of training in available DT

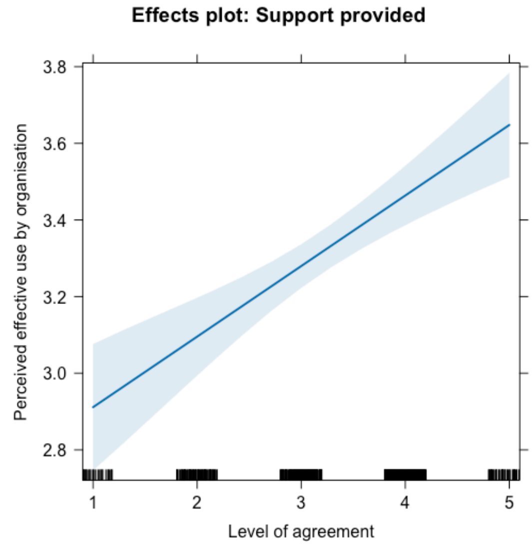


Figure 58: Effects plot: Support provided

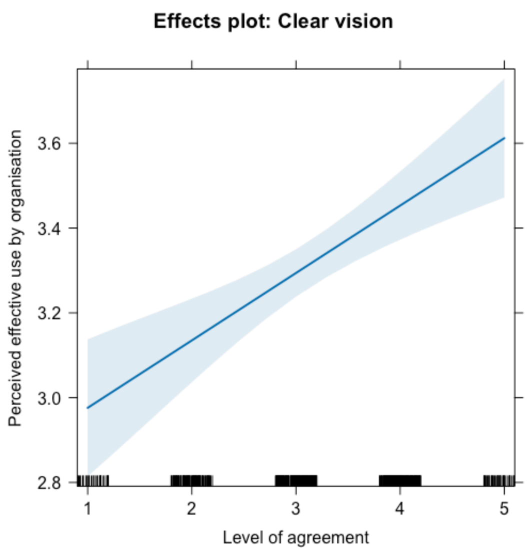


Figure 59: Effects plot: Clear vision

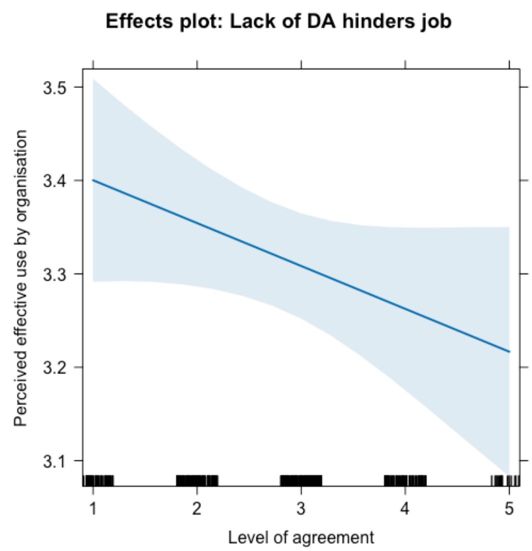


Figure 60: Effects plot: Lack of DT hinders job

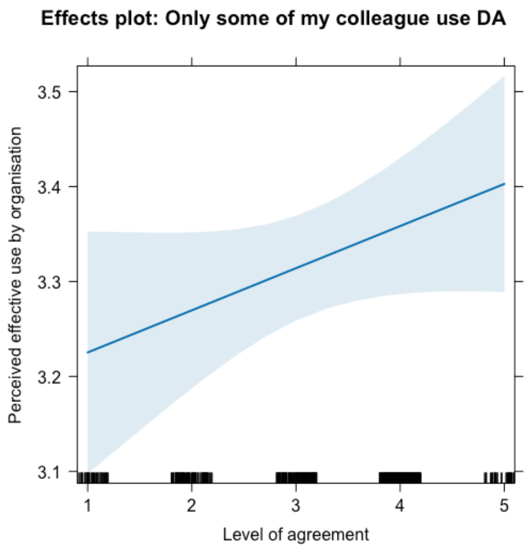


Figure 61: Effects plot: Only some colleagues

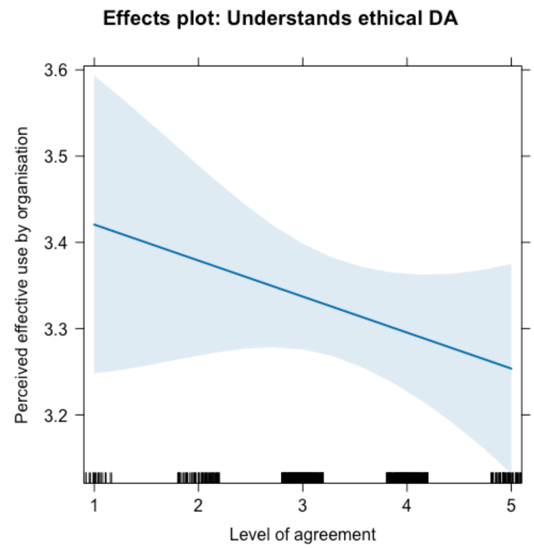


Figure 62: Effects plot: Understands ethical DT

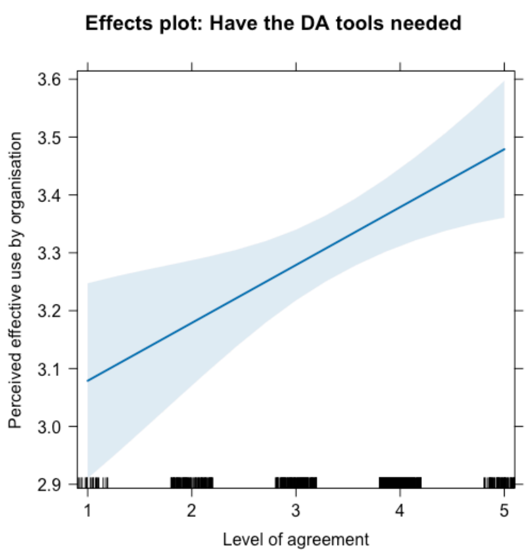


Figure 63: Effects plot: Have the DT tools needed

Figure 64: Effects plot: Management understands

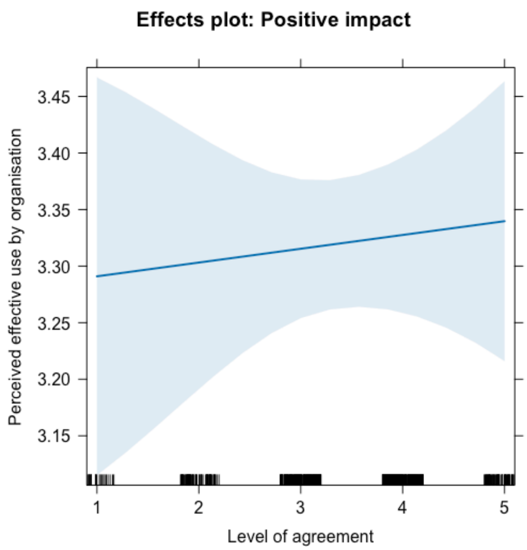


Figure 65: Effects plot: Positive impact

13. Appendix: Latent Class Analysis of User Types

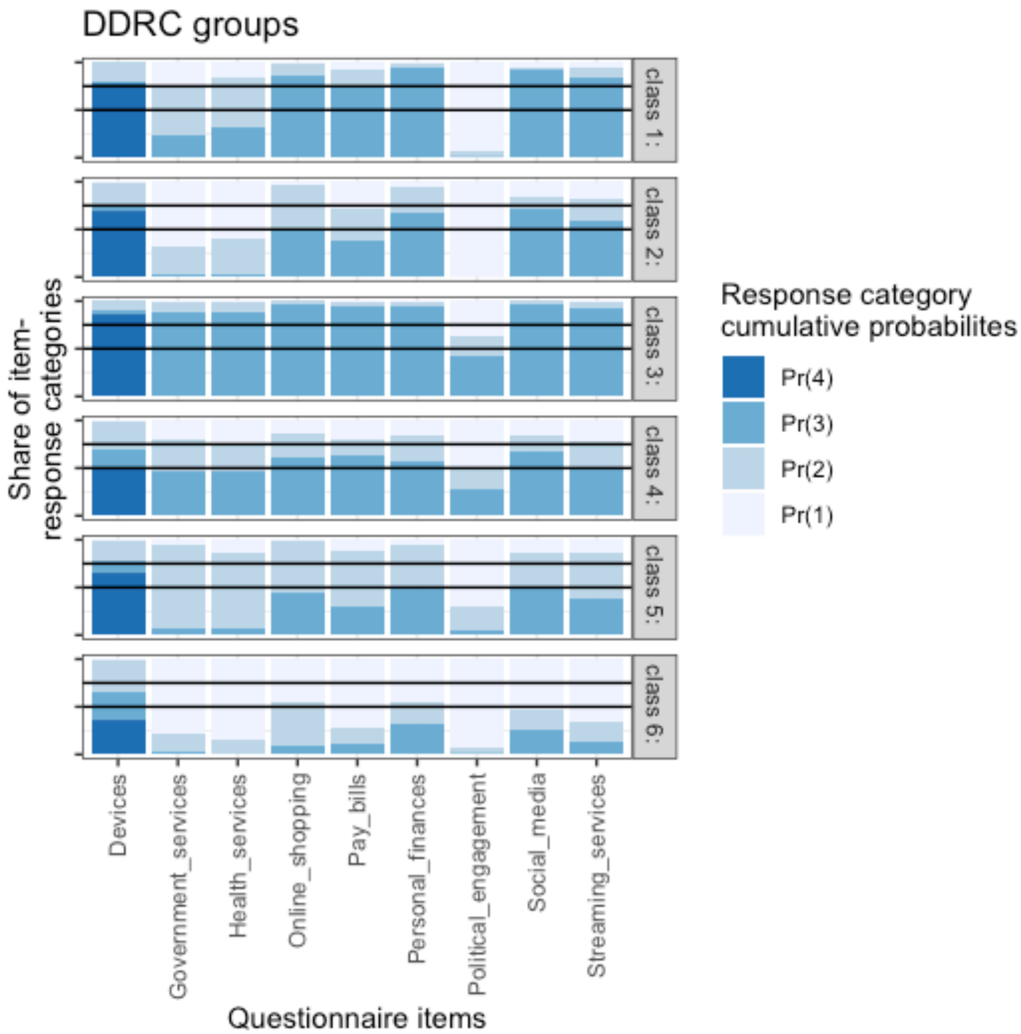


Figure 66: LCA probabilities plot 1

Extensive political users	Class: 1
Extensive users	Class: 2
General users	Class: 3
Social media focused users	Class: 4
Limited users	Class: 5
Very Limited users	Class: 6
Nonusers	Not on graph

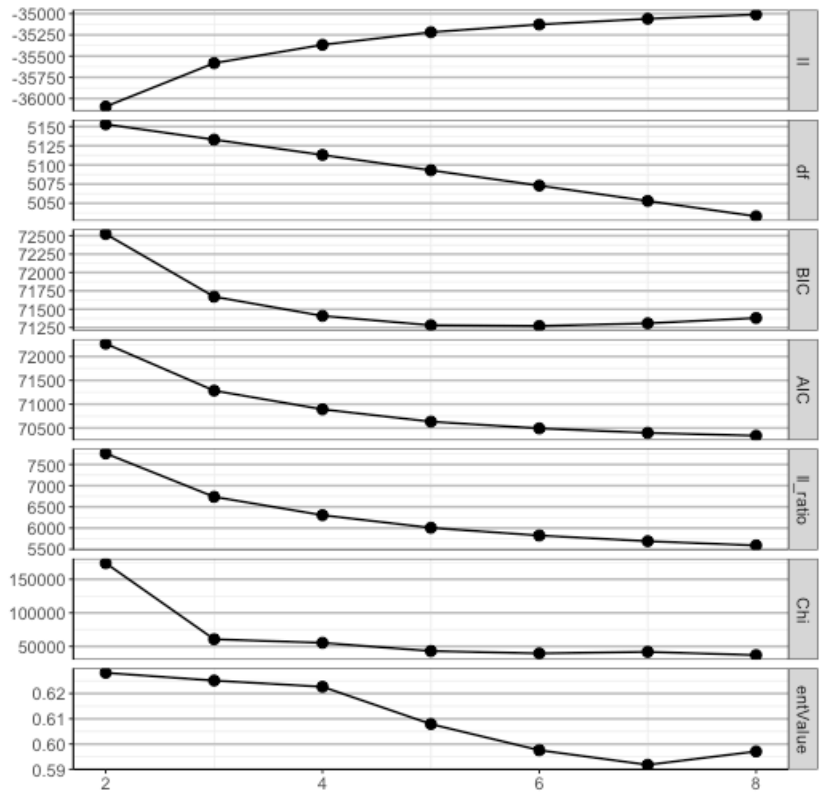


Figure 68: LCA BIC, AIC, and Entropy plot

DEFENCE DATA RESEARCH CENTRE

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