Author:
Gemmell, Laura

Title:
Skilling the gap

identifying barriers in AI education to open up pathways and broaden opportunities

Skilling the Gap

Identifying Barriers in AI Education to Open Up Pathways and Broaden Opportunities

By

Laura Gemmell

Department of Aerospace Engineering

UNIVERSITY OF BRISTOL

&

Department of Engineering Design and Mathematics

UNIVERSITY OF THE WEST OF ENGLAND

A PhD dissertation submitted to the University of Bristol and the University of the West of England in accordance with the requirements of the degree of DOCTOR IN PHILOSOPHY in the Faculty of Engineering.

FEBRUARY 2022

Abstract

As technologies such as Artificial Intelligence (AI) and Robotics advance, it becomes more and more important for the public to understand these technologies and how to retrain in these areas if they wish. Further to this, the rapid advancement of these technologies has created a ‘skills gap’ which means companies need more workers with skills in AI-related areas to conduct their business. This thesis aims to understand the barriers preventing the public from taking advantage of opportunities to learn about or retrain in AI, particularly those who have the desire and resources to do so. Initially, 21 stakeholders (7 thought leaders, 2 industry experts, 6 adult educators and 6 members of public) were interviewed about AI training. This study was used to gain an understanding of current thoughts on AI training for the public. To further probe into the barriers identified by the interviews, two online surveys were designed to understand the requirements to work in AI-related areas. Firstly 39 members of the public were surveyed. They were questioned on what they believed were the skills, qualifications and traits needed to work in AI-related areas. As well as how these requirements could be obtained and how easy or difficult obtaining them would be. The second survey asked similar questions of 15 hiring managers about the requirements they looked for when hiring for these jobs. They were also asked about their company’s involvement in retraining and allowing employees to move into AI-related roles. Finally, a co-design strategy is proposed for development of community AI education (which did not go ahead because of the pandemic) as future work. The barriers identified include a lack of a clear path on how to move into AI-related roles and a stereotypical view of those who work in AI. Further to this there exists a narrow view of AI roles (as highly technical), and as such there is a lack of education for those who work alongside AI (rather than build or create it). Importantly, there is gatekeeping coming from experts, hiring managers and people themselves which prevents AI education from reaching those who are not technical or degree educated. Recommendations on how these barriers can be addressed and an outline of a co-design programme for community AI education have also been included.

Acknowledgements

This research would not exist without the 75 people who participated in the various studies, so I would like to dedicate my thesis to all of them. First, the 6 members of public who candidly spoke to me about AI in a park in London, and made my first go at qualitative interviewing very enjoyable. The 'AI expert' interviewees and survey respondents who gave their time and wisdom to help shape my plans. The people from many walks of life who completed my online survey and whose words have inspired my plans for my business. Finally, to the adult educators who I had the absolute pleasure of interviewing early on in this research, and whose passion for teaching and deep respect for their students have had a lastly impact on both this research and me.

Some personal acknowledgements to those who made this PhD possible - my partner JJ who has been there through all the ups and downs of the PhD process, and who continues to support and inspire me. My Nanny Josie and Grandad Hugo, without their love and support I wouldn't be where (or who) I am today.

Figure 1 - Me in a park conducting interviews with members of public at a community festival (Chapter 4).

Author's Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

Laura Gemmell 24/02/2022

SIGNED: .... DATE: ....

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

Much like the wonderful Elle Woods in Legally Blonde, I began this research with a level of naivety. To paraphrase her iconic line about getting into Harvard Law:

> "*You* are going to design AI education for the public?"
>
> Me: "What, like it's hard?"

However, from this place of (potentially mis-placed) enthusiasm has spurred a slightly different line of research which I believe is an important piece of the puzzle to creating a future which benefits more people.

Despite courses and training being provided, there are barriers blocking people from learning about Artificial Intelligence (AI) and moving into AI-related jobs which need to be identified and overcome. This is becoming an increasing problem as the demand for these jobs is growing faster than the number of people with needed skills – creating a 'skills gap'. Significant resources (time, effort and money) are being invested by the government, companies and universities on reskilling and retraining in AI-related areas. This investment is an important step to closing the skills gap. However, these efforts are not reaching everyone in society, and it is important to understand what is preventing people from learning about AI and retraining in these areas.

There are many reasons (both internal and external) preventing people from being interested in AI, or being able to retrain in a brand new area. These include socioeconomic, cultural, geographic, fear, internet access, lack of interest or exposure. However, what is happening over and over again is education being created for certain people, and these opportunities not being extended or co-designed with the communities it would help.

Personal Preamble

While researching robotics and AI education for children, I saw an interesting gap in actual AI education for the public which I felt needed to be addressed. The need for AI education was discussed many times, without any action (and then I fell into the same trap). I saw this research as a chance to combine my passions – coding, education and social justice – with research which is vital for creating an equitable future. I can wax lyrical about how learning coding and working in technology has changed my lot in life, and I work hard to ensure others have the same opportunity, so this research felt like a natural flow for me. The need to ensure everyone in life is brought along as technology advances, to me goes without needing justification, but it does not receive the needed attention and efforts.

I am a technologist (or engineer), I love data particularly numerical data which I can run through fancy algorithms and make beautiful charts about. I love teaching people, particularly about technology and data. I have taught over 200 young women how to code (through building websites), and countless people how to analyse data. While loving data and technology, I love the stories behind the data more. As such, I set out to speak to people, and I was introduced to the beauty of qualitative research. Combining my analytical background, and subject matter expertise with these methods has allowed me to provide a new insight into this topical area. As such, I believe my perspective coming into (and developed during) this research sets it apart from other research in this area, I am coming at this question from a different angle.

Initial Plan

Initially, I set out to co-design a community-led education curriculum to teach those at risk of being left behind as technology advances, such as AI. My initial scene-setting study revealed a number of potential barriers which instead became the focus of my research.

Based on the findings of these interviews, I began working on a co-design exercise for members of the public. This involved speaking with community interest points throughout Bristol (including libraries, Knowle West Media Centre and Barton Hill Settlement).

A Small Pivot in Focus

The initial aim of this research was to conduct grassroots interviews with members of public, adult educators, industry and thought-leaders, use the findings to inform a co-design with local communities to create AI education for those potentially left behind.

The interviews revealed some unexpected barriers which need to be addressed. Also, the Covid-19 pandemic meant the co-design sessions would have to be moved online rather than in person, and would likely not have reached the target audience. These two reasons motivated a shift of focus for the rest of the research (although I would love to continue the work I started in the future).

My research became focused on the barriers preventing people (even those who were interested in AI-related jobs) learning about and moving into jobs in AI-related areas. Instead of focusing solely on those who were most likely to be left behind as the digital divide deepens, and as such extremely difficult to access during the UK lockdown (an issue which requires much more time, effort and resources than my PhD project), this new focus was on those who were already online (on Facebook, in Slack groups).

Motivation

> *"The potential benefits of creating intelligence are huge. We cannot predict what we might achieve, when our own minds are amplified by AI. Perhaps with the tools of this new technological revolution, we will be able to undo some of the damage done to the natural world by the last one — industrialisation. And surely we will aim to finally eradicate disease and poverty. Every aspect of our lives will be transformed. In short, success in creating AI, could be the biggest event in the history of our civilisation.*
>
> *But it could also be the last, unless we learn how to avoid the risks. Alongside the benefits, AI will also bring dangers, like powerful autonomous weapons, or new ways for the few to oppress the many. It will bring great disruption to our economy. And in the future, AI could develop a will of its own — a will that is in conflict with ours.*
>
> *In short, the rise of powerful AI will be either the best, or the worst thing, ever to happen to humanity. We do not yet know which."* - **Stephen Hawking** (Hawking, 2016)

AI is fast becoming a shaping technology of our time (Schwab, 2017). The impacts of AI are far-reaching, and will have consequences for all aspects of life (both positive and negative), similar to previous industrial and digital revolutions (Makridakis, 2017). Industries are already feeling the effects of AI, for example medicine has seen many advances due to AI (Cheng *et al.*, 2012), including better diagnostic tools and increased automation making roles safer and reducing errors. However, there is still a lot of work to be done to ensure trust from patients and workers, and ethical use of AI (Kabir, 2019).

Another industry which is already using AI is customer service – 92% of online shoppers have experienced AI when browsing online (Li *et al.*, 2020). Despite the adoption of AI in various customer service roles, research with consumers suggests AI may not be trusted or provide a good customer experience (Li *et al.*, 2020; Libai *et al.*, 2020; Prentice, Dominique Lopes and Wang, 2020). These examples are repeating a pattern seen in the digital revolution with bank tellers (Hanspal, 2021) – firstly, technology (mainly automated teller machines (ATMS)) began to replace the role of bank teller and many banks decreased the number of bank tellers they employed. However, the ATMs reduced the costs of operating a bank, and new banks were opened – hiring more bank tellers. The role itself also changed as it became less repetitive and more about customer service. The example of bank tellers is used as evidence for the advances in AI increasing the overall number of jobs, but with the nature of the roles changing. Due to the number of industries and jobs AI is changing, it is important everyone has the opportunity to learn about AI and to retrain as necessary (Moritz and Stubbings, 2019). It is worth noting that while there was a correlation for a while between ATMs and bank teller increase in the US, it is more complex than technology advances simply leading to more jobs. Another example of complexity can be found in the impact of word-processors and micro-computers on office workers (particularly female office workers) – "*While these new technologies erode certain traditional forms of office patriarchy, they also introduce new mechanisms of deskilling and control which operate to the detriment of female office employees"* (Wharton and Burris, 1983).

The potential power of AI provides an opportunity to build a society that works for everyone (Schwab, 2017). For this to happen, people from all walks of life need to be involved in shaping AI or there is a risk of inequalities being further increased (Bughin *et al.*, 2018). Education is a first step to understanding and participation, as was the thinking by the Finnish researchers who created the online Elements of AI course which aimed to provide basic understanding of AI to Finnish citizens (FCAI, 2018). Therefore, understanding the barriers preventing people learning about AI is crucial.

The importance of AI skills for everyone, particularly those often excluded, was highlighted in the AI Roadmap (UK AI COUNCIL, 2021), particularly in a section on "***Skills and Diversity":***

1. *Scale up and commit to an ongoing 10 year programme of high level AI skill-building. This would include research fellowships, AI-relevant PhDs across disciplines, industry-led Masters and level 7 apprenticeships.*
2. *Make diversity and inclusion a priority. We suggest benchmarking and forensically tracking levels of diversity to make data-led decisions about where to invest and ensure that underrepresented groups are given equal opportunity and included in all programs.*
3. *Commit to achieving AI and data literacy for everyone. The public needs to understand the risks and rewards of AI so they can be confident and informed users. An Online Academy for understanding AI, with trusted materials and initiatives would support teachers, school students and lifelong learning.*

The first point is being addressed by significant efforts being put forward by governments, universities and companies to provide training and education in AI for individuals. These are often aimed at specific groups (including recent graduates and those with technical skills). The efforts in AI education are summarised in **Figure 2**. This research aims to address the gaps in current efforts, and to understand what is preventing people from learning about AI. Further, as a first step in creating a pathway for people to move into AI-related jobs.

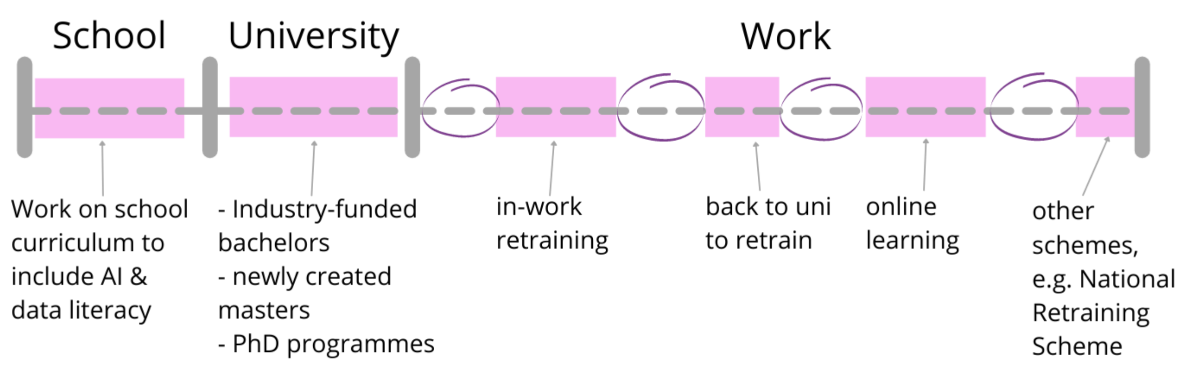


Figure 2 *- A timeline of life used for illustration, not accurate or to scale). Life is split into three parts – School, University and Work. The pink rectangles indicate where AI education efforts are being concentrated. The gaps in AI education (for adults) are circled which is where this research is focused.*

Research Aims and Questions

The aim of this thesis is to identify the barriers preventing people from learning about AI or moving into AI-related jobs. It further aims to offer suggestions for next steps to overcoming these barriers. I aim to do so by speaking with people - people whose buy-in is needed for any actions to be successful, as well as people who the actions will directly impact. Allowing these people to be candid by using qualitative anonymous methods may give voice to those who would not have otherwise participated in research, or who may not have been able to speak freely.

Key Research Questions:

- Do people want to learn about AI, and what is stopping them learning about this topic?
- What are the barriers stopping people retraining or moving into AI jobs?
- Are these barriers coming from people themselves, or employers and experts?

List of Chapters, Contributions and Publications

The core of this thesis is based on 3 publications which are provided in full in the relevant chapters. The structure and chapters of this thesis will be:

Chapter 2: Literature Review

The literature review chapter will set the scene for the rest of the research by providing an overview of previous work in AI literacy and education. The following three chapters also include specific literature reviews in the corresponding paper which cover the individual topic and methodology.

Contributions:

- Overview of state of the art of AI education for adults, identifying the gaps and why they matter.

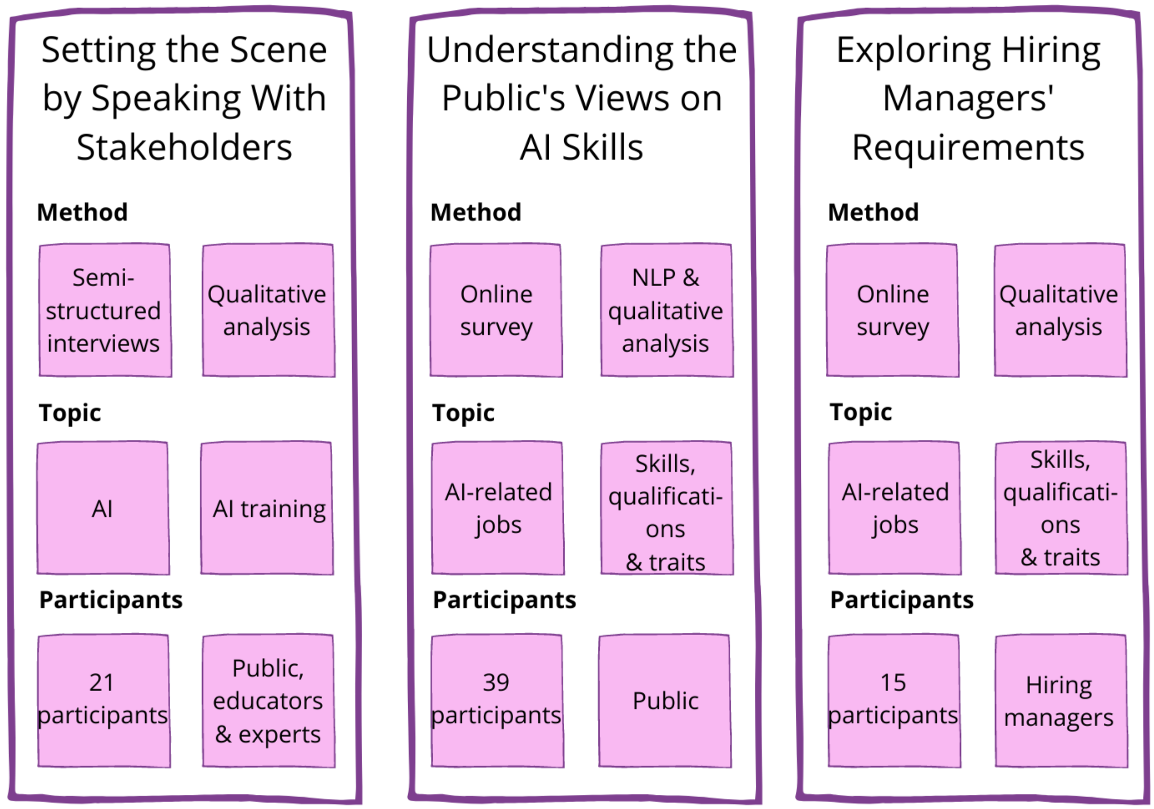


***Figure 3** – Overview of three studies included in this thesis. They make up Chapters 3-5 respectively.*

Paper:

Gemmell, L., Wenham, L. and Hauert, S. (2019) 'Leaving No One Behind: Educating Those Most Impacted by Artificial Intelligence', in *AIED 2019: Artificial Intelligence in Education*, pp. 344–349. doi: 10.1007/978-3-030-23207-8_63.

Chapter 3: Methodology

Chapter 4: Interviews

The interviews chapter includes the first study of this thesis – 21 interviews with stakeholders in designing AI education (members of public, adult educators, industry and thought leaders). This includes a published paper with an extended literature review on the AI education for adults landscape, and analysis of these interviews. The findings of this chapter set the groundwork for the rest of the thesis.

Contributions:

- An in-depth literature review into the AI skills gap in the UK.
- Insight into barriers preventing members of the public learning about AI.

Paper:

Gemmell, L., Wenham, L. and Hauert, S. (2021) ‘Skilling the Gap: 21 Conversations on Designing Education for Those Left Behind as Robotics and Artificial Intelligence Advance’, Advanced Intelligent Systems, p. 2000169. doi: 10.1002/aisy.202000169.

Chapter 5: Survey with Members of the Public

Chapter 4 discusses the first of the online surveys in this research, which was conducted with members of public. There were 39 participants who came from various online groups. The members of public were asked what they thought the requirements were to work in AI-related jobs – skills, qualifications and traits. They were further asked how these requirements could be gained, and how easy or difficult this would be. The survey responses were analysed in two ways – using a novel Natural Language Processing (NLP) method I developed, and qualitative methods (coding, categorisation and thematic analysis).

Contributions:

- Identification of barriers to people, even those who are interested and able, training and moving into AI-related roles.
- NLP method for analysing survey responses.

Paper:

Gemmell, L., Wenham, L. and Hauert, S. ‘Clearing the Path - Understanding How Inaccurate Assumptions Muddy the Route for People to Move into AI Jobs’ (SUBMITTED)

Chapter 6: Survey with Hiring Managers

Chapter 5 focuses on the second online survey in this research, which surveyed individuals who were hiring managers in AI-related areas. This survey examines similar themes to Chapter 4 while further understanding companies' role in closing the AI skills gaps (i.e., were the companies offering training to close the skills gap). There were 15 hiring managers from various industries (although many worked in Data Science). The survey responses were analysed using qualitative methods (coding, categorisation and thematic analysis).

Contributions:

- Identification of barriers to people hiring in AI.

Paper:

Gemmell, L., Wenham, L. and Hauert, S. 'Reaching the Baseline - Understanding Employers' Requirements for Data Science, Machine Learning and Artificial Intelligence Jobs' (SUBMITTED)

Chapter 7: Future Co-Design

A further pseudo-results chapter has been included, this outlines the work conducted to creating a plan for a potential community co-design (which was derailed by covid). It further outlines suggestions for creating a roadmap for moving into AI-related roles.

Contributions:

- An outline of a potential community co-design.
- Next steps to continue this work.

Chapter 8: Conclusion

Finally, the conclusion will wrap up the thesis, building on the findings, discussion and conclusions of the three studies and co-design of this research.

Key Terms and Abbreviations

AI – Artificial Intelligence

DS – Data Science

ML – Machine Learning

RAI – Robotics and Artificial Intelligence

STEM – Science, Technology, Engineering and Mathematics

NLP – Natural Language Processing

MoPs – Members of Public

Chapter 2: Literature Review

This literature review highlights the gap in AI Education for adults which this research is addressing, with a particular focus on adults who will not be retrained through their jobs or via university studies. As the main focus of this research is AI it felt appropriate to begin by examining what AI actually is and how it is impacting people's lives. Then moving on to discuss AI Literacy and Education, and the barriers to accessing these for working adults. Finally, this chapter discusses the choice to use qualitative methods. Each individual chapter also has its own literature review aimed at providing the specific motivation of the work and the methodology used.

What is AI?

> "Artificial intelligence is a constellation of many different technologies working together to enable machines to sense, comprehend, act, and learn with human-like levels of intelligence." Accenture (Accenture, 2021a)

> "Artificial intelligence leverages computers and machines to mimic the problem-solving and decision-making capabilities of the human mind." IBM (IBM Cloud Education, 2020)

> "It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable." John McCarthy (Mccarthy, 2004)

Definitions of AI are varied and often debated, so much so a New York city task force work was stalled for over a year as they could not agree on a definition of an "automated decision system" (Budds, 2019).

Researchers have been discussing the correct definition of AI for many years (Schank, 1987), and it is not always easy to formulate such a definition. To demonstrate why, let's begin with a description of AI from Wikipedia (as many of the public will do):

> “Artificial intelligence (AI) is intelligence demonstrated by machines, as opposed to natural intelligence displayed by animals including humans.”[1]

The reason I like this definition is it is simple, far reaching, and open to interpretation. However, the definition raises more questions than it answers – what is intelligence? What counts as a machine? As with most things on the internet, we can get lost in a loop – both intelligence and machine in this definition are clickable links to Wikipedia pages. Both of these pages contain definitions - and more clickable links to explain other terms used.

The intelligence side of the discussion is an interesting one, it reminds me of a time when I had recently purchased a coffee percolator which could be set to come on a specific time (and thus have coffee ready for sleepy me to drink first thing in the morning). A colleague of mine remarked it must be one of those smart IoT, AI devices to be able to do this. It really was not. It was a £30 electric coffee machine, with a clock timer. However, is this not intelligence demonstrated by a machine, and according to Wikipedia, would this not make my coffee machine AI?

This story, and my response, very much illustrates the issue with defining AI. It is very easy to say what is not AI, but writing an all-encompassing definition which does not miss or include any glaring outliers is difficult. The definition from Wikipedia does not include any reference to AI making decisions (autonomy) or being able to respond to new information (adaptivity). A useful paper on the topic, *What Do You Mean by “AI ”? The Problem of AI Typical Ways to Define AI*, discusses the pitfalls in the common ways to define AI (Wang, 2008). Wang points out different researchers have different definitions of AI and they should make this both suitable for this research topic and known. As my research is focused on the public and how they think of AI,

I have taken a non-academic approach and will be using the Oxford English dictionary definition of AI which alludes to the properties of autonomy and adaptivity with examples as the working definition of AI throughout this thesis:

---

[1] https://en.wikipedia.org/wiki/Artificial_intelligence

> "The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages."

This definition is in line with research highlighting researchers tend to focus on the technical aspects of AI definitions, whereas policy definitions focus more on the function (Krafft *et al.*, 2020). As the nature of this research leans on the side of policy and the future, the Oxford English dictionary definition feels appropriate.

Something which then comes into play is the *AI Effect* (Raspberry Pi, 2021), which was summed up by Nick Bostrom in an interview with CNN (Bostrom, 2006):

> "A lot of cutting edge AI has filtered into general applications, often without being called AI because once something becomes useful enough and common enough it's not labeled AI anymore."

An example of the AI Effect is voice assistants, particularly Apple's Siri who was once dubbed as an amazing breakthrough in AI. Many experts now argue voice assistants and chatbots are not AI, they are similar rule-based systems (Yudkowsky and Bostrom, 2011; Luckin, 2017).

Therefore, throughout this thesis, the term "AI" will be used loosely. It includes voice assistants, chatbots and recommender systems (used in Amazon and Netflix to predict what you want to buy or watch next). Often these technologies are not advanced (or "smart") enough to be considered AI by experts. However as this research is about the public taking their definition (or lack of one) and not adding another barrier to entry is important.

The term "AI-related" will also be used throughout this thesis and it will as well be loosely used. The different studies in this research used different wording (refined and updated based on findings throughout):

- The interviews in Chapter 4 asked specifically about "Artificial Intelligence"
- The survey to the public in Chapter 5 has questions about "Data Science, Machine Learning and Artificial Intelligence"
- The survey to hiring managers in Chapter 6 mentioned "Data Science, Machine Learning, Artificial Intelligence and Robotics"

As such, when AI-related is used it encompasses all of “Data Science, Machine Learning, Artificial Intelligence and Robotics”. Experts may quibble over the differences, but the public often do not.

AI Skills Gap

AI is one of the technologies at the heart of the 4th Industrial Revolution (Schwab, 2017). Schwab identified one key aspect of the fourth industrial revolution, in comparison to the previous ones (see **Figure 4**), is the velocity with which it is advancing.

As the technology advances, more companies are using AI (Open University, 2019). This adoption of AI technology is increasing the number of jobs requiring AI skills. The surplus of jobs is growing faster than people are gaining the skills - creating a *Skills Gap*. This costs companies money and holds back advancement (Open University, 2019; UK AI COUNCIL, 2021).

Explicit efforts to quickly close the skills gap are concentrated on university students, those willing and able to return to university and those who work for large multinational companies. Examples can be seen in Accenture retraining 17,000 workers rather than laying them off (Brinded, 2017) and PwC committing billions of dollars to upskill their entire staff (Moritz and Stubbings, 2019).

First	Second	Third (Also known as Digital Revolution)	Fourth
When?			
1765 Late 18th - Early 19th Century	1870 Late 19th - Early 20th Century	1969 Mid 20th Century - Present	Now?
Technologies			
Steam engine Factories Machines Iron and steel production	Mass production lines Electricity Steel production Telegraph networks Railroad network Sewage and water systems Telephones	Electronics Information Communication (Also Nuclear Power)	Emerging technologies, including: AI Robotics IoT Autonomous Vehicles 3D Printing Nanotechnoloy Biotechnology and so on
Industry Impacts			
Big impact on Textiles Chemical production Mining Agriculture Paper making	Science Telecommunications Bicycles Maritime Petroleum Paper making Engines	Mobile phones The Internet Data	Predicted to impact all
Social Impacts			
Mass movement from country and towns to cities Change in conditions for workers (highly debated, often seen as bad) Luddites - those who worked in the highly skilled Textiles industry protested the use of machines for fear of being replaced	Improved Living Conditions for workers Fastest ever period of economic growth Many businesses closed, leading to the Long Depression	Newly created tech billionaires Gig economy Creation of WWW and with aims of freedom of access to information Privacy concerns for individuals Part of society left behind by lack of digital skills	Unknown as of yet

Figure 4 *- Comparison of the Four Industrial Revolutions, showing the industry and social impacts. The impacts of the Fourth Industrial Revolution is not yet understood, but is predicted to be far reaching.*

The Impact of the AI Skills Gap on Individuals

The skills gap often looks at the problem from a company's perspective – it is even defined as companies requiring more workers with certain skills than currently exist. However, the impact of AI advancing is not only impacting companies, but is also worrisome for individuals.

Media Representations

The advancement of AI (including robotics and automation) can be portraited in the media in a negative way – one study looking at mentions of AI in the media (Ouchchy, Coin and Dubljević, 2020), found over 50% of the issues discussed were on the "undesired results" of AI. These undesired results included "prejudice," "privacy/data protection," and "job loss to AI/economic impact of AI."

A study of AI new stories in the New York times found there has been an increase in news on the topics of AI (Fast and Horvitz, 2017). These were on the whole more positive than negative.

Replacing Jobs

The study of the New York Times (Fast and Horvitz, 2017) also found specific concerns about the impact on jobs, particularly those of blue collar workers were commonly found. For those of us who work in the field, we understand these worries are overhyped and sensationalised. On the other hand, the public do not have this "insider knowledge" and have understandable fears and worries about their jobs and the future of society. PwC reported in *Hopes and fears 2021* (PwC, 2021) that 39% of workers think their job will not exist in 5 years. The report further found 40% learnt new digital skills during the pandemic, and 77% would learn new skills or retrain (however, nearly three quarters think this is their own responsibility, not their employer's).

AI Literacy

Often, alongside the AI Skills Gap discussion, pops up the term AI Literacy. Mostly this discussion centres around the lack of AI Literacy among businesses, workers or the general public. According to the UK AI

Roadmap, an AI Literate society is beneficial as it will address both the skills gap and the impact advancement has on the public (UK AI COUNCIL, 2021).

Digital Literacy

Before jumping into AI literacy, it is important to discuss digital literacy as the two are highly related and digital literacy is much more imminent to the public and their lives than AI literacy. Similar to the term AI, digital literacy means different things to different people. The original definition is attributed to Paul Gilster in the late 1990s. He said digital literacy was “the ability to both understand and use digitised information” (Gilster, 1997). Academic research on digital literacy says it must always be “plural”, “culturally situated”, and “political” (Lankshear and Knobel, 2008). However, as my research focuses on the public, literacy (as opposed to literacies) will be used throughout this thesis as non-academic work aimed at the public continues to do so.

The National Health Service (NHS) in the UK defines digital literacy as “those capabilities that fit someone for living, learning, working, participating and thriving in a digital society" (National Health System, 2018).

An important aspect of Digital Literacy (as with AI Literacy) is the actually the lack of digital literacy – there is a massive discrepancy in Digital Literacy across society called the *Digital Divide*. Looking specifically at the UK and the Essential Digital Skills Report 2021 produced by Lloyds bank (Lloyds Bank, 2021), 10 million people (nearly 15% of the population) do not currently have the most basic digital skills (which includes being able to access the Internet independently). The report further reveals 67% of people would improve their digital skills if they knew support was available.

Digital literacy opens a discussion around what it means and what is needed to be a citizen in the digital world. The World Economic Forum use the term “(dis)empowered citizen” to describe the double-edged sword of technology advances (World Economic Forum, 2016). While the online world allows people to be more empowered and engaged, it also creates a sense of dis-empowerment as people feel they do not have the power or ability to enact change. Even when citizens have an opportunity to be involved, such as in smart city design, there is often power

> and knowledge imbalances. Education can be used to address these imbalances and ensure citizens can be involved in these discussions which ultimately could help reduce inequality in these smart cities (Manchester and Cope, 2019).
>
> Digital literacy needs to be constantly updated due to how rapidly technology and required digital skills are evolving (Pangrazio, 2016). AI literacy could be considered as an extension of digital literacy. However, AI literacy could be such rich an area, I believe it deserves to be discussed as its own "literacy".

AI literacy is a newer term, which has been greatly increasing in popularity – in 2020, there were nearly 200 journal papers published on the topic of AI literacy (up from 12 in 2015) (Ng *et al.*, 2021). The term is still lacking a formal definition (much like the term AI itself). While no one clear definition of AI Literacy exists, there seems to be a consensus around the needs for multiple levels of AI Literacy.

A definition given on the popular blog, *Towards Data Science* (Schouten, 2020), succinctly sums up the multiple levels of AI Literacy:

> "AI literacy is about knowing what AI is, about how AI can benefit you, what it takes to make AI systems work, and ultimately how to engage with AI solutions." Afke Schouten

A review of publications on the AI literacy frameworks outlined the four main aspects: *know and understand AI; use AI; evaluate and create AI; AI ethics* (Ng *et al.*, 2021). Defining AI Literacy based on competency levels of learner creates an interesting hierarchical structure – *Creators of AI, Collaborators and AI Implementers, Co-Workers and Users of AI Products; Consumers, the General Public, and Policymakers* (Faruqe, Watkins and Medsker, 2021).

A further definition of AI Literacy is given in an article titled "*Why AI literacy is critical, even for non-technical employees*" (Morgan, 2020). This definition frames itself around the outcomes of AI Literacy, which it splits into two levels – basic and enough to deploy AI:

> "Basic AI literacy accomplishes two things: It provides a common vocabulary and foundational level of understanding, and it helps quell fears about AI as an existential threat.
>
> To deploy successful AI, most employees should have enough understanding about how the technology works, how it can be applied and what the end results are likely to accomplish."

While the aims and outcomes of AI Literacy vary depending on the individuals. Focusing on the general public, not specialists, there are two main aims which can be summarized as:

1. To ensure people have the skills needed for the future of work
2. Equipping citizens to exist in a highly technical, AI-driven world

(Note: this would be those in the bottom two parts of the hierarchy - *Co-Workers and Users of AI Products; Consumers, the General Public, and Policymakers* (Faruqe, Watkins and Medsker, 2021). Both sections would be included as many people in non-specialist roles will be working alongside AI.)

It is worth pointing out, the first point is the one generally focused on the needs of companies to close the skills gap. This can be seen in the two levels of AI Literacy (Morgan, 2020), which quickly become about deploying or making AI systems work. It is in a company's interest to have AI Literate employees (Morgan, 2020). However, as with the employees' of the skills gap discussed previously, it is important for individuals to feel they have useful skills which will not become obsolete as AI advances.

A very prevalent aspect of AI Literacy is to ensure no one is left behind as AI advances. In previous industrial revolutions, there have been extensive impacts on society (see **Figure 4**). However, the fourth industrial revolution could be used to benefit all of society (Schwab, 2017). A basic AI Literacy, including what AI can and cannot do, will help people understand how truthful the hype around AI in the media is, allow people to safely use new technology to avoid scams and other technology issues, and how to use the technology in a less stressful way (e.g. knowing how to speak to a voice assistant or use search engine). Another outcome of basic AI Literacy would be understanding their rights around AI technology – can an AI system make a decision about them? Finally, it is important for individuals to comprehend the technology enough to critically evaluate the impact on their lives and sensibly participate in voting on these topics. This was the original aim of the Elements of AI course which was piloted in Finland and is now being rolled out in EU languages (FCAI, 2018).

A potential framework for developing AI Literacy was put forward by researchers in the Human-Computer Interaction (HCI) community (Long and Magerko, 2020). They firstly define AI Literacy as "*AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace*". The main concepts in their framework were:

1. What is AI?
2. What can AI do?
3. How does AI work?
4. How should AI be used?
5. How do people perceive AI?

AI literacy and its concepts are a good foundation for any AI education.

AI Education for Working Adults

Although there are other methods to achieving AI Literacy (including proximity and digital citizenship), education to achieve AI Literacy is the most commonly discussed and the focus of this research. The majority of AI education is focused on particular groups:

1. Children and school curriculum (Zimmerman, 2018; Touretzky *et al.*, 2019; Cui and Wheatcroft, 2021)
2. University students (Ingargiola *et al.*, 1994; Parsons and Sklar, 2004; Hingston, Combes and Masek, 2006; Eaton, 2017)
3. Particular types of employees (particularly business leaders and technical roles)

The efforts from the UK government and gaps in AI education are shown in **Figure 2**. This topic is also explored deeper in the published paper in Chapter 4, and the specific efforts are depicted in **Figure 6**.

This thesis focuses on AI education for working adults, particularly for those who will not be retrained and upskilled in their current jobs. Working adults very loosely means post-university age (including those who have completed degrees and are now working, and those who did not ever complete a degree). However, it is unlikely to be relevant to those who have recently completed their degrees and are on graduate schemes.

AI education for working adults is often online and self-directed (Long and Magerko, 2020), and therefore aimed at computer confident individuals with resources (including time, money and internet access). Other options include short in-person courses, but these are usually informal (e.g., one off exhibitions at museums) and therefore helpful to achieve confidence and understanding of AI, but not for attendees to gain the required skills. Finally, formal education, such as degrees, are available but not every working adult has the ability or desire to return to university (and often there are pre-requisites for these courses).

Barriers to AI Education (and AI Literacy)

It is worth taking some time to discuss some well-known barriers which prevent AI Education and AI Literacy.

Existing Diversity Issues

There is an issue with diversity representation in AI. It is a very poignant and important issue (and one which I am very passionate about). It deserves more time than could ever be given in this thesis, however it is worth noting some research on the topic.

The most discussed is the lack of women in AI, which has been reported on by Nesta (Stathoulopoulos and Mateos-Garcia, 2019a). However, the importance of racial diversity specifically in AI has become a prevalent topic, summarised in the paper *The Whiteness of AI* (Cave and Dihal, 2020). An example often arises around facial recognition technology. The importance of this lack of diversity is highlighted when datasets and algorithms created are biased and have an impact on society. An analysis of gender classification using facial recognition software firstly showed the datasets were mostly composed of light-skinned subjects , and secondly dark-skinned females were the most likely to be misclassified (Buolamwini and Gebru, 2018). Real world examples of biased algorithms include marketing schemes causing their targets to go into debt, policing algorithms focusing on petty crimes instead of dangerous ones, and the criminal justice system unfairly sentencing based on race (these are taken from the book Weapons of Math Destruction (O'Neil, 2016)).

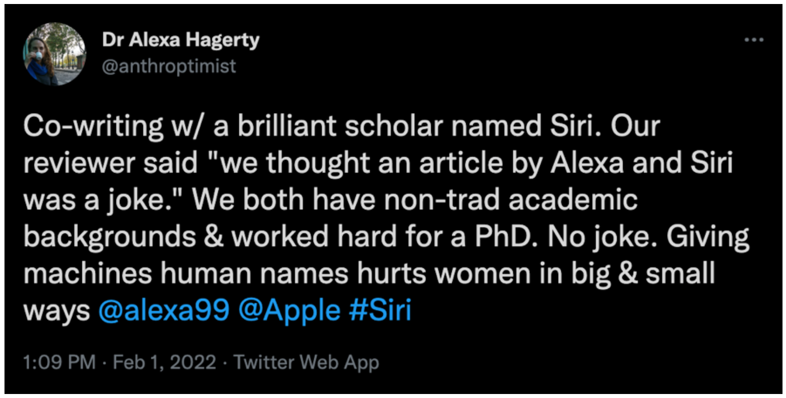


Figure 5 *– Tweet[2] illustrating the impact of giving machines women's names. Two researchers having the names "Alexa and Siri" being assumed to be a joke when submitting an article.*

A further illustration of bias in RAI and the potential impacts on diversity in RAI comes from the naming and sexualization of RAI. Many of the mainstream smart assistants have female names, for examples Apple's Siri, Amazon's Alexa and Microsoft's Cortona. As well as female names, these assistants have female voices. Studies have shown female chatbots are preferred to male in customer service and health care settings as they are perceived as more human and more likely to consider the users' needs (Vega, 2019; Borau *et al.*, 2021). There are many ways creating female smart assistants impacts women, both in the RAI world and outside. One example recently highlighted on Twitter by a tweet which read,

> "Co-writing w/ a brilliant scholar named Siri. Our reviewer said "we thought an article by Alexa and Siri was a joke." We both have non-trad academic backgrounds & worked hard for a PhD.

[2] https://twitter.com/anthroptimist/status/1488499817164771330?s=20&t=YRXNfKDHMAQCQ07oO4Qt0g

No joke. Giving machines human names hurts women in big & small ways @alexa99 @Apple #Siri" - full tweet[2] shown in

Figure 5.

Researchers, with names "Alexa and Siri", had their article assumed to be a joke which shows negative impacts of naming machines in such ways. The narratives around women and RAI in the media, particularly movies such as *Ex-Machine* and *Her,* and the stark difference to how male RAI are depicted is discussed in a chapter of AI Narratives – *The Measure of a Women: Fembots, Facts and Fiction* (Devlin and Belton, 2020). The chapter concludes with a prevalent message,

> "*By creating a more diverse and more inclusive culture around technology, it may be possible to make more diverse and more inclusive tech products. In a world where we already exist alongside the not-human – a world where we can imagine or create new forms of intelligence – we would do well to envisage a new future, both in real life and in science fiction, where we leave behind the trappings of thousands of years of gendered inequality."* **- Kate Devlin and Olivia Belton** (Devlin and Belton, 2020) p378

Socio-Economic

Despite not being a protected characteristic within the UK, socio-economic status has an impact on every aspect of life. A report by KPMG on their socio-economic pay gap revealed discrepancies which need to be addressed (KPMG, 2021). The Digital Divide is impacted greatly by socio-economic status (OECD, 2015; Mubarak, Suomi and Kantola, 2020; Lloyds Bank, 2021), and as such it is not a stretch to infer AI Education and Literacy is as well (Han and Siau, 2020).

Education

It is clear lifelong learning is becoming more important as a tool to not be left behind as the fourth industrial revolution advances (The Royal Society, 2017; KPMG, 2018; PwC, 2020). Education levels play a significant part in people's ability and opportunities to participate in lifelong learning (OECD, 2021). When asking if employers provided opportunities to upskill, PwC found a discrepancy between those with postgraduate degrees and school leavers – nearly double the amount of advanced degree holders (46% vs 21%) said they were offered training (PwC, 2021).

Digital Literacy and Tech Competency

While these are quite inter-related to a number of the previous barriers, digital literacy and tech competency have an impact on AI perception and exposure to these technologies (KPMG, 2018; Han and Siau, 2020). Therefore, it is sensible to suggest they have an impact on interest in learning about AI. Further to this, digital literacy and tech competency are highly linked to an individual's job, and therefore related to opportunity to learn about AI. Also, location plays a role in these issues - people who work in cities are 1.5 times more likely to be offered training opportunities from their jobs (PwC, 2021). Another issue specifically interlinked with anything digital is age – those without essential digital skills are more likely to be 75+ (Lloyds Bank, 2021).

These are only some of the existing barriers to AI Education for working adults, it is not an exhaustive list. This thesis does not intend to examine any of them at length. The aim of this research is to reveal other, less systemic barriers which also need to be addressed for more adults to be AI literate and the skills gaps to be smaller.

Chapter 3 - Methodology

This methodology chapter will give an overview to the methodology used in this thesis. Each study has its own further methodology to discuss the specific methodology used in that particular study, therefore this chapter will not be exhaustive and some of the content in this chapter may be duplicated elsewhere.

All ethics statements, questions, and additional resources (such as worked examples and links to code) are in the appendices.

Why a Qualitative Methodology?

With the barriers to AI education for working adults discussed in the previous chapter in mind, I wanted to *talk* to people to understand whether these barriers are well known, and whether there are others at play, stopping people from learning about AI.

> "The most basic definition of qualitative research is that it uses *words* as **data**" Chapter 1, page 3 (Braun and Clarke, 2013).

Therefore, despite my technical, data-driven background, a qualitative methodology was chosen over a quantitative one as this research would focus on the words people say and the meaning, thoughts and experiences behind them (Austin and Sutton, 2014). An important driver for this choice of method was allowing people to use their own words, and steer how the conversations progressed, rather than be confined by pre-defined questions and answers (as would be typical of quantitative interviews and surveys). For this reason also, in selecting a data gathering method for this qualitative research, I selected semi-structured interviews (Kvale, 2008). (Semi-structured interviews precisely keep the interview on topic yet allow enough freedom for the participant to steer the discussion, hence influencing the data (Strauss, 1987).

Another factor in the choice of methodology was to ensure my own opinions and views did not impact the initial interviews, to allow directions not known or predicted by myself to come up organically. This factor is of particular importance as the parts of this research with members of the public aimed to be as unintimidating for these participants as possible (Atkins and Duckworth, 2019).

Reflexive Statement

A further aspect of qualitative research which was important to the decision was being able to position myself in the research to a certain extent (Austin and Sutton, 2014). Quantitative research focuses on removing the researcher, and their lived experiences from any research (Braun and Clarke, 2013). In contrast to this, qualitative research acknowledges the researcher cannot be fully removed from the research, and as such the need for reflection throughout research is important to avoid research being impacted by the researchers' own biases and perspectives (Lichtman, 2011).

My previous experience and reflection, combined with the knowledge gained through exploring the literature, can be seen as 'sensitising concepts' (Blumer, 1954), underpinning and acting as a backdrop for the research. This allows my experiences (particularly those teaching women and families how to code and interact with technology) to provide context and, where appropriate, guidance for this research. As an interpretivist researcher, my positionality and all such sensitising concepts are inherently brought to my work. In reflecting on my interview data and approaching my analysis, I must be aware of these experiences, concepts and perceptions, so as to account for their influence as and when I need to. As is standard for ensuring rigour in qualitative analysis, I will be clear and open about my analytic process, making the stages available for alternative readings (Strauss, 1987; Nowell *et al.*, 2017).

My passion for education is something which was brought into this research and was a large part of the motivation in the first place. However, as I am someone who has always been good at maths, loves technology and is educated in AI, it was also important to remove myself from the research to avoid the any potential expert gatekeeping (which was actually an important finding of this work). Thus, the methods of data collection (semi-structured interviews and free-text online surveys) and data analysis (thematic analysis) were chosen to ensure the participants and the data were allowed to speak for themselves, and the themes for analysis were not predefined based on my "expertise" rather what was said by participants. Indeed, thematic analysis can have deductive and inductive elements, allowing for some codes and overarching themes to be constructed in advance, giving space for prior understanding, experience and research to feed in, as well as keeping space for participant ideas to provide unanticipated, completely new perspectives (Fereday and Muir-Cochrane, 2006).

Another aspect of reflexivity is the consideration of insider and outsider positions (Le Gallais, 2008). Often these are not black and white – as in a researcher is not completely an insider or an outsider. As there were multiple groups of participants in this research, there were multiple positions to assume as a researcher. In the interviews study, each group was interviewed differently – with the members of public, I was assuming an outsider position (as an academic researcher), however the interviews were conducted at a community event for an area where I also lived at the time creating a slight insider point of view; with the adult educators, I was more of an insider, as I too am an educator, however I still held the outsider position of academic researcher; with both the thought leaders and industry, I was assuming a different type of outsider position as a researcher seeking their expertise rather than a colleague or expert myself. The online surveys were similar – ultimately, I was an outsider as an academic researcher, the hiring managers were similar to the thought leaders and industry from the interviews (I was seeking their expertise on a topic). With the members of public, I was more of an insider – these were friends, family and people in shared online groups with myself or my supervisors. Of course, these positions are something to be considered throughout the research to ensure a level of subjectivity and to avoid my own biases creeping in, but I do believe being able to assume different positions as needed enhances the research (and is an excellent reason for choosing qualitative research methods).

Thematic Analysis

In all research design, it is essential that the researcher positionality, the data gathering tools and the data analytic techniques form a coherent design, chosen to address the research questions. In exploring the perspectives of various stakeholders an interpretivist qualitative design is suitable. Collecting data through semi-structured interviews fits with taking a thematic approach to analysis. These approaches are frequently combined (Matthews and Ross, 2010; Cohen, Manion and Morrison, 2017).

For all the reasons previously discussed I chose to use thematic analysis to analyse both the interviews and online surveys (Braun and Clarke, 2006). The data from these interviews was analyzed using qualitative techniques of initial coding and categorizing to draw out emergent themes, both within and across groups (Strauss, 1987; Boyatzis, 1998; Braun and Clarke, 2006).

After reading multiple methods of thematic analysis (Braun and Clarke, 2006; Cohen, Manion and Morrison, 2017) and based on the data in question, I developed and fine-tuned these ideas for my own method for coding, categorization and thematic analysis. The precise qualitative methods used throughout this research varied based on the data collected in each study. The interviews and both the online surveys included open questions and gathered qualitative data.

- The interviews provided richer data, the ‘thick’ qualitative description (Cohen, Manion and Morrison, 2017), which allowed deeper narratives and insights in analysis. *Appendix 1 – Illustrations of Code “Examples of AI”* shows an example of these methods used to analyse the interview transcripts in Chapter 4. This analysis resulted in the diagram shown in **Figure 7**.
- The online survey with members of the public had the most participants which allowed for comparisons and contrasts to come through in the analysis. *Appendix 2 – Illustration of Coding Answers to One Survey Question* which shows how one survey question from Chapter 5 was analysed. This analysis resulted in two diagrams (**Figure 26** and **Figure 27**).
- The hiring mangers online surveys were specific in their answers (due to subject matter expertise) which allowed for nuances in detail to be analysed. *Appendix 3 – a – Illustration of Coding Answers to One Survey Question* and *Appendix 3 – b - Illustration of Coding Answers to One Survey Question (Zoomed In)* show the method used to analyse one survey question from Chapter 5. This worked example resulted in the diagram in **Figure 29**.

Chapter 4 – Skilling the Gap - Interviews

This research began with a set of interviews. There were four groups of participants in this study – members of public, industry, adult educators and thought leaders.

Video 1[3] – *introduction to why qualitative reason was chosen for this study, sampling and ethics restrictions on demographic information. (See Appendix 7 for ethics email, Appendix 8 for transcript and Appendix 9 for references used in the video)*

[3] Link to video - https://www.youtube.com/watch?v=2RMWbCTO2es

Semi-structured interviews

This initial study was exploratory in nature, as such the aim was data gathering and scene setting. Therefore, it was decided to use semi-structured interviews, (Oppenheim, 2000; Kvale, 2008). Using semi-structured interviews, where a number of pre-defined questions guide the interviews, allows interviewees to elaborate or steer the conversation towards topics which are important to them. This allows unforeseen issues to arise and be discussed, while the conversation remains largely focused on the research topics. Thus, semi-structured interviews find a nice balance between the rigid, often restrictive format of a structured interview and the often inefficient nature of an unstructured approach (Kvale, 2008; Cohen, Manion and Morrison, 2013).

The interview questions can be found in **Appendix 4 – d**. More details on the participants are provided throughout Chapter 4.

Demographics and Anonymity

To ensure the methods of data gathering suit the research questions, an important aspect of this study was the anonymity of the participants. In making decision about how to conduct interviews (Kvale, 2008) with ethical considerations in mind (Alderson and Morrow, 2011; Wyse *et al.*, 2016), there was consideration of balancing the desire to gather rich data and the inclusive goals of reaching out to access voices less heard in research. In considering this balance, after much thought, the decision was made to not record interviews and not appear too intrusive about personal details. All this was intended to create a more relaxed, open and unintimidating tone and context for greater inclusion. It is precisely those who may be put-off by academia and the trappings of much formal research, whose voices are most sought here.

As some of the interviewees were speaking in a pseudo-professional manner (i.e., they were recruited due to their job and expertise, but were not speaking in an official capacity), it was believed anonymity would also be important to these participants. Without the promise of anonymity, these interviewees would not have been free to express their opinions freely and this would have impacted the candidness of the interviews.

Several of the interviewees (both members of the public and experts) expressed the anonymity of the interviews and the lack of recording was important to their decision to participate.

For similar reasons, demographics were not explicitly asked (other than job). Some demographics, such as age and education, did come through during the interviews; and were appropriate (and relevant) they have been included in the Findings section of Chapter 4.

Job titles will only be shared for the members of public, as their job titles were vague and unlikely to identify the participants (for example, “engineer” and “social media manager”). For the *expert* interviewees, job titles were asked but will not be shared. Some of the titles were company specific and the participant could easily be identified from these details.

Where possible (with respect to the given ethics approval and the importance of anonymity), details and nuances have been added to the Findings section of Chapter 4 (rather than the Methodology) as these helped tell the story of the data.

Sampling and Recruitment

Two different recruitment methods were used for different groups:

1. Members of public – these interviewees were all recruited, and interviews conducted, at a community fair. The process was the interviewers were positioned at a stall (see **Figure 1**) and those who approached were asked to participate.
2. Thought-leaders, industry, and adult educators – a more purposeful approach (Suri, 2011) was taken to recruitment of the three other groups as the participants had to work in specific areas. All participants were contacted through connections of myself, or my supervisors, based on their roles and companies.

The initial aim was to try and recruit 5 participants in each group, then assess whether this proved rich enough data or more interviews were needed. Here it was not anticipated that saturation would be reached, as this is rarely if ever the case, but rather if the broad scope of concerns and issues raised were being reiterated, indicating some commonality and a step towards thematic saturation. This sample size of interviews is in line with some recent research thinking around thematic saturation

(Fusch and Ness, 2015; Guest, Namey and Chen, 2020). A different approach to deciding the final number of participants in each of the groups was in fact taken in practice (Byrne, 2001).

The first interviews were with members of public who were all recruited and conducted in one afternoon, initial data analysis on these interviews revealed the richness of the data and a decision was made not to continue recruiting in this group (Braun and Clarke, 2016).

With the adult educators and thought leaders groups, the interviews were mostly conducted one by one (except for the interviews with the council run adult educators, who were interviewed on the same day). As such, the interviews were analysed and a decision to stop was made when initial analysis suggested a level of saturation was reached (Fusch and Ness, 2015; Saunders *et al.*, 2018).

The industry group proved difficult to recruit (due to potential interviewees being busy, or unable to find someone suitable at the company), and only 2 interviews were conducted despite efforts to recruit more participants. These interviews provided an interesting narrative about two different views on companies' involvement in employee retraining. Although having only two interviews can be seen as a limitation, their considerable length (35 and 55 minutes respectively) and thus level of detail go some way to mitigate this, when considering research on approaching qualitative saturation (Fusch and Ness, 2015; Saunders *et al.*, 2018; Guest, Namey and Chen, 2020).

Chapters 5 and 6 - Surveys

To further explore the findings of the interviews, two online surveys were conducted – one for members of public and one for hiring managers. They surveys were conducted using Google Forms. The questions designed for these surveys were similar with split differences (due to the participants) and can be found in **Appendix 5 – b** and **Appendix 5 – c**.

Online Surveys

Online surveys were chosen over interviews for several reasons, including reaching more people, time constraints and the on-going pandemic (Evans and Mathur, 2005). To allow participants freedom to speak in their own words, a qualitative survey (Braun *et al.*, 2020) was chosen with open-ended questions and free text boxes for answers (Sischka *et al.*, 2020) (as opposed to taking a quantitative approach or using constraining closed questions with pre-defined answers to choose from).

Similarly to the interviews, the responses were also anonymous, and the demographic questions were optional in order to encourage participation (Alderson and Morrow, 2011; Wyse *et al.*, 2016). There is wider research which recognises that there is tension and nuance in trying to decide what demographic data to collect, in terms of inclusion, privacy and what constitutes meaningful consent (Andrus *et al.*, 2021). While having this data may enrich the qualitative picture, insisting on gathering this information may inhibit some marginalised participants from responding. It was decided that accessing these voices was more important in the context of this research than obtaining these specifics. This was of course a compromise and it is acknowledged that different choices would be enriching in other ways, while perhaps excluding some voices

The surveys were designed to be inclusive, particularly for the members of public who may not feel they have the expertise to comment on matters related to AI. To ensure the surveys were accessible to a range of members of the public, the wording was clear and non-technical (both in the survey itself and any accompanying text). Everyone, even those who did not know how to answer or had no experience in DS, ML or AI, was encouraged to participate and would be important to the results (Atkins and Duckworth, 2019). The initial text on the online survey was:

> The goal of this research is to find out what **skills people think are needed for working with artificial intelligence**. Your thoughts and opinions are valuable, whether you know absolutely nothing about artificial intelligence or are an expert.
>
> Your voice is important to this discussion so please respond in your own way, in your own words, as short or as long as you wish.

Demographics

Demographics were asked at the end of the survey. All demographics were optional and in the form of free text boxes, except for one – are you based in the UK? – which was a Yes / No.

The demographic questions for the members of public survey were:

1. (Optional) Are you based in the UK?

    a. Yes
    b. No
2. (Optional) Region / Country
3. (Optional) Would you describe your location as rural or urban?
4. (Optional) Company Size
5. (Optional) Industry
6. (Optional) Current job

The demographic questions for the hiring managers survey were:

1. (Optional) Are you based in the UK?
    a. Yes
    b. No
2. (Optional) Region / Country
3. (Optional) Would you describe your location as rural or urban?
4. (Optional) Gender
5. (Optional) Age
6. (Optional) Current job

The demographics for both survey chapters are included at the beginning of the Finding sections of Chapters 5 and 6 respectively.

Chapter 5 – Clearing the Path - Member of Public

Sampling and Recruitment

The main sampling strategy used for this study was convenience (Marshall, 1996). This method seemed appropriate as the desired survey participants were the public. Participants were recruited from friends and family, as well as closed online groups (more details in Chapter 5 – Methodology). Only closed groups were chosen to avoid spamming from bots or other online issues.

The survey was left open for two months, then an initial analysis was conducted. The data met two important sample size criteria – richness (Suri, 2011; Roy *et al.*, 2015)and thematic saturation (Fusch and Ness, 2015; Saunders *et al.*, 2018) – so this was deemed enough data and the survey was closed.

Combination of Natural Language Processing and Qualitative Methods

As well as the qualitative approach for data analysis, using thematic analysis, NLP was also used to analysis the members of public survey. As this method uses frequency of words and phrases, and algorithms to analyse bodies of text (i.e., survey responses), it is inherently a more quantitative approach than many typically qualitative methods. A combined method (qualitative and NLP) has been used successfully and rigorously in public health (Leeson *et al.*, 2019; Oyebode, Alqahtani and Orji, 2020) and social media analysis (Andreotta *et al.*, 2019) With the data analysis strengthed through having these two, mixed methods approaches. Although these previous studies often use NLP to create a code book for thematic analysis (Guetterman *et al.*, 2018), NLP was conducted prior to thematic analysis and used as an additional lens - with which to view the codes and themes. These different approaches to analysis nonetheless complement each other here also, again strengthening the research as a whole.

To me, this felt like a natural complement to the qualitative approach (which is all about *words*), as NLP is about language and context. Using NLP as additional tool with which to interrogate the survey data (such as word length, occurrence of particular words and calculated sentiment) allowed different patterns and emphases to be found in the survey responses and demographics. The clustering method was of particular interest as it provided a different lens to group the respondents and view the words and phrases used. I firmly believe this additional analysis provided a level of richness and context which may not have been found by thematic analysis alone. It has much in common with a typical mixed methods analysis, where qualitative and quantitative methods are used in sequence or in parallel to triangulate the arguments, as strengths of one help to limit the weaknesses of the other (Cohen, Manion and Morrison, 2017). The combination of qualitative methods and natural language process used in Chapter 5 nicely sums up the fusion of computation and the human which is an important theme throughout this research.

Chapter 6 – Reaching the Baseline - Hiring Managers

Sampling and Recruitment

Similar to the recruitment for the *experts* in the interviews study, the hiring managers were recruited using purposeful sampling, again based on their job (Suri, 2011). The requirements to participate in this study were specific to ensure the participants were subject matter experts on the topic of AI-related hiring. These requirements included the participant:

1. Currently being employed by a company
    a. The company had a specific data science, machine learning, AI or robotics department
2. Having the ability to hire, fire and make staff / training decisions for this department

As such, the participants were contacted via LinkedIn (either as a direct contact or a second contact). 30 potential participants were contacted, 15 completed the survey within 2 months.

Chapter 4: Interviews

Preface

The previous chapter outlined the gap in AI education for working adults, in this chapter I begin my research by speaking with 21 people about AI training. The aim of this study was to understand the needs and opinions of different stakeholders in any potential AI education. The study focuses on those who the AI education would be designed for, the members of public. This study sets the scene for further work in designing AI education. As such, the paper presented in this chapter has an extended literature review which explores the AI skills gap and AI education for adults.

The paper then goes on to present the results of the 21 interviews conducted at the beginning of this research. Speaking with relevant stakeholders in AI education was an important first step to identifying barriers to designing AI education. These people were grouped into four categories: members of the public, industry, thought leaders[4] and adult educators. An important aspect of this research was not to put words in people's mouths. Often education in this space is designed with the skills gap, companies or experts (who often double as the educators) in mind, rather than the learner. These interviews were semi-structured and qualitative in nature. Where possible they were conducted in person, although some were via video conferencing or on the phone when needed. The transcribed interviews were analysed using qualitative methods of coding, categorizing and thematic analysis. *Appendix 1 – Illustrations of Code "Examples of AI"* shows an example of these methods which resulted in the diagram shown in **Figure 7**.

[4] Thought leaders refers to anyone who is deemed an expert on a topic – for example, due to their job, publications, talks or books.

Publication: Skilling the Gap: 21 Conversations on Designing Education for Those Left Behind as Robotics and AI Advance

Authors - Laura Gemmell, Lucy Wenham and Sabine Hauert** (*Provided supervision over the work)

Keywords: Education, Skills, Artificial Intelligence, Robotics, Inequality

This paper has been published and peer-reviewed in Advanced Intelligence Systems journal (Gemmell, Wenham and Hauert, 2021). The paper has been added as published with a few small changes to formatting, and the figure and table captions have been expanded to be in line with the rest of this thesis.

Abstract

Robotics and Artificial Intelligence (RAI) is advancing rapidly (Schwab, 2017). These advances risk exacerbating existing inequalities unless the benefits are shared across society. Those who have more knowledge of these technologies are less likely to be impacted by job losses (KPMG, 2018). Education in RAI is often aimed at business leaders and students (Gov, 2019b). While education designed for these groups is needed, it is not accessible by everyone and there is potential for people to be left behind.

To understand the barriers to designing a RAI educational scheme for those often missed by other initiatives, a pilot study was conducted. Twenty-one semi-structured interviews (Kvale, 2008) were held with Thought-Leaders, Industry, Adult Educators and Members of the Public. Thematic analysis (Braun and Clarke, 2006) was used to allow themes not previously thought of to arise.

Looking at the findings through the lens of leaving no one behind presented three themes which need to be addressed for education to be successful. Firstly, as well as education for those designing RAI and education for everyday life, there needs to be education for those working *with* RAI. Secondly, work needs to be done to overcome preconceptions. The views of learners on RAI influenced by their individual lives, potential "gatekeeping" of experts, and attitudes to training from industry could create

barriers to education. Finally, co-designing with communities to ensure the education is relevant to the learners' needs and lives is paramount to create a meaningful education.

Introduction

Robotics and Artificial Intelligence (RAI) are becoming increasingly common in both everyday and working life. Adult education will be central to this transformation and can be used to empower citizens to use technology to improve their lives and communities. To understand how adult education could be used, exploratory interviews were conducted with various stakeholders required for a successful educational initiative. Thought leaders on AI were interviewed as their support could be the difference between success and failure of such education. Industry were interviewed as creating an education aligned with industry could allow for a future path-to-work to be created. Adult educators were interviewed to understand the needs of adult learners and how such an education could be realised. Finally, and most importantly, members of the public were interviewed to understand their views on AI and training. The interviews were conducted with individuals and companies based in the UK, and as such the findings and discussions are largely UK-centric. These interviews have revealed some areas which need to be considered and addressed when designing education on RAI aimed at the general public. Throughout this work the term “education” will be used as the aim of these interviews and the design stage is to create education which works best for the learners. As such, the type of education (this could be formal or non-formal, linked to business or community lead, digital or in-person) should be dictated by the findings.

As has happened with previous technological advances, there is a risk certain groups of the population will be left behind as RAI grows. Existing inequalities could be deepened if the benefits (and disadvantages) created by these technologies are not shared equally throughout society (Schwab, 2017). Education is one method of minimizing the number of people being left behind. Often those at risk are the same people who could not or would not avail of other formal educational offerings, and whose employers would be unlikely to provide such education. Thus, any education must be specifically designed with these people and their needs in mind. This research aims to be the initial data used to inform further research and development of an educational initiative for those potentially missed and left behind.

Fourth Industrial Revolution

The advancement of emerging technologies, including RAI and related technologies such as autonomous cars and the Internet of Things (IoT), is often referred to as 'The Fourth Industrial Revolution'. This phrase was coined in 2016 by Klaus Schwab, Founder and Executive Chairman of the World Economic Forum (WEF) and author of a book by the same name (Schwab, 2017). The UK Government's whitepaper on the Fourth Industrial Revolution (Clark, 2019) lists four grand challenges, the first of which is AI and data technology. A further two of these grand challenges, *mobility* and *aging population*, are also heavily linked to RAI.

Examples of Robotics and Artificial Intelligence[5] are increasingly being seen in every aspect of modern life. Voice assistants, such as Siri, Google Assistant and Alexa, are used in many phones and devices. Navigation devices or Sat Navs use complex algorithms to find the best routes based on several data sources, including Waze and Google Maps. Software claiming to use Artificial Intelligence (AI) is used in many workplaces, for example accounting software Auto Encoder reads bank statements and sorts transactions into categories required for tax calculations. Chatbots are now used in healthcare, including those by the NHS, Babylon Health and Ada Health. And RAI technologies are often reported on in the media, including from companies like DeepMind with their champion Go playing algorithm, AlphaGoZero (Silver *et al.*, 2016). Moving towards the hardware side of things, robots are already used in manufacturing lines, warehouse logistics, surgery, and cleaning. Autonomous driving is featured prominently in research, startups, industry, and government strategies. And Boston Dynamics' robots have been backflipping, opening doors and inspiring episodes of Black Mirror.

[5] The definition of Artificial Intelligence (AI) is a largely debated topic as this research focuses on members of the public, the definition has been taken loosely and from their point of view. Thus, it includes examples such as Voice Assistants and more general algorithms which experts may not class as AI.

Will Robots Take Our Jobs?

RAI is often depicted in the media, including the news and films, in extremes - either RAI will save or destroy us. Positive examples include reports of algorithms diagnosing patients better than doctors, robotics making factories and disaster sites safer and RAI saving companies money. On the other hand, the narrative of "killer" robots and jobs being lost to RAI are common. Research into public perception of RAI has been carried out by institutions (such as the Royal Society (The Royal Society, 2017)), consultancies (such as KPMG (KPMG, 2018)) and academics. (Boyd and Holton, 2018; Zhang and Dafoe, 2019). The research reports varying attitudes towards RAI found within the public. Some found more Americans were in support of AI, (Zhang and Dafoe, 2019) while another found 70% of US adults were "weary" of AI (Smith and Anderson, 2017). One aspect raised in this study was the implications for jobs. This can be seen in other countries with one third of Irish adults (Lero, 2018) and two thirds of UK (Foundai, 2020) adults concerned RAI will replace their jobs in the future. KPMG found those who knew less about AI were more likely to worry about losing their jobs (KPMG, 2018).

One of the most cited papers found 47% of jobs in the US (Frey and Osborne, 2017) were at "high" risk of automation. When the same method was applied to the UK and Europe, 35% and 40-60% of jobs were at risk respectively (Bowles, 2014; ONS, 2019a). Other reports from PwC (PWC, 2017) have predicted three waves of job losses resulting in overall automation of 30% jobs. This report along with one from the ONS (ONS, 2019b) did see these job losses as being equally shared across society (both agreed those with "low" levels of education would be most impacted). The WEF's Future of Jobs (WEF, 2018) report gave a slightly different angle, reporting 50% of businesses said they felt they would reduce their full-time workers or hours by 2022. However, 38% said increased technology and automation would increase their employment and productivity.

Rather than looking solely at jobs lost, some reports take a more holistic view of the overall impact on jobs. The OECD data notes 14% of jobs are likely to be automated, but further to this 35% of jobs are likely to change by 2030 (OECD, 2019). The Centre for European Economic Research predicts an increase in overall jobs, but with these jobs being of a different nature, thus resulting in job losses for some (Centre for European Economic Research, 2018). In 2018, McKinsey reported that up to 14% of workers worldwide (375 million people) will need to change jobs and reskill because of automation and AI by 2030 (Manyika *et al.*, 2017).

Regardless of the net impact on the number of jobs, the Fourth Industrial Revolution will definitely have an impact on the future of work. This is likely to transpire in a number of ways:

1. Jobs will be lost due to automation.
2. Jobs will be created due to advances in RAI.
3. Jobs will change as tasks are automated and more RAI systems are introduced.

The rise of these technologies is also creating jobs already. Facebook announced 1,000 new jobs in the UK in 2020 due to their increased use of AI (Browne, 2020). The Royal Society reported a 231% increase in job postings requiring Data Science and Advanced Analytics skills (Royal Society, 2019). This increase in jobs requiring specific RAI and data skills has created a *Skills Gap* as there are not enough people with the necessary skills to fill these roles, which has impacts on businesses. According to the Open University Business Barometer, over 90% of businesses surveyed have not been able to find the talent needed, and 61% believe this has worsened in the past year. This skills gap is costing the companies £63 billion a year in additional recruitment, retraining, temporary staff and higher offers (Open University, 2019). While adult education will not address the immediate need for RAI experts, the skills gap is predicted to increase as these technologies grow. Educating adults in such a way could increase demand for re-training initiatives becoming accessible by a greater proportion of the population, leading to a larger, more diverse RAI workforce.

Education to Overcome the Skills Gap

There have been many measures to overcome the Skills Gap. To illustrate who these measures may overlook, it is useful to look specifically at the UK, where the government has many initiatives to combat the digital skills gap (shown in **Figure 6**). This example is for illustrative purposes and not a complete example. Complex issues such as unequal access to education and unemployment have not been considered as they deserve more attention than this paper can devote. They are, however, extremely important in ensuring no one is left behind.

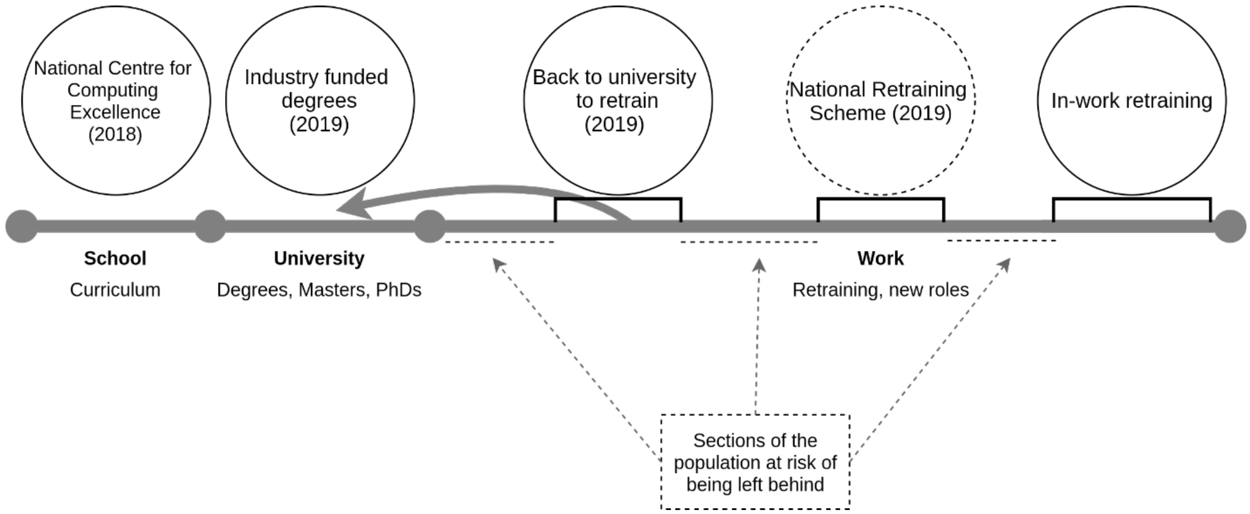


Figure 6 - Government efforts to close the skills gap in the UK. The line is a representation of stages of life (this is illustrative, not to scale or all encompassing). The circles represent current interventions funded by the UK government. There are gaps in these efforts which need to be addressed,

Figure 6 shows the three typical stages of life - school, university (which is not compulsory) and work. The school curriculum is being addressed by the National Centre for Computing Excellence (Gov, 2018) which aims to ensure all children of school age receive the necessary computing school for the digital age. Several initiatives aimed at the University section will create a number of Industry-funded degrees, as well as extra funding for Masters and PhDs in AI (Gov, 2019b). A further scheme to help those in work retrain at university was also proposed in 2019 (Office for Students, 2020). This scheme, which is a necessary step in creating more AI talent in the UK, has a degree requirement for participation which creates a barrier to entry. Once in work the reskilling options become more dependent on the employer. Many companies offer in-work training, including opportunities to undertake Apprenticeships and degrees while working. Others do not and the responsibility and cost are passed to employees.

While these initiatives go a considerable way towards addressing the Skills Gap, there are still segments of the population which may be left behind, as can be seen from the figure. This includes those who cannot, or do not want to, return to university to retrain and those who do not work for companies which will provide the opportunity for in-work retraining. In an effort to close these gaps, the UK Government has created a National Retraining scheme (Gov, 2019a). This scheme is not available to everyone and will provide support for those over 24, currently in work, without a University degree and earning below a certain yearly threshold.

RAI Education for Everyone

RAI education, as it exists today, is largely focused on students and business leaders. Large, multi-national companies are offering their employees retraining and opportunities to study towards relevant qualifications (Noble, 2018; PwC, 2020). In-work retraining has already been seen to be successful in a number of cases. One notable example is the Professional Services company Accenture, who, due to a large effort which included repositioning to new roles, and even reskilling in IT skills where needed, had no job losses when 17,000 jobs were automated (Brinded, 2017).

There are a large number of new courses and funding for students wishing to study related topics at all levels of Higher Education (Office for Students, 2020). The AI Index reports a five- and twelve-fold increase in enrollment for introductory AI and Machine Learning (ML) courses respectively at certain US Universities (from 2012 to 2018) (Perrault *et al.*, 2019). Children have also been a focus of attention, with curriculums expanding to include coding accompanied by a rise in the number of coding and RAI after-school and holiday clubs offered (The Royal Society, 2017).

Courses offered on the internet have also provided greater reach for education on RAI as free courses or Massive Online Open Courses (MOOCs) have become popular on this topic. These courses are offered by a number of platforms, such as Coursera, Udacity and EdX, and include a range of free and paid for courses from World-Renowned Universities, such as Stanford, and technology companies, such as IBM. These courses also range from beginner to expert level, and include Andrew Ng's *AI For Everyone*. While this course is an excellent starting point for a non-technical person wanting to learn about AI, it is geared towards business people who wish to learn about AI rather than the general public. "Tech Giants" also offer their own range of courses on AI, for example Microsoft's AI School and Google Education's Google AI. While these courses are accessible and free, they are aimed at technologists and business people who wish to learn more about AI. A further online option to learn about AI is the competition website Kaggle which allows companies to host “data competitions” in return for cash prizes, jobs or reputation prizes (it has become common for people to include their Kaggle wins on their CV and LinkedIn). Kaggle also offers a range of online resources and training, which are listed for beginners (however some technical skill is needed to use these resources).

These educational initiatives move towards closing the Skills Gap and provide opportunities for many people to learn about RAI (mostly AI). However, education is needed for everyone. Not everyone works for a company providing retraining, or is in a position to return to further study (whether at a University or online). Online education is not without challenges - of particular concern are time and resources (both equipment and digital skills). Several of the studies into which jobs will be impacted suggest the very people who need education the most could be those who are missed (e.g. factory workers, retail staff, call center workers). Rather than current educational offerings being modified to work for everyone, education needs to be designed specifically to target those people at greatest risk of being left behind.

An example of such an initiative aimed at the general public, focused on increasing knowledge of RAI, rather than the Skills Gap, is the online course *Elements of AI.* This course originally intended to educate 1% of the Finish population in the basics of AI, but is now working towards 5% (FCAI, 2018; Delcker, 2019). The success of this course has resulted in Finish Government pledging to translate the course into all EU languages to educate 1% of the EU. Whilst Finland can be seen as a trailblazer in terms of AI education, and their work can be built upon or used as frameworks in other countries, it is important to note that Finland's approach to education cannot simply be replicated in other countries. Their attitudes to adult learning certainly differs from that of many other countries, with 76% of Finish adults already participating in formal adult learning (OECD, 2018b, 2018a).

It was not easy to find any readily available research papers, news articles or websites for non-online RAI courses aimed at the general public. These could include community or informal learning, which do exist for coding and technology (as well as non-technical subjects such as languages and literature), for example at local libraries or community centres. Such courses may be more accessible to the general public and could help AI education reach more people. One example, although not of the general public, was efforts being made to teach prisoners in Finland about AI (Varghese, 2019). This highlights the need for such an education to be created.

Methodology

The aim of this research is to better understand attitudes towards RAI, particularly around retraining for those at greatest risk of being left behind as these technologies advance. Recognizing the different viewpoints and concerns from a range of stakeholders (Thought-Leaders, Industry, Adult Educators and

Members of Public) will provide much needed insight to better inform the future design and delivery of any tailor-made educational initiatives.

To meet this aim, a quantitative method would not be appropriate. This research is not testing a hypothesis or attempting to find statistical relationships or patterns in the data. The aim is to explore perceptions, thoughts and opinions of the four groups of stakeholders surrounding RAI and retraining of those potentially left behind. In seeking to discover potential barriers to participation in education, for those potentially left behind, unforeseen, subtle issues may emerge. These may be personal and unexplored, making them unlikely to come through in quantitative research.

Within social sciences and education, robust qualitative research methods have been long-established (Strauss, 1987; Kvale, 2008). These methods advocate for qualitative, over quantitative methods, when seeking a deeper understanding of the how and why of a societal issue or individual perspectives and opinions. Due to the context specific nature of these methods, there are limitations to applying the findings of qualitative research beyond the particular setting, places and spaces. As such, the findings of this research are not generalizable but aim to add depth to the discussion of RAI education for the general public. Even with these limitations, a qualitative research methodology was the most appropriate with exploratory interviews, specifically semi-structured interviews, being used for data gathering (Oppenheim, 2000; Kvale, 2008).

Using semi-structured interviews, where a number of pre-defined questions guide the interviews, allows interviewees to elaborate or steer the conversation towards topics which are important to them. This allows unforeseen issues to arise and be discussed, while the conversation remains largely focused on the research topics. Thus, semi-structured interviews find a nice balance between the rigid, often restrictive format of a structured interview and the often inefficient nature of an unstructured approach (Kvale, 2008; Cohen, Manion and Morrison, 2013).

There are no hard and fast rules to determining the appropriate sample size for qualitative research (in comparison to quantitative methods were there is often a formula to determine the needed sample size), as discussed by Braun and Clarke (Braun and Clarke, 2013). Commonly, 15-30 interviews are used when the aim of the research is to identify patterns across the data generated (Gough and Conner, 2006; Terry and Braun, 2011).

The target number of interviews for each of the four groups of stakeholders was five interviews. This target was met in three out of the four groups, where the numbers exceeded five. In the Industry group five was not met. The number of interviews per group was:

- Thought-Leaders: 6
- Industry: 2
- Adult Educators: 7
- Members of Public: 6

The Thought-Leaders and Adult Educators were recruited through contacts - either directly or indirectly (i.e. introduced by a colleague at the same companies who were deemed more suitable to interview). All asked in these two categories were interviewed. Members of Public were recruited and interviewed at a community event. Potential industry interviewees were contacted through connections (both personal and those formed at conferences) and posts on social media. Companies with workers who were likely to be impacted by AI in near future (for example, retail, warehousing and delivery) were targeted for these interviews. Twelve companies in these industries were contacted regarding interviews - nine responded, five interviews were agreed to or arranged, although only two actually materialized. There was interest in this topic, but often finding someone who could discuss the company's plans for training and automation, or concern about how answers would reflect on the company, prevented interviews.

The interviews were not recorded, but notes were taken by hand. Recording would have prevented several interviewees participating or speaking freely. This was considered of particular importance for the Members of the Public group where the interviewees were already arguably talking about unfamiliar ideas, perhaps outside their comfort zone. This was important in ensuring we hear from them, as they are often the voice that is not included in education and RAI discussions.

The data from these interviews was analyzed using qualitative techniques of initial coding and categorizing to draw out emergent themes, both within and across groups (Strauss, 1987; Boyatzis, 1998; Braun and Clarke, 2006). These themes are presented in the Findings and explored through the lens of leaving no one behind in the Discussion. As the Members of Public are often missed from such discussions, their interviews have been placed at the beginning of the Findings to signify their importance.

Findings

Everyone interviewed knew about AI, and were keen to discuss (including those who stated upfront they did not like AI). The conversations were diverse and interesting providing an insight into attitudes on AI.

When discussing AI, the interviewees used several terms:

- Artificial Intelligence or AI
- Machine Learning or ML
- Data Science

The Members of Public (MoPs), and the Adult Educations and Thought-Leaders who work with them, used the term AI freely. These interviewees did not mention Machine Learning, or Data Science. This supports The Royal Society Report (The Royal Society, 2017) which found only 9% of people had heard of the term Machine Learning. Interviewees from the other three groups with any form of technical training, or technical interest, used the phrase Machine Learning. Some interviewees stated this was due to their skepticism that current technologies are actually AI.

> "if it's ML it's Python, if it's AI it's in PowerPoint. It's a buzzword"[6]

> "it is a term that can encompass a lot of things, but most people mean Machine Learning"

> "AI is a very general word. I think about Machine Learning or ML"

The term used by those considering AI from a business perspective tended to be Data Science. One Thought-Leader described Data Science as "statistics, modelling to enhance and accelerate human knowledge". The term Data Science was used by Thought-Leaders and Adult Educators.

---

[6] The quotes included are the interviewees own words, and have not been amended to modify grammar.

Members of Public

The members of public (MoPs) who were interviewed were vastly different in age (while the ages of interviewees were not explicitly asked, two interviewees gave their ages throughout their interviews as “nearly 20” and 78. It has been assumed all other interviewees fall within this age range), and had a variety of jobs (including warehouse worker, retired engineer, teacher, social media manager, childminder trainer and first-aider).

Have you heard of AI?

All but one MoP knew what AI was when asked and were able to give a definition. The person who was unable to give a definition when asked, nodded at the definition of Artificial Intelligence given by the interviewer. The interviewee was able to answer subsequent questions demonstrating understanding of the concept. Thus is could be reasoned not knowing the terms AI or Artificial Intelligence could be due to a language barrier.

Definition of AI

All definitions included the word "computer" or "robot", and most included an example.

> "It is using robots to hoover or build a car."
>
> "It is computer based and relies on databases that aren’t up to date so is suspect. Used in laptops, flight controls."
>
> "It is robots that will do things for us and make us lazier."
>
> "It is…[pause]... computers learning from themselves like the IBM... [Watson]"
>
> "It is computers controlling everything - work, rest and play. It is used in medicine."

All of these definitions, bar one, include an example, and all include a more complex example than 'everyday AI', such as voice assistants or recommender systems.

Examples of AI

When asked to give examples of AI, only one person gave a "voice assistant" as an example of AI without the example being raised by the interviewer. All MoPs had heard of or used voice assistants and recommender systems when prompted.

> "Of course I have used those. Everybody uses Netflix and Amazon."

When discussing AI the MoPs mentioned nearly forty examples of AI in total. These examples are shown in **Figure 7.** The majority of them occurred when asked a specific question (e.g. "Can you give me examples of AI?"), however some examples came up naturally in conversation when they were answering other questions. The examples in response to another question are denoted by a dashed outline in **Figure 7**. Only one MoP did not bring up any examples in response to other questions. A large number of the examples which came up naturally (i.e. not in response to the specific question on examples) where in response to the question around issues with AI. These 'unprompted' examples were about translation, hoovers, Siri and Aviation.

> "We need to be careful. This technology doesn't always work. A very famous example of translation. There was a translation of English to Russian 'out of sight out of mind'. When translated from English to Russian and back it was 'invisible idiot'."

> "I often talk about Siri taking over the world with my kids. Everyone is giving away so much data which makes AI more intelligent and powerful. Eventually we won't need to leave the house or do anything - shopping will be delivered, talk to everyone via messages and VR for holidays."

> "Those little hoover things move around your whole house. They could be mapping the size of your house and selling this to someone."

> "I heard of a story where a plane was grounded because of the AI on board... It due to simulations not working properly. They were showing something the pilot knew to be wrong. AI use can cause issues."

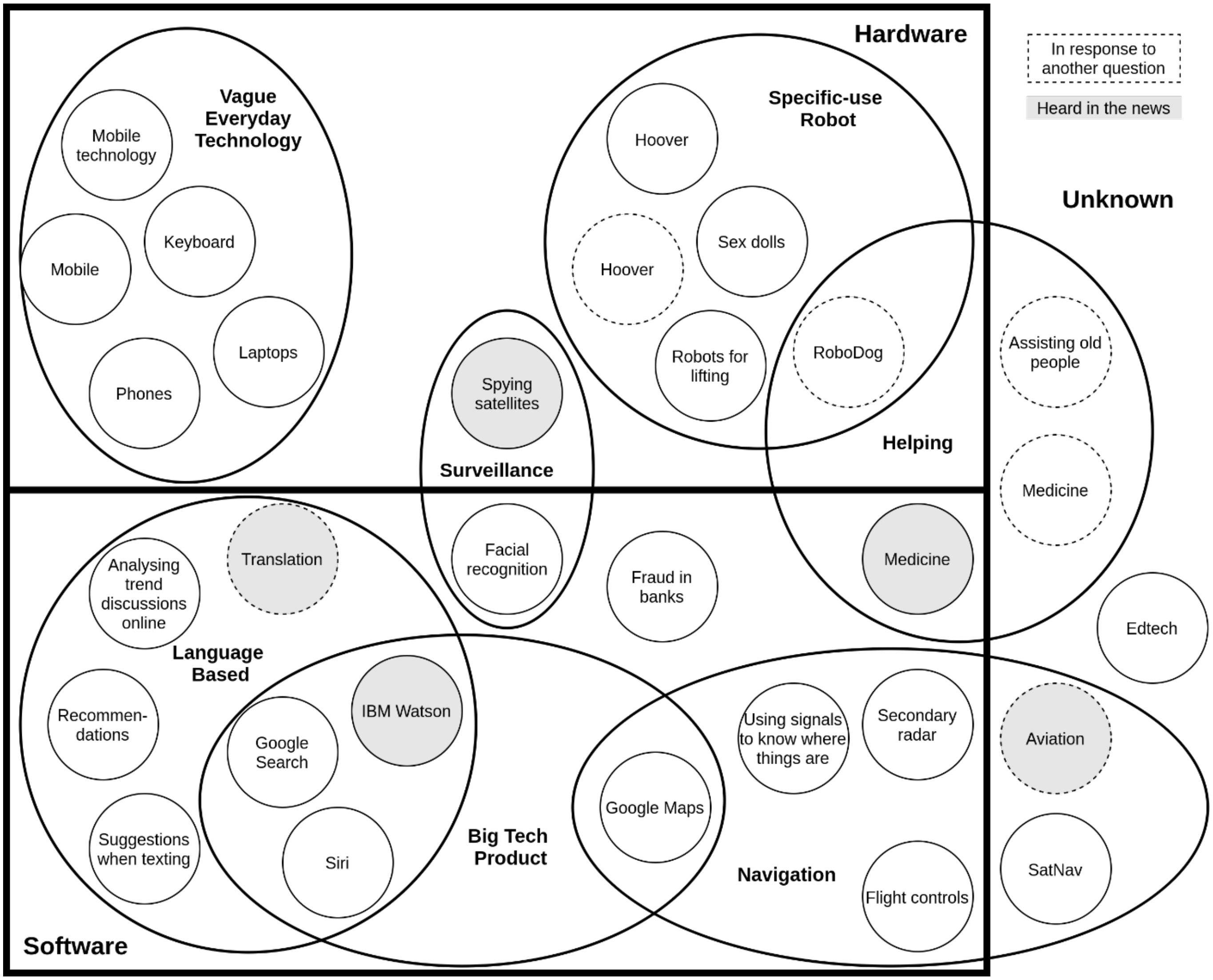


Figure 7 *- Examples of AI given by members of the public. Each small circle represents an example. The examples have been split into various categories, first - hardware / software / unknown indicated by the large rectangles. The larger circles represent themes of examples, such as 'language based' and 'helping'. The majority of these examples were given in response to the specific question on examples, small circles with dashed outlines represent examples given in response to other questions and grey circles represent examples which were 'heard in the news'.*

The stories told about translation and aviation were identified as being something the individuals had heard from another source (for example, the news). Other examples also identified as having been heard from another source included those about a robot dog, spying satellites and IBM Watson.

> "I saw in the news that Japan has a Robot Dog. But it's not like having a real dog."

> "Things in films, that are not real, but not far off and actually out there. [interviewer: "such as?"] like spying satellites, which are good for looking at people doing bad things but don't like this Big Brother style nation."

> "It is [pause] computers learning from themselves like the IBM … [long pause] [interviewer: "Watson?"]. Yes, the question AI. I would have said Willis or something."

These *heard in the news* examples are shown as grey circles in **Figure 7**. In the majority of these examples, the individual did not seem confident of the details and could not answer any follow up questions, with the exception of the translation example.

The examples could also be defined based on whether they were hardware, software or unknown. Several examples were unknown as they described a use-case or a large subset of technology which could be either hardware or software, e.g. "old people", "in hospital", "Edtech". The rest of the examples were almost evenly divided into software ("recommendation", "translation", "Siri") and hardware ("robots for lifting", "hoover", "keyboards"). This split has been shown with the rectangles in **Figure 7**.

The examples can be further categorized based on "type" of AI and uses. These categories are shown in **Figure 7** by the large circles grouping together examples. The categories (in descending size order) are:

- **Language Based** - examples which use either text or speech-based interactions and involve analyzing language to give results. This was the largest category, made up of all software examples. One example of *Language-Based* AI given was "suggestions when texting".
- **Navigation** - examples which involved giving directions, guiding or another aspect of safely navigating individuals, cars, robots or planes. The range within this category was large - from "SatNav" to "secondary radar", and included both software and unknown examples.

- **Big Tech Product** - examples which included one of the "Big Tech" companies. All of these were specifically about a product from one of these companies, e.g. "Google Maps", and were all software.
- **Specific-Use Robot** - examples describing a physical robot used for an explicit reason, e.g. "hoover". All examples were hardware.
- **Vague Everyday Tech** - some examples were of a simple ubiquitous device, e.g. "mobile". All examples were hardware.
- **Helping** - some examples were explicitly designed to help people, e.g. "medicine". This was the only category which spanned hardware, software and unknown.
- **Surveillance** - examples which could be used to observe or monitor the public. These included hardware and software examples. Some examples, e.g. "Robot Dog", come under two categories (Specific-Use Robot and Helping). All of the Big Tech Products come under another category to describe their use, e.g. "Google Maps" has been categorized at Navigation. Some other examples did not fit under any of these categories, e.g. "Edtech" and "fraud in banks".

Impact on jobs

The MoPs were asked about their jobs (current or past if retired), including the tasks they carry/carried out in their roles. They were further asked if they could think of any uses for AI in their job. Their responses are recorded in the **Table 1**. All MoPs gave examples of how AI could be used in their jobs, including "Edtech" from a teacher and "secondary radar" from an engineer. Most readily gave examples without any prompting. Others had to be reminded to think of the tasks they performed in their job, or being given one example and asked for others. A number of the MoPs were positive about these uses:

> "I’ve actually been thinking about this recently"

> "I can see AI used in teaching"

Not everyone gave positive responses. One MoP explicitly stated it was why they left engineering. Another described themselves as "not an adopter of technology". However, after thinking about the potential uses they concluded they were "curious" about AI being used in their job. One other MoP was extremely neutral and matter of fact when describing uses in their job. Their neutrality could be due to them being retired from their job.

Job	Prompted?	Uses	Positive or Negative Sentiment
Engineer *(retired)*	N	"Secondary radar", "SatNav"	Neutral – extremely matter of fact
Teacher	N	"Edtech, phones, tablets"	Positive
Trainer	Y – Not an adopter of tech	"For those who like online training"	Negative But curious
Works in a warehouse	Y – Did not seem to consider hardware as AI	"Robots for lifting, or using signals to know where things are."	Positive
Social Media Manager	N – Had actually been thinking about it	"Analysing trend discussion online"	Positive
Ex-Engineer *Current first aider*	N – It was why he left engineering	"Aviation"	Negative

***Table 1** - Responses to AI impacting each member of public's job. The table shows the interviewee's job, whether their response was promoted or given conversationally, the uses of AI they saw in their specific job and whether they spoke about AI impacting their job in a positive or negative way.*

Concerns About AI

MoPs were specifically asked if they had any concerns. Concerns were also expressed throughout the interviews in response to other questions. One individual did not raise any concerns about AI, and one other had nothing positive to say about AI. All others gave a somewhat balanced view, with some coming off slightly more positive or negative overall.

The concerns expressed by the MoPs could be grouped together into themes:

- Data Privacy and Control
- Doesn't Work
- Negative Societal Impacts
- Laziness
- Data Quality
- Power Source

The size and depth of these themes are shown in **Figure 8**.

All MoPs, who expressed concerns, brought up worries about the data being used in AI. These could be divided into two themes - *Privacy and Control* and *Quality*. *Privacy and Control* was mentioned by all these MoPs, sometimes more than once in the same interview. This theme was the largest in terms of number of references throughout all of the interviews. The MoPs mentioned their concerns about the amount of data being collected.

> "Everyone is giving away so much data..."

> "Sometimes I'm not very happy with the amount of data and lack of control."

The previous quote mentions "lack of control" with regards to their data. Other MoPs also brought up concerns about who owns or controls their data.

> "The challenge is ownership of data and what can be done with it… Privacy is the big issue."

> "The big challenge is the lack of control..."

Data - Part 1 (Privacy and Control)

“Everyone is giving away so much data which makes AI more intelligent and powerful.”

“Sometimes I’m not very happy with the amount of data and lack of control.”

“Spying satellites, which are good for looking at people doing bad things but don’t like this Big Brother style nation.”

“The challenge is ownership of data and what can be done with it… Privacy is the big issue.”

“The big challenge in the lack of control - for example, those little hoover things move around your whole house. They could be mapping the size of your house and selling this to someone.”

Doesn’t work

“The technology is early days, doesn’t always work. A very famous example of translation - There was a translation of English to Russian - out of sight out of mind - when translated from English to Russian and back it was “invisible idiot”. Need to be careful.
AI is all based on a power source. What happens if this goes out? There means geography is a barrier for some as service varies, for example, there is no Wifi in rural America.”

“AI seems to work sometimes, but not all.”

“I heard of a story where a plane was grounded because of the AI on board. It due to simulations not working properly. They were showing something the pilot knew to be wrong. AI use can cause issues.”

Negative Societal Impacts

“It could cause unemployment.”

“I’m concerned about people being left behind.”

“Online takes the human element out of a very human activity.”

“Could do someone out of a job.”

“I often talks about Siri taking over the world with my kids.”

Laziness

“Eventually we won’t need to leave the house or do anything - shopping will be delivered, talk to everyone via messages and VR for holidays.”

“It is robots that will do things for us and make us lazier.”

Data - Part 2 (Quality)

“Relies on databases that aren’t up to date so is suspect.”

“Good data is also a problem. For this you need cooperation”

Power Source

“AI is all based on a power source. What happens if this goes out? There means geography is a barrier for some as service varies, for example, there is no Wifi in rural America.”

Figure 8 *- Concerns about AI given by members of the public. Each post-it note represents a category of concerns. The size of the post-it represents how much (either through number of mentions or detail) that category was discussed. Within the post-its, the number of quotes show how many times the concern was brought up. For example, the category ‘Doesn’t work’ was only mentioned three times, but two of these mentions were detailed stories, therefore the post-it is large.*

The MoPs also mentioned privacy concerns about specific technology such as "spying satellites" and "those little hoover things that move around your whole house".

The next largest category in terms of how many times it was raised in the interviews was *Negative Societal Impacts*. The main concern in this theme was the impact on jobs and potential unemployment.

> "It could cause unemployment."

> "Could do someone out of a job."

One MoP was "concerned about people being left behind" and another worried AI (and other online activities) "takes the human element out of a very human activity".

The *Quality* of the data used was mentioned twice, by two MoPs who had previously worked as engineers.

> "Relies on databases that aren't up to date so is suspect."

> "Good data is also a problem. For this you need cooperation."

These MoPs also both mentioned examples of AI not working correctly (the examples of failed translation and aviation discussed in the **Examples of AI** subsection). The issue of power sources for AI was also brought up by one of the engineers.

> "AI is all based on a power source. What happens if this goes out? This means geography is a barrier for some as service varies, for example, there is no Wifi in rural America."

One MoP, who self-identified as skeptical but was very well informed about the topic, was concerned with how well AI worked.

> "AI seems to work sometimes, but not all."

They were also the only MoP to mention laziness, and they brought it up twice.

> "Eventually we won't need to leave the house or do anything - shopping will be delivered, talk to everyone via messages and VR for holidays."

> "It is robots that will do things for us and make us lazier."

The same MoP expressed concern about AI, specifically Siri, "taking over the world" albeit in a slightly joking manner which was considered a *Negative Societal Impact*.

Optimism Regarding AI

As well as concerns, MoPs were specifically asked about the benefits of AI. Similar to concerns, positive views and optimism regarding AI were also expressed throughout the interviews not just in response to the question. The breakdown of optimistic views expressed by interviewee is shown in **Figure 9**. Most of the MoPs expressed optimism towards AI more than once during the interviews (a, b, c, f). The social media manager, whose job is largely digital and seemed actively interested in AI, gave the highest number of optimistic statements (b). AI being "useful" was mentioned a number of times.

> "AI is useful for finding out information"
>
> "It is useful"
>
> "It is beneficial because it is practical and efficient to use AI in real life, both home and work"
>
> "AI works well and can be useful. It is very helpful for old people. It can be assistive in general."
>
> "These technologies are useful, and they are improving."
>
> "AI would be useful in my role."

Other optimistic comments on AI, included it being "a good idea", "the future" and an MoP being "very open to AI". One MoP was positive about a specific technology, Siri.

> "Siri. Which I like a lot and use all the time."

On the other hand, one MoP gave two marginally positive statements (d).

> "AI seems to work sometimes, but not all."
>
> "Recommendations from AIs are fine"

One gave no positive statements throughout the whole interview (e). Both these MoPs identified themselves as skeptics, and came across as very well informed, albeit negative, throughout their interviews.

Comparing **Figure 8** and **Figure 9** shows the number of negative statements expressed was greater than the number of positive. This was despite both concerns and benefits of AI being asked as questions.

Figure 9 *- Optimism regarding AI given by members of the public. Each post-it note represents one interviewee's optimism regarding AI. Interviewee e gave no positive or optimist statements throughout the discussion.*

AI Training

To understand the demand or resistance towards AI training, the MoPs were asked if they would be interested in AI training. They were further questioned on particular types of AI training, including for work or home, understanding AI or building AI.

One MoP did not respond to whether they would like AI training or not, this may be due to them missing the AI part of the question and responding only with their views on training in general:

"I am training as a carer. It is important to keep learning, especially as you get older, but in line with your interests. This is key!"

Only one MoP was positive and interested from the beginning. They would be interested in training both in general and if the technology was introduced in their job. They were enthusiastic about training on AI "because it is the future". The other MoPs all originally said they would not be interested in training.

"No, definitely not."

"No."

"No to training. I'm not into training in general, I read online when I need to know things."

"How will it benefit me? Do I look like an academic? Such training is only for experts, given by experts. That's how they want it."

However, either due to them reconsidering for themselves or further questioning, they all changed their mind and said they would be interested in particular training relevant to their lives.

"Yes actually I'd like to understand how it works and how to build something, but not how to use AI and I definitely wouldn't use what I build."

"Actually, I would be interested in training, particularly to make things more efficient for either work or home life... I would like to know how to use and how to build things."

"Actually training to understand how AI works would be useful."

"Tell you what I would be interested in, training around awareness of the implication and downsides. The news only shows the good side of AI, never shows the bad side. However society prides itself on keeping people ignorant, so why would that kind of training exist? It's not what they want."

When asked whether they thought this type of training already existed, none of the MoPs responded positively. One thought it existed but not easily accessible, and another thought it would only be for experts.

"I do not think this type of training is available."

> "I don't think this AI training exists."

> "I think the training exists - but it's only for experts or scientists. I'd be interested in the general public getting training."

> "I think training like this may be available, but not easily accessible."

Final Thought

When asked whether they had anything else to add, one MoP responded with a number of important points which should be addressed by industry, academia and government if AI is to successfully work for everyone. Concerns were about diversity and culture, particularly the focus on white, euro-centric and middle-class points of view. Their comments also raised the issue of trust in academia, and the need for wider participation to ensure it represents everyone in society.

> "I'm interested in diversity. Universities, AI, engineering. There is a white, euro-centric, middle class focus to everything. There is a culture dimension not being addressed. Need more diversity to make sure these things work for everyone. Good data is also a problem. For this you need cooperation [interviewer: what do you mean?] Like in this study, why would I be honest if this doesn't have my interests at heart? AI fails on balance of culture and class. There is not wide enough participation. Good luck on PhD from your very comfortable position of privilege."

Industry

Both companies interviewed are household names in the UK (and potentially further afield), with yearly turnover greater than 1 billion pounds. They are both online retailers but in different industries. Both consider themselves technology companies, and both are thought of as technology leaders in their industries. Company 1 has over 20,000 employees, while company 2 has roughly 3,000 employees. In one company the interview was with the General Manager of Warehousing, and in the other the Head of Engineering and Automation in Warehousing. Both mentioned they were speaking candidly about their own opinions and teams, and what they said did not necessarily represent the company view.

Use of AI in Their Company

Both companies said AI is being used in their companies, with more of a focus on the website and customer data than their respective warehouses.

> "It is used extensively. Used throughout systems - such as modelling customer behavior or optimization of processes." (Company 1)

> "It is being used on a smaller scale than it will be in the future twelve months. It is being used more on the website, using customer data than in the warehouse, where it is in its infancy." (Company 2)

Company 2 went into more detail of how AI is being used in their warehouses to predict what items will be ordered next.

> "The order buffer system. Have you seen Monster's Inc? It's like the hanging door system but with hanging bags. Based on historical data, we may believe an item is going to be ordered. For example, if a stripy t-shirt is selling well, it would be useful for it to be at the front." (Company 2)

To understand the use of AI in these companies, they were asked why AI was being used. In both companies AI was being used to improve the customer experience. Company 1 said it was used where humans could not give insights as the data was so large. Company 2 said reducing human interaction would improve the customer experience.

> "… to optimize and make more efficient. Give better recommendations. Gain insights into large amounts of data, where humans can't. Due to the large volume or intricacy of the data." (Company 1)

> "To take away the human element. If the system can predict actions before they happen, there are less touches and less cost, less time. It's about giving the customer the best experience." (Company 2)

This is where the similarities in answers ended. The themes covered in these interviews are shown in **Figure 10** which demonstrates the similarities and differences between the two companies.

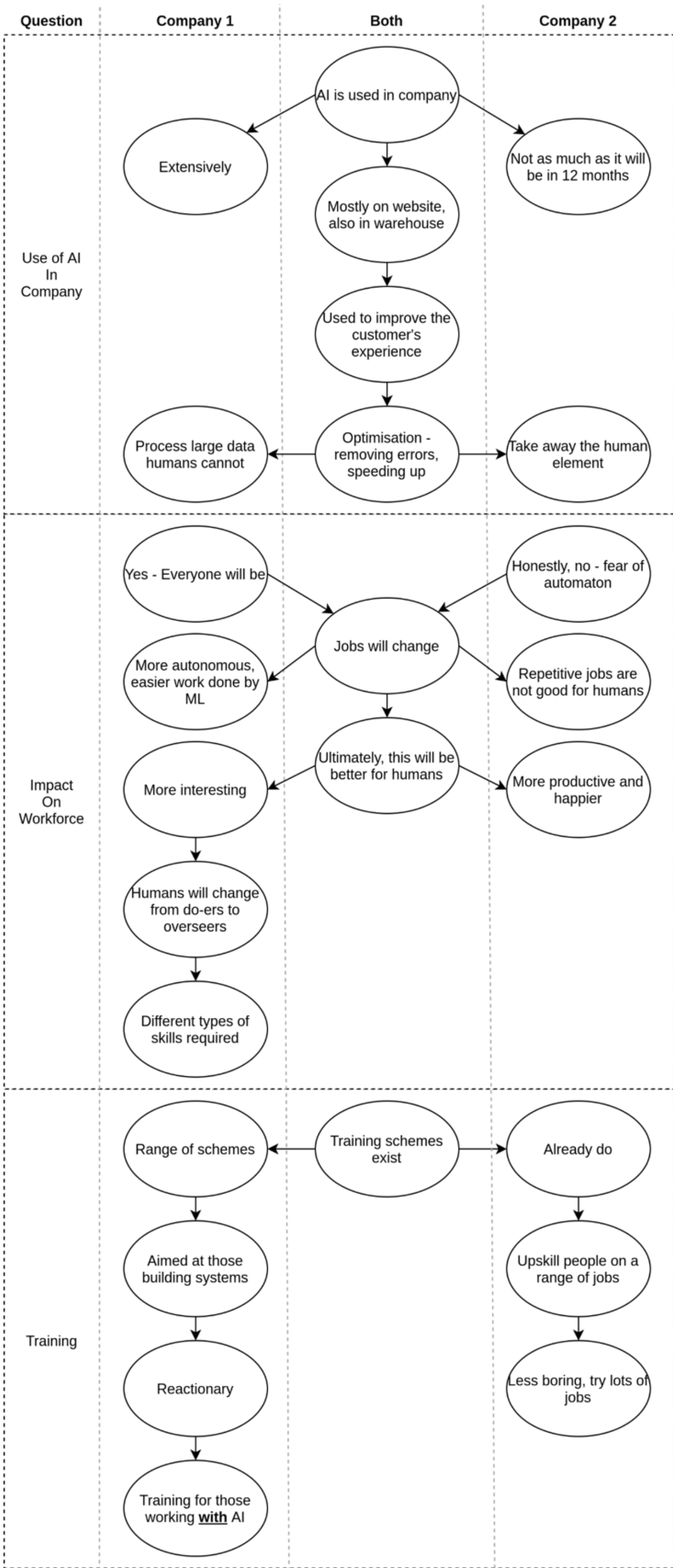


Figure 10 *- Comparison of two interviews with Industry. Each circle represents a topic which was mentioned. If only company 1 mentioned a topic, the circle is in the left column, only company 2 in the right and when both mentioned in the middle. As the questions progressed, the shared topics decrease.*

Impact of AI in Their Company

The impact of AI on their workforce had polar opposite initial responses, with Company 1 saying everyone would be impacted, and Company 2 saying they did not think there would be an impact.

> "Yes - everyone will be impacted by AI." (Company 1)

> "Honestly no. Fear of automation in general are horror stories." (Company 2)

Both companies continued, and softened on their initial stance. Company 1 discussed how things will change, but this will be a good thing as it will result in more interesting careers requiring new skills. The change from people "do-ers" to "overseers" was touched upon in interviews with Thought-Leaders and Adult Educators as well.

> "Roles will change, they will become more autonomous. I want to say easier, but I actually think ML will do the easier stuff. People will end up with more interesting careers. People are currently the do-ers, they will be overseers. It will require a different type of skill." (Company 1)

Along a similar vein, Company 2 went on to say that repetitive jobs will be not be for humans anymore. They viewed this as a good thing which will result in a happier, more productive workforce.

> "Repetitive jobs that aren't good for humans will be reassigned… People will be more productive and happier." (Company 2)

Training

Industry interviewees were also asked about current and future training plans. Both offer a range of training for their employees. Company 1 said these schemes were for those who would be building AI systems (rather than working with them) and for their executives. They also described their attitude to training as "reactionary", meaning they did not plan for advances rather responded to them.

> "We have a range of schemes, but they are focused on training people who build systems to optimize. At the executive level, we have a lot of training. Operator training is in its infancy… this is reactionary." (Company 1)

Company 2 had a different approach. They currently train their warehouse staff in multiple roles and in a number of tasks. This means workers have a more varied role, and as tasks are automated there is less chance of jobs being replaced.

> "We do anyway. We train people on multiple roles and tasks, we upskill people. It’s less boring and it means they are tried on lots of jobs." (Company 2)

The interview with Company 1 touched on training throughout. One point that was raised, with "picking robots" as the context, was the need for courses for those working with robots rather than building the systems.

> "There are lots of courses in coding, programming, etc, but not in working with robots or AI. For people who don’t need to build, but you need to work with them... courses on how to use AI and robotics as a collaborator, rather than a builder. " (Company 1)

The interviewee further went on to say that if such training courses do not exist, then it is understandable people in certain roles (where they may have to work with or may be replaced by AI or robotics) are more worried. These courses, the interviewee added, need to be general - about available careers and about a new way of working.

> "If almost no training courses are non-developer training course, then it makes sense that people in these areas are worried. We need to develop some general courses about the career paths available. We also need to shift people from one way of working to another." (Company 1)

Final Thought

While the interviews revealed very different stances on RAI and surrounding issues, both were extremely knowledgeable and interested in the topic and both offered further interviews or testing a potential educational course.

> "Interesting topic. Contact me if you need a second chat" (Company 2)

> "If in your research you come across or create any course, I would want to know and would be happy to do a fitness test" (Company 1)

Thought-Leaders

Is it AI?

A theme which came up throughout the conversations with Thought-Leaders was whether what we were discussing really counted as AI and what was defined as AI rather than ML or Data Science. One Thought-Leader used the term "data driven technology" which covered more than just AI, as discussions on this topic often include concepts not actually considered AI.

> "We use the term data-driven technology rather than just AI. As pure AI is far off. But decision based services, like logistic regression are already being used and we need to account for that. So it is to include up to and including AI."

This view was shared by another who saw AI as the future goal for Data Science.

> "For me AI is the end product of Data Science."

Others thought the term AI was too general, and that Machine Learning should be used instead.

> "AI is a very general word. I think about Machine Learning, ML - it is automation, lots of numbers..."

Social Challenges

Thought-Leaders were specifically asked about the challenges which need to be considered when designing an educational scheme on AI aimed at the general public. A lot of the challenges brought up were to do with social issues faced by members of the general public.

Demographics

The most common theme raised by this question was the differences in demographics. The sentiment of the target demographic changing the challenges was expressed by several Thought-Leaders. The different questions included young people vs adults, age, job and whether or not they were still in formal education.

> "Well my first question would be are you thinking about young people or adults?"

> "Depends on the people - age, job, like have they worked in a factory. 40 is harder than 20."

> "Training a 20 year old student is easy. Takes more time to train people who have other things going on."

> "I'm just checking it's not individuals in further education, higher education or apprenticeships?"

One Thought-Leader discussed research already carried out regarding attitudes to AI from different demographics.

> "There is research around different demographics and their knowledge about AI."

Barriers

Another challenge raised was barriers to physically attending such an educational scheme. They included time, working (i.e. getting time off to attend) and not having a computer or the internet. Barriers such as social mobility, affluence and not being in education were also brought up.

> "If you have part time jobs, it might be hard to attend. To attend training courses you need time and affluence."

> "Also, need to consider the barriers to retraining. People can't just take time off work to retrain."

> "Everything is aimed towards those with computers and the internet."

> "I think the main problem is affluence and social mobility if people not in education or apprenticeship to have the chance to learn about tech."

Lifelong Learning

The issue of people being out of education was discussed in more detail with regards to lifelong learning. One Thought-Leader explained that education is front loaded thus it would be difficult to return to education, but that lifelong learning does exist in particular careers such as doctors due to their professional development. Another suggested thinking about what lifelong learning is, and speaking to companies who do this.

"Not AI specific, but there is a long tradition of front loading education - school, uni, done. My parents are doctors and must do learning throughout their careers as part of their professional development as it's required. So lifelong learning exists in niches. So returning to education is difficult."

"You should be thinking about what is lifelong education? … Have you thought about talking to companies who do lifelong education?"

"Think about this like lifelong learning."

Understanding / Language

Several of the Thought-Leaders mentioned the issues around understanding, language and examples. Specifically, that the language is "over-technical in AI" and there are "no real examples". They further went on to say there is a "need to use realistic language" when discussing AI. One Thought-Leader gave a detailed example of issues that occur when common language and examples are not easily accessible:

"A basic example, we did some research with [a charity working with older people] patients where the youngest person was 65 and all ages upwards. We were very underprepared as this is conceptual. Unless people can touch or play with it, it was hard to have a meaningful conversation without leading them. There are groups of people, for example old people but others who don't even know what Siri is. We eventually got them to understand because one mentioned these old house wives books which everyone had and they had step by step instructions of how to treat a sick child. We were able to communicate using these as examples."

Attitudes to AI

The need to change "the narrative around AI", or "clear the air about AI", by explaining "what it can do and can't do" was discussed a number of times. The reasons for this were often cited as the media who "overhype" AI and are "obsessed with tech bros".

"oversell/hype about the patterns found"

"over-hyped media"

"We are often told bad points"

One Thought-Leader thought changing people's perceptions would be difficult, but needed.

"There is a need for general knowledge about setting the scene. It will be hard changing people’s mind about what AI can actually do."

The Thought-Leaders expressed a perceived lack of interest from the general public in learning about AI which needs to be addressed.

"Making anybody want to do it."

"Why should people care?"

"Inspiration is needed, students need to understand the point."

"There is a lack of agency for people. AI is bigger than them, life is bigger than them. It won’t change the needle, so why bother."

Teaching Challenges

A topic which repeatedly came up in the discussion of challenges was what should be taught and what needs to be taught on such an educational scheme.

"The second challenge is what to actually teach."

There was one general comment about how to teach. Projects should be included as students learning through discovery would help with their understanding.

"Project based learning. Make them fight to figure it out."

One Thought-Leader mentioned including ethics in the course as AI is used for decisions.

"AI teaching needs to have ethics as computer science will be optimizing and decision making."

There were conflicting opinions as to whether coding needs to be included in this type of education. It is worth noting that one Thought-Leader who claimed that coding "always" had to be included when teaching AI, also does not think "everyone should learn to code". Another questioned whether coding needed to be included at all, or just understanding AI from a personal perspective was enough.

> "Do people need to understand the technical side? Or is it just enough to understand how it touches their lives?"

> "Being able to code"

One Thought-Leader thought that statistics needed to be included in AI education.

> "From principles - understanding probabilities, Bayesian statistics as a way of looking at the world, distributions… Once you understand statistics, hook them in with what these can do - attractive applications."

Another issue pointed out was the lack of basic numeracy in the general public.

> "Basic numeracy is a big issue, as a lot of people leave school without this."

They went on to further say this would be an issue for teaching the coding side of AI.

> "If you were going to teach coding for data science and AI this [lack of basic numeracy] would be an issue, you'd need to understand the gap."

Communities

A concept raised repeatedly in these interviews was around communities. It was pointed out by one Thought-Leader this could be approached "from a national, regional and local level" and how such an education scheme is approached "depends on how long you have and what resources".

The challenges faced by different demographics has already been mentioned, but here was specifically mentioned in relation to AI training. No specific challenges or solutions were proposed, just that consideration must be given to the impact of AI and such courses on people's lives.

> "Communication with different demographics is often very different and needs to be given consideration. Need to consider where will the courses be, how will they be delivered."

> "What are the challenges met by these people? Envision how AI would make their lives better."

> "It raises the question are the tools we are designing even suitable or useful for these people?"

The potential impact of working with these communities and allowing their voices to be heard was pointed out by one Thought-Leader.

> "One of the most powerful things you can do is to go and speak to communities, and give them a voice in parliament."

One solution to reaching the target demographic was putting a large effort and numerous resources across society behind such an idea to ensure success.

> "A big national campaign. Every single fibre of academia, government and industry working on this. Using popular culture and a big spend."

Charities

Another proposed way of connecting with relevant people was through charities, as they allow a link to those who may have been "forgotten" by other initiatives. This wealth of resources and expertise is often overlooked.

> "The charity sector is often forgotten. How can we leverage charities, and how can we enable their people. For example, age concern, neurodiversity, mental health. Considering the off piste part of the population. Best way to connect to them is through charities. Those who are forgotten end up there."

A particular company, Simtlon, in France was discussed by one Thought-Leader as they could be relevant to such an education scheme. They offer training in data science and programming, targeted at disadvantaged communities where they will have the largest impact.

> "Simtlon - French large... training company. In programming and data science... What I like is that they target disadvantaged community. Who don't pay much to attend. They go to places with maximum impact social project. Training a 20 year old student is easy. Takes more time to train people who have other things going on. Most social impact is where the money is rarest. It's a paradox."

Women

A Thought-Leader brought up focusing on women as this could be a forgotten angle, but one which could have the greatest impact.

> "Returning-to-work workforce. Half the world's population - typically women who care for babies and parents. They come back to work and tech has moved on."

Working WITH AI

The notion of different levels of "AI literacy" was a topic of interest in several of the interviews. One Thought-Leader described these as "three types of skills":

1. "fundamental skills - numeracy, literacy, digital skills and ethics. These are the skills needed to function in everyday life"
2. "people who have jobs where they will work alongside AI in work - lawyers, doctors, accountants. Need to understand how it works, but not how to design it"
3. "tech people - academics, developers - who will be building and designing the AI"

Another Thought-Leader gave farmers as an example of the second group. They will need to work with AI, but will not need to code or build it.

> "It's actually past tech, for example farmers of seeds don't need to know the AI, but they will work with AI. Don't need to code, but need the ethics as they are a human supervisor."

The example of mechanics was given with reference to how humans interact with computers. Mechanics need to know the inner working of a car and how to fix it. Everyone needs to understand the basics if they use a car.

> "I'm more interested in Human Computer Interaction, which everyone should have a basic understanding. An example I like to think of is the mechanic - who needs to understand exactly how a car works and how to fix. But everyone who has a car needs to understand the basics. It is a more holistic understanding, and it must include ethics and the social impacts of their work."

The word "coworking" was used to describe how machines and humans should be working together. It is noted companies do not use this properly.

> "There should be coworking with machines and humans. But companies don't know how to utilize this."

This is further emphasized by discussions around tasks changing rather than jobs, and the need for empathy:

> "Job losses. It's not jobs being automated, it's little tasks. McKinsey studied the change in hours worked. They think it'll be 52% more on technical stuff. You need social empathy - understanding how the tasks change."

A Final Thought

One Thought-Leader emphasized the importance of work done on this topic not being accessible only by those in academia.

> "Make a version of your PhD that isn't academic. For normal people."

Adult Educators

Interviews were conducted with companies who provide education for adults (generally 18 or 19+). These ranged from council run adult learning services based in a local library, an 8-week software engineering bootcamp and a provider of Data Science Apprenticeships. The last two can be grouped together as 'for-profit' education providers.

The Adult Educators interviewed had a variety of roles - including director, tutor, head of subject, product manager and learning designer. Prior to their current roles their experiences ranged across industry, academia and teaching bringing a wealth of unique experiences and viewpoints to the discussions.

What is AI?

All Adult Educators said they knew what AI was, and were able to give a definition. These definitions were varied as some only claimed to know about AI in general, some taught or studied it and one was a self-professed "hobbyist".

Understanding and interest

All interviewees thought their learners would understand and be interested in learning about AI. All council-run tutors thought their learners would understand unreservedly. Some of those interviewed raised caveats to their learners understanding.

The director of the council-run service pointed out, that understanding and interest would be dependent on how such a course was delivered.

> "It would entirely depend on how it was pitched"

This was expanded as the course not having a "lengthy, academic feel" or including watching "hour long videos".

Those who claimed to know about AI (either through studying at university or by being a "hobbyist") were more skeptical of what level their learners would understand.

> "Understand is a big thing… Like I don't understand AI like someone with a PhD would… Given enough time. They would require a few more problems to understand abstract. Also, they would need help with analytics skills."

> "Basic concepts, yes. It is possible, depends on the depth... Basic classification, yes. More advanced maths, they might struggle with - like matrix multiplication."

Challenges

Maths

Adult educator with a mentioned interest in AI (either through their studies or hobbies), all further specifically mentioned maths skills as being pivotal to an AI education. This may explain their reservations about everyone understanding an AI course.

"We need to explain the underlying mathematical ideas"

"More advanced maths"

"For example, for the maths, doing the exercises over and over doesn't work"

This transcends the interview categories and came across in other categories (particularly Thought-Leaders) - if the interviewee had studied anything related to AI they mentioned the importance of mathematics. In all instances, this was brought up as a concern or challenge in teaching learners about AI. Maths was also mentioned by interviewees from council-run services, but more from the perspective of other courses they offer.

"In any subjects, maths is embedded throughout all courses. We like to ensure all our learners understand basic calculus."

"Our Maths tutors are amazing - they more than teach, change people's minds."

Analytics

Those already teaching courses related to AI (all happen to be 'for-profit' courses) all mentioned "analytics" in terms of skills or curriculum. Conversely, those teaching different courses did not mention this concept at all.

"they would need help with analytics skills."

Career-focus

'For-profit' companies are very career focused, particularly in terms of technology or data-science careers.

One interviewee actually mentioned the company was not considering the education from the learners' point of view.

"They are not thinking about this from the learner's point of view - they've not been in education for years, so don't understand the rigor. They also have a full time job, a life, a family. It's not an easy thing"

Design Considerations

Relevant and Embedded

The importance of making the education relevant to the learners was discussed by all Adult Educators.

> "People incorporate education that they need and which affects their lives."

> "Adaptability… Flexibility of both platforms and formats… Bitesized approach."

> "touches on their lives"

One suggestion to make it relevant was to find what motivates the learners (money, family, career and community), and make the education about these.

> "Money, immediate family and career are the main things that motivate our people. They also have a strong duty and agreement with their local community. They care more about this than any national scheme."

One way to make AI more relevant to their learners was to embed the subject into other topics. This was discussed by those in a more strategic role, such as director, product or learning designer.

> "It is also woven throughout."

> "How can we incorporate learning into work?"

> "I would embed it as a topic in other courses."

> "embedded into other activities…"

Co-Designing

One interviewee suggested an education scheme should be "co-designed with learners - actually adult learners, those with negative experience of education, diversity, unemployed".

They continued by discussing what would work for such a course would be "bitesize", "could be done in chunks", "embedded into other activities", "this is AI, you should know what it is" "co-designed" "include things like what are you doing about your family or talking to your kids, their careers, the market."

Charities and Women

A suggestion which was also made by a Thought-Leader was reiterated by an Adult Educator. They mentioned a possible way of reaching people is through charities, and highlight one particular charity, Smartworks, which target out of work women who would potentially be available to attend training.

> "Maybe look at the dress for success charity - Smartworks. They help find outfits for women and do interview prep skills. They are usually out of work, so could be a potential for classes."

Final Thought

A piece of advice which was given by one Adult Educator which is useful to keep in mind is:

> "It is important people have the headache before you give them any aspirin."

This quote was to illustrate that offering education on a topic irrelevant or unsuited to members of the public may not be deemed useful. To ensure such an education scheme was needed and wanted, conversations with industry and members of the public were considered to be needed.

Discussion

All the data presented in the findings is important, and provides insight into the AI education landscape. In considering this data through the lens of leaving no one behind as technologies such as RAI advance, three main themes have emerged which could have significant impact on any future educational initiative aiming to ensure we leave no one behind:

1. Education for those working *with* RAI
2. Overcoming preconceptions (of learners, industry and experts)
3. Co-designing in communities

It is important to highlight some limitations with these findings and the resulting discussion. As described in the method, due to the nature of this research, the results are not meant to be taken outside of the particular settings, places and spaces of the interviews. The interviews were focused on the UK, as the initial aim is to design education for a UK audience. The UK has a strong focus on AI, and it seemed logical to start with one country and expand from there in future research as AI education is a global discussion. Education is also not something which can be easily replicated country to country (take for example the Danish school system) as many political, social and economic factors impact education, making the decision to focus on one country feel necessary. There are a wide range of socio-cultural issues which would influence the attitudes and adoption of AI education that have not been covered by these interviews. This research does not touch on the many very important technological, psychological, social and environmental reasons which impact attitudes towards technology and automation. These were not brought up in any of the interviews, so have not been included in the discussion.

Education for Those Working With RAI

There is a focus on education and retraining for those who will be developing, designing or researching RAI. These are the group referred to by one of the Thought-Leaders as "tech people". Typically, people in this group are already highly skilled and have a high level of education. It is predicted these type of roles will increase in the short-term, however whether this will continue or be at risk of automation in the future is debated. However, this is not a group at risk of being left behind.

The original focus of this research was into education for the general public, in particular those at greatest risk of being left behind. However, a third piece seems to be missing - education for those working *with* RAI. This type of education was brought up in one of the Industry interviews and by several Thought-Leaders, and would include those working in warehouses alongside robots and those working in call centers who may be working with algorithms and digital assistants. Roles such as these would not require employees to create or change the RAI systems. Employees would not need to understand in detail how these systems work, or how to code them. They would need a basic understanding of the workings, how to troubleshoot the systems and some knowledge around limitations and suitable uses. Creating working environments where humans and technology work alongside each other could be an important step as the Fourth Industrial Revolution advances. Education for these workers could prevent jobs losses and allay fears of RAI.

Overcoming Preconceptions

Previous work has highlighted the need to overcome preconceptions (both in education and in RAI systems themselves). The interviews highlighted three areas of preconceptions which would need to be overcome for the planned education to be successful. First is the preconceptions which every individual member of public will bring to such an education. Secondly, there are presumptions regarding the ability of members of public to learn about RAI from experts which create potential barriers for learners. Finally, the attitudes found in industry towards training will also need to be confronted and addressed.

Individual Preconceptions

All MoPs came across as comfortable discussing AI. They had opinions on AI which were influenced by their individual lives, including their jobs and the news they consume. Such influences towards RAI need to be considered in the design of education.

The interviews in this research focused solely on AI, but due to the lack of distinction between AI and Robotics for MoPs, any future education scheme should be Robotics *and* AI. Their lack of distinction is shown by the examples of AI given being equally software and hardware examples (as can be seen in **Figure 7**). Very generally, AI is seen as software and robotics is seen more as physical devices by experts (although this is not a hard rule, and potentially becomes confusing as AI and Robotics can exist in the same device). KPMG (KPMG, 2018) had a similar finding - those with less knowledge of AI did not distinguish between AI and Robotics. The examples given by MoPs were very broad - ranging from everyday hardware to use-specific software. The software examples included a lot of products from "Tech Giants". The examples given were not ones which would necessarily be expected, and overlooked a lot of more common examples of AI, such as self-checkouts. The examples from the news were mostly negative, which suggests how AI is sometimes portrayed by the media.

It is interesting to note that the inability to define AI is not limited to MoPs – no one from any of the other groups had a clear definition of AI. Within academia, industry and policy, this is a constant discussion. This could be due to the word “intelligence” causing confusion, and further research into whether omitting this term in research for “data” or “coding” education could provide more clarity. The

Elements of AI [33] course goes as far to begin by saying, a definition is not important. Perhaps a similar attitude should be taken, and the focus shifted from definition to action.

Throughout the interviews MoPs expressed more concerns than optimism (comparing **Figure 8** and **Figure 9** confirms this). Several negative stories come from the news. The concerns also tended to be more specific and personal, while the optimisms were very general (e.g. it being useful). All of these perceptions of AI suggest there is a lot to be addressed in any AI education before anything substantial can be taught. This includes what RAI is, where it is used now, limitations and how concerns can be addressed. Perhaps this itself is more important than the general public actually understanding or building AI.

The MoPs shared concerns surrounding their data being used and shared. People in the UK are most comfortable sharing their data with the NHS, (KPMG, 2018) and this could be a useful way to help people understand AI.

When asked explicitly about AI training, most MoPs said they would not be interested. However, with discussion or further questioning, they all expressed an interest in training. Some rethought how training would be relevant to their lives, and others were interested in specific aspects, for example understanding how AI works or the impact of AI on the public. This highlights the importance of language when discussing AI education, and how reframing can attract more positive attitudes and different insight. The responses from MoPs regarding AI training showed this type of training is viewed as not widely available and only for experts or those in academia. This could reflect a wider view of education, as not being seen as for everyone. This barrier also needs to be overcome in the design of the education - ensuring the education does not feel academic or elitist and is relevant to those who need it most.

Expert Gatekeeping

An unexpected theme which arose across groups, particularly the Thought-Leaders and Adult Educators, was the attitude of those who had studied AI from a technical perspective, or were self-confessed "hobbyists". These technologists expressed their concern or disbelief that the general public could learn about AI. The issues they saw were with the mathematical ability, and coding skills of the general public. Such an attitude from those already exposed to AI could potentially be a form of gatekeeping which will only enforce or increase inequality and digital exclusion. The responses on this theme seem to suggest some assumptions - firstly, an AI education requires understanding of underlying mathematical educations, and any AI education must include a coding component. Secondly, the general public would not be able to grasp these elements. These assumptions could stem from RAI education being focused on the technology side (for ''tech people"). A further factor could be the lack of compulsory post-16 maths education in the UK, and the so-called ''maths anxiety" experienced by many. It would be important to understand if these assumptions are held throughout the RAI community, particularly with technologists. If they do exist, understanding why they exist and how to overcome them would be necessary for an educational scheme to have the necessary support of the community.

Others questioned whether the general public would want to learn about AI. This ties in with the responses from the Members of Public into whether or not they would be interested in training in AI. It is worth noting, these views from those experts could feed back into the perception from the public that training on AI is not for them.

Industry Attitudes to Training

For any education or training in RAI specifically aimed at workers (including for those working *with* RAI) to be relevant and useful, industry needs to be involved in its design and delivery. Understanding the attitudes and approaches to retraining and education from companies likely to be impacted by RAI is imperative as they will be major players in avoiding workers being left behind.

The interviews with industry revealed two varying stances to retraining on AI - proactive and reactive. The proactive company was consciously thinking about the retraining needs of their warehouse employees. They ensured employees were trained on a number of roles and tasks to minimize disruption as tasks are automated. They also felt this gave employees a more satisfying experience in work. The reactive company waited until change happened to provide retraining only once there was a business need for such training. While it is still positive that training is offered to some employees, this approach could cause potential job loss and does not focus on the employees and their needs.

Both companies involved in the research were founded in the past 20 years (in the same year), and both are publicly traded companies. They are both e-Commerce companies, with warehouses who deliver to consumers homes, but operate in different goods. Based on their publicly available 2018 company reports, the proactive company has double the revenue and profit of the reactive one. The reactive company had three times as many employees as the proactive one. Both of these factors could go towards explaining the difference in attitudes towards automation and retraining. Having more money and fewer employees, and thus more money available for training per employee, could allow a proactive attitude to training more easily.

While these interviews show two varying attitudes in industry, other attitudes may exist and also need to be addressed. Working with companies to get a deeper understanding of these attitudes and how they would impact potential educational schemes for their employees, and if retraining could be leveraged to prevent job losses, could greatly increase the impact of such schemes. For education for those working *with* RAI to be impactful, the different attitudes will need to be understood and, perhaps, different ways for these companies to incorporate such education needs to be developed. Both PwC (PWC, 2017) and WEF (WEF, 2018) discuss the need for corporate training and education, particularly to negate the impacts of automation on those in roles which do not require high levels of education or specifically sought after skills. WEF further discusses the need for collaboration between employers, government and local education institutions. A potential way forward is co-designing education which works for employers and employees.

Co-Designing with Communities

One concern raised by Thought-Leaders was how to reach the people this type of education would benefit most. One pointed out the areas where the most social impact can be made, often attract the least funding. A solution was also put forward in several interviews which would be working with charities. Charities work with those often left behind and excluded. Several charities were suggested, and many more found which could be partners for an educational scheme.

Educating women was also mentioned in the interviews. RAI, technology and engineering are still male dominated fields, educating women could work towards a more equal workforce. Working with local communities, such as libraries, adult learning schemes and other community points of interest, was discussed by the Adult Educators. A focus on making the education relevant and useful, with regards to families and local communities would help its success. "Co-designing" the education with the people it would benefit was also seen as extremely important. Embracing co-design and working with local communities, through charities, would likely go a long way towards creating a relevant, useful educational initiative for those at risk of being left behind. Similarly, working with industry and unions, were appropriate, could create a more appropriate education for those working *with* RAI).

The final point in the MoPs findings alludes to a viewpoint which could be detrimental to the success of any RAI education of the public. Mis-trust of education, academia and technology are complex, work to understand and address these issues (Snodgrass, 2017; The Royal Society, 2017) should be built upon and incorporated into education design and delivery.

It is worth noting here that co-design is a potential tool for rethinking a more equitable future. Ensuring the outcome of the fourth industrial revolution works for everyone needs more than just education, and co-design can be used to deliver this. Co-designing technology, laws, systems and cities are becoming more common and have had success delivering solutions which work for all parties involved. (Bourazeri and Stumpf, 2018; Bassetti *et al.*, 2019; Naqshbandi *et al.*, 2019) Co-designing RAI is another aspect which could greatly improve attitudes and outcomes, having RAI education either separate or part of this process could be an important way to drive success.

A framework for co-design as collaborative research is laid out in the work of Zamenopoulos and Alexious (Zamenopoulos and Alexiou, 2018). Using such a framework to guide any further research could lead to greater inclusion, as the co-design could help understand why the initial response to AI training was negative. The aim of using co-design is to involve the learners from the beginning of the design process and to allow them to guide what they need and want. This type of flexibility in education design is often missing from formal education. Therefore, co-design may be a useful method for reaching those potentially left behind.

Conclusions

As technologies such as Robotics and AI advance, there is a risk of people being left behind if they are not given opportunities to learn about and use these technologies in both everyday life and work. Education for those most likely to be left behind needs to be designed specifically with these people in mind, as often other educational initiatives (such as returning to University) would not work for this group. To better understand the needs and attitudes towards RAI, particularly RAI training, semi-structured interviews with four groups of stakeholders were carried out. 21 individuals were interviewed from Thought-Leaders, Industry, Adult Educators and Members of Public, as buy in from these four groups would be needed for any educational initiative to be successful. The data was analyzed using Thematic Analysis, and the findings viewed through a lens of no one being left behind.

The interviews with various groups were received positively which suggests the needed support for such educational initiatives would be found. The interviews also highlight the amount of work which still needs to be done. One important next step is to create separate educational initiatives for the community (to learn about RAI and the impact on their lives) and for those working *with* RAI (to learn about RAI and how to use it for their jobs). Both these educational initiatives need to be **co-designed** with the relevant communities (socially or industry). There are many preconceptions which need to be overcome for education to be successful. The opinions of the learners based on their individual lives need to be addressed in any education. Potential gatekeeping from experts towards barriers may be preventing the public from learning about RAI and need to be understood and overcome. As do the varying attitudes to training within industry.

Postface

The paper in this chapter explored the conversations with 21 potential stakeholders in AI education. An aim of this chapter was to give focus to the discussions with the members of public to ensure their voices are foregrounded and central to of any education design. The findings from the 21 interviews highlighted some barriers which were unexpected and need to be addressed either prior or in the design of any education curriculum, tool or package. First, as was highlighted in Chapter 2, there is a need for education for those who will be working with or alongside AI. Second, there are a number of preconceptions which need to be overcome. These came from all groups of stakeholders interviewed in this chapter. The members of public were highly influenced by their jobs and background which needs to be factored into any AI education design. Important points to be noted about members of public – how they are asked about AI training is really important in terms of how they respond , and their definition of what AI is, and examples of AI differ from experts. An unexpected preconception came from experts who were interviewed and who demonstrated a level of gatekeeping in their pre- (or mis-)

conceptions about members of public (mainly their abilities or desires to learning about AI). A final preconception noted in this chapter was the varying attitudes to training within industry, which could hinder any collaborate effort for designing work-based education. Finally, the importance of co-designing with the communities who will be partaking in the education was highlighted. They bring their own viewpoints and needs to the table which could easily be overlooked by an expert (such as myself) designing AI education. These finding, to me at least, highlight the necessity and beauty of qualitative research – allowing voices which may not be heard otherwise to have a say and an impact.

Chapter 5: Survey – Members of Public

Preface

The previous interviews chapter highlighted some unexpected barriers which need to be addressed either before or during any co-design of AI education for working adults. The initial plan was to work on a community co-design with local community hubs based on the findings of the interviews, however as the pandemic pushed everything online, and the barriers highlighted warranted some extra attention, online surveys to understand requirements to work in AI were conducted.

With this new overall focus for the research, two online surveys were designed with comparable questions. One for members of public which will be the focus of this chapter, and one for hiring managers which will be covered in the next chapter. These surveys were, again, qualitative rather than quantitative to allow freedom of expression (all answers were free-text boxes rather than pre-defined choices). The members of the public survey aimed to understand their perception of requirements to work in AI-related areas. It further asked how these requirements could be obtained and how difficult this would be. There were 39 responses to the survey, which greatly varied in length. The responses were analysed using both a novel NLP technique I developed and qualitative methods to provide a depth of insight into the viewpoints on the requirements to work in AI-related jobs. An example of these qualitative methods (coding, categorization and thematic analysis) can be found in *Appendix 2 – Illustration of Coding Answers to One Survey Question* which shows how one survey question was analysed. This analysis resulted in two diagrams in the following paper (**Figure 26** and **Figure 27**).

Paper - Clearing the Path - Understanding How Inaccurate Assumptions Muddy the Route for People to Move into AI Jobs

Authors - Laura Gemmell, Lucy Wenham*, Sabine Hauert* (*Provided supervision over the work)

Keywords: AI, retraining, gatekeeping, NLP, survey, lifelong learning

This paper has been submitted to a journal.

Abstract

There has been a drastic increase in jobs in Data Science, Machine Learning and Artificial Intelligence, as well as a push for more people to retrain in these areas. A survey was conducted to better understand what members of the public see as the requirements to work in these areas. They were asked about what skills, qualifications and traits would be needed. They were also asked how to obtain the requirements and how difficult they thought it would be. The responses were analysed using both natural language processing (sentiment analysis and clustering) and qualitative methods (qualitative coding, and thematic analysis). The analysis showed there still exists stereotypical thinking surrounding these areas, with a focus on coding, maths and problem solving. There was no mention of any roles other than technical ones, despite the survey not specifying these. The respondents, even those who considered a degree was necessary, did not see a clear path into these areas. Also, there were clear clusters of thinking influenced by age, working in technology, current interest in the areas and attitude towards technology. These clusters show that the messaging should be different for different populations to encourage participation.

Introduction

Data Science, Machine Learning and Artificial Intelligence are all growing job areas; however, it is unclear whether the public perception of what is needed to work in these areas matches the job requirements. To gain a better understanding, a survey was designed for members of the public asking what skills, qualifications and traits they believed to be necessary; as well as how these could be obtained, and how easy it is to do so.

Previous research shows the public do not see a difference between Data Science (DS), Machine Learning (ML) and Artificial Intelligence (AI) (The Royal Society, 2017; KPMG, 2018; Gemmell, Wenham and Hauert, 2021). This research also suggests the public do not differentiate between robotics and AI. Following these findings, DS, ML and AI have been grouped together in this survey and paper; as the public do not see a difference, robotics was not included in the survey questions.

Background

Demand

PwC's *Sizing the prize - What's the real value of AI for your business and how can you capitalise?* report (PwC, 2017) predicts $15.7 trillion increase in the global economy due to AI by 2030. In this report, AI is used in a broad sense, including automation, digital assistants and ML. The report also warns companies of potential skills shortages (particularly for roles including data scientist and robotics engineer).

As a result of these increases, it is predicted demand for DS, ML and AI roles will continue to rise in years to come. The AI Index 2021 (Zhang *et al.*, 2021) found despite COVID-19 AI-hiring continued to grow in all countries included in their sample, with Brazil, India, Canada, Singapore, and South Africa having the highest growth from 2016 to 2020.

A 2019 report by the Royal Society (Royal Society, 2019) saw a 231% increase in data science roles advertised across the UK from 2013 to 2018. Both *AI Practitioners* and *Data Science Specialist* made it into LinkedIn's 2021 jobs on the rise in the US (Insights from LinkedIn, 2021).

Job Requirements

While demand for these roles is increasing, there is not a clearly defined list of requirements for the roles. The OECD looked at AI-related skills for jobs (both related to and not-related to AI) in 2012 and 2018 (Squicciarini and Nachtigall, 2021). The report found 30% of skills in 2018 were software skills, however software engineering and development lost importance from 2012 to 2018. In 2018 there was much more of a focus on Natural Language Processing (NLP) and deep learning. Throughout the time period, there were spikes in certain specific skills (such as data mining, machine vision and deep learning). The report also found communication, problem solving, creativity and teamwork skills become more important between 2012 and 2018. Another report by the OECD (Grundke *et al.*, 2018) found similar skills (self-organisation, management and communication) were needed by future workers, particularly those working in digital related roles.

The Royal Society (Royal Society, 2019) reported the top ten skills from advertised data science roles as Data Science, Python, SQL, Machine Learning, Big Data, research, Apache Hadoop, Communication Skills, Java and Scala. The vast majority of these skills are specific technology skills. Data Science, Machine Learning and Big Data are broader technology areas. Only two of these skills were non-technical – research and communication skills.

Each of these reports paints a very different picture of what is required for these roles, as such it may not be easy for members of the public who do not already work in these areas or closely related areas to understand what they should focus on if they wanted to learn more about DS, ML and AI or change jobs. This survey aims to provide some insight into public perception of requirements as a first step towards creating a clearer path for anyone interested in DS, ML and AI.

Methodology

Survey Design

An online survey was chosen over interviews for several reasons, including reaching more people, time constraints and the on-going pandemic (Evans and Mathur, 2005). To allow participants freedom to speak in their own words, a qualitative survey (Braun *et al.*, 2020) was chosen with open-ended questions and free text boxes for answers (Sischka *et al.*, 2020) (as opposed to taking a quantitative approach or using constraining closed questions with pre-defined answers to choose from).

The survey was designed to be inclusive, so as to be accessible to a range of members of the public - the wording was clear and non-technical (both in the survey itself and any accompanying text) everyone, even those who did not know how to answer or had no experience in DS, ML or AI, was encouraged to participate and would be important to the results (Atkins and Duckworth, 2019). The responses were also anonymous, and the demographic questions were optional in order to encourage participation.

Survey Questions

The survey began with a series of filtering questions to determine the individual’s current relationship with DS, ML and AI. These were a series of Yes / No questions. If a respondent answered Yes to any, they were not shown the rest.

1. Do you currently work in a data science, machine learning or artificial intelligence job?
2. Are you currently working towards a data science, machine learning or artificial intelligence job?
3. Are these types of jobs something you would be interested in?
4. Is learning about artificial intelligence something you would be interested in?

The next section of the survey was the main body of questions, related to DS, ML and AI requirements for jobs. These questions were open text boxes. The aim of this section was to allow respondents to give as much or as little detail as possible to gain a deeper understanding of their views around the needed skills, qualifications and traits for working in DS, ML and AI.

1. When thinking about roles working with artificial intelligence, are there any specific skills, qualifications or traits which are necessary? Please list as few or as many as you like.
    a) Skills
    b) Qualifications
    c) Traits
2. How might you learn / develop / obtain these? Please give any specific details. (If you are already working on these, please add any details you feel necessary)
3. In your experience or opinion, how easy or difficult is it to gain the necessary skills, qualifications and traits for these roles? Can you say a little bit about why you gave this answer?

Finally, some optional demographic questions were included to determine the respondents’ location, age, gender and job.

Survey Recruitment

The recruitment for the survey was conducted through friends, family and online groups (either closed or private groups to ensure the link was not shared publicly to avoid spamming and bots). These groups were on Facebook, WhatsApp and Slack and included social, technology and community groups.

The survey was conducted using Google Forms, and as such a link was shared with potential respondents and in groups.

Analysis

The responses were analysed in two ways - using Natural Language Processing (NLP) and qualitative analysis methods – both required different analytic approaches.

NLP Processing of Combined Survey Responses

All NLP analysis was carried out in Python 3, the responses were uploaded from a CSV file and sorted in a Pandas dataframe. All five answers were combined for each respondent, separated by a space.

Preprocessing

Before any NLP is performed, it is important to ensure the data is cleaned (or preprocessed) to provide the best results from the algorithm used. Preprocessing for NLP usually follows some standard steps – cleaning, parts of speech tagging, stemming or lemmitisation and stop word removal (Krishna *et al.*, 2014; S Vijayarani, J Ilamathi and Nithya, 2015; Denny and Spirling, 2018). Firstly, contractions (shortened versions of words, for example “don’t” and “can’t”) were expanded to their non-contracted form using the library *Contractions*. As a consequence of how some answers were written (for example, “programming/coding”) *Regex* was used to remove punctuation and replace with a space. All words were made lower case, and *Regex* was again used to remove whitespace (including extra spaces and new lines).

The next step is to split the responses into tokens, this was done using
the *NLTK* library. Tokenisation was carried out after downloading the *punkt* package. Within this package, *ntlk.tokenize.wordtokenize* was used on every individual response to separate into an array of individual words. The *NLTK* package *averaged_perception_tagger* was used to tag the tokens as particular Parts of Speech using the *pos_tag* function. These parts of speech were mapped into the NLTK wordnet parts of speech using the *nltk.corpus.wordnet* package. Finally, the tokens were lemmitised by feeding the tokens and the parts of speech into the *WordNetLemmatizer* function from the same package. If the pos_tag could not be mapped to a wordnet tag, only the token was passed to this function. Lemmitisation was chosen over stemming as this often produces more accurate results, particularly when words will be used of tokens during analysis (Balakrishnan and Lloyd-yemoh, 2014).

The lemmatization had removed the "e" from the end of the word "code" (when it was used as a verb) and "ing" from "coding", to give "cod". These were both changed to "code" before continuing.

As some of the common words were actually part of a phrase which changed the meaning - for example, "machine learning" and "online learning" are specific terms and not necessarily similar to the word learning being used by itself. This step was included before removing stop words due to phrases such as "on the job" and "i do not know" which would be changed with stop word removal.
The *phrases* function from *Genism models* library was used with the parameters set as min_count = 1 and threshold = 2. This means phrases (in this case bi-grams) which occur more than once will be counted as phrases. The results were run through the same function again to create 3-word phrases. Phrases are saved as words separated by an underscore.

Finally, stopwords were removed using the *NLTK stopwords* list in English. To ensure the phrases included were not completely made up of stopwords, a phrase was removed if all words are a stop word (for example, "in_a").

Sentiment

Sentiment analysis was used to determine how positive or negative the responses to the survey were. The sentiment of the combined answers (after the lemmitisation step (Angiani *et al.*, 2016)) was computed using the *Textblob* library.

Clustering

Clustering was performed on the survey responses to determine if any interesting grouping would be found by the algorithm. The similarity between the responses was computed using hierarchical clustering with Euclidean distances and Ward's method for stopping. The method involves looking at how often particular terms occur in each response.

Further steps are required before carrying out any clustering analysis (Krishna *et al.*, 2014). The first step to the clustering analysis was to create a similarity matrix.

The *Sklearn.feature_extraction.text* library was used. The following function was used to create a similarity matrix based on the Term Frequency Inverse Document Frequency of the responses:

TfidfVectorizer(preprocessed_combined_response, Max_df = 0.9, min_df = 2, lowercase = True, use_idf = True, norm=u'l2', smooth_idf=True)

The similarity matrix was used to create a distance matrix with itself. To compare the results, both a Euclidean Distance and Cosine Similarity matrix was created used the *Sklearn.metrics.pairwise* library (functions Euclidean_distances / cosine_similarity).

The clustering algorithm used was hierarchical clustering. This was implemented using the *Scipy.cluster.hierarchy* package, function *linkage* on the Euclidean distance matrix with the method set to 'ward'. From the same package, the *dendrogram* function was used to plot. Finally, from the same package, the *Fcluster* function was used to on this matrix to assign the cluster labels (with max distance set to 2.3 and criterion = 'distance').

Mapping the difference between these clusters produced a dendrogram (**Figure 11**). Each line represents a response to the survey. Initially, all responses start in their own cluster with each iteration of the algorithm, the two most similar clusters are joined together. This is repeated until there is only

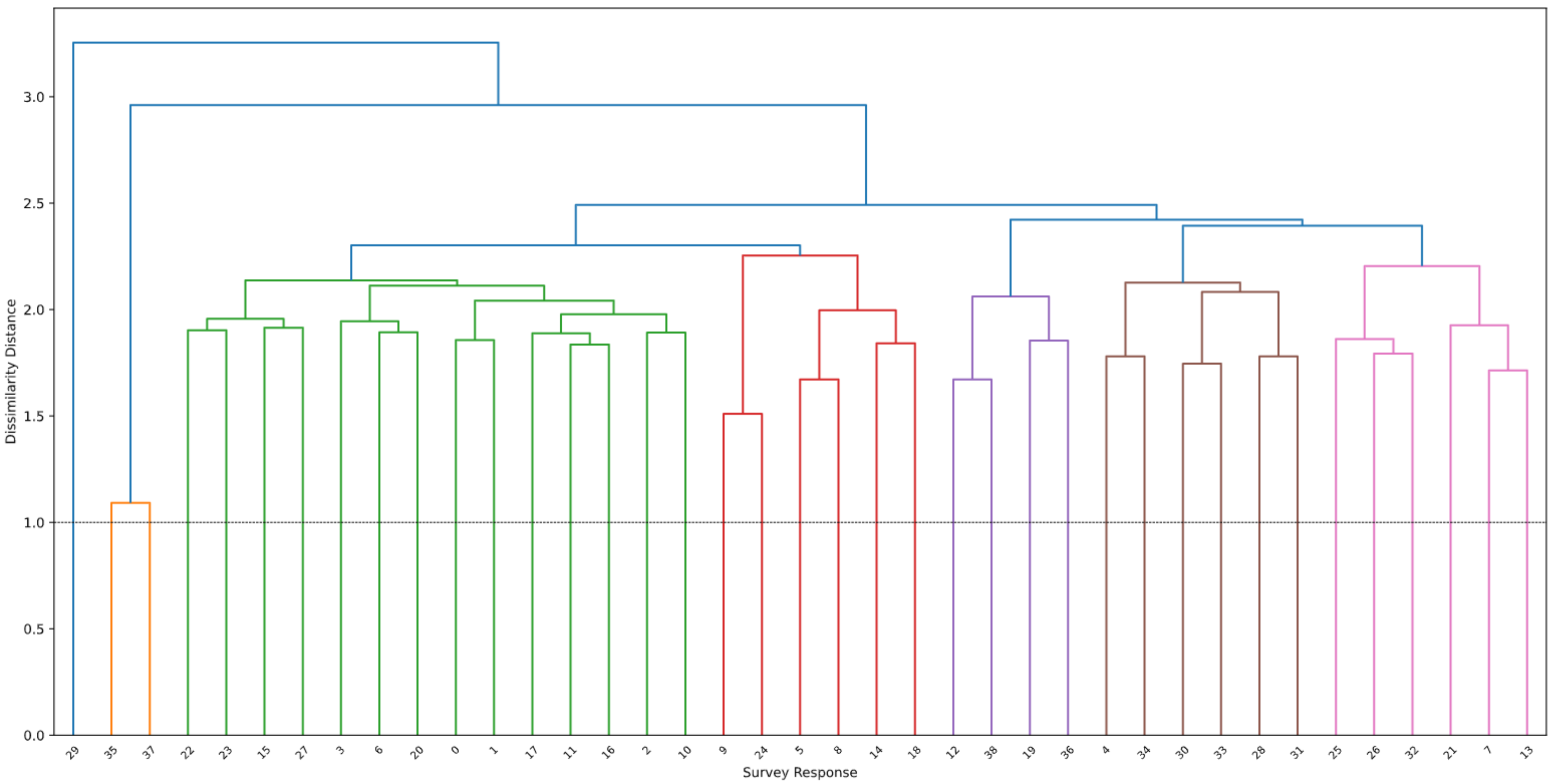


***Figure 11** – Dendrogram Showing the similarity distance between survey responses. Colours indicate different clusters. The height of the lines shows how dissimilar the survey responses, and clusters, are (i.e. shorter lines show clusters are more similar).*

one cluster containing all responses. There are many methods for how clusters are decided, in this case the max_distance criterion is used to determine the threshold above which clusters will not be merged. The clusters are represented using a different colour. The length of the lines showing dissimilarity, i.e. responses 35 and 37 (second and third from the left) are the most similar as their lines are shortest. Conversely, the response further left is the most dissimilar from all other responses.

There were 7 clear clusters (taking a distance of maximum 2.2), these can be seen in distinct colours in the dendrogram and have been numbered from 1 to 7 left to right. Euclidean similarity was used rather than Cosine similarity due to certain clusters (one where the respondent only answered "." and another of two respondents who gave only "don't know" or one-word answers) being clearly identified as separate from the other responses. These two clusters can be seen as the blue and orange lines to the furthest left in the dendrogram. The clusters identified by Cosine similarity were quite similar to those identifed by the Euclidean – one was exactly the same and the majority of the others only differed by one or two respondents.

Qualitative Analysis of Responses

The answers were looked at individually without any NLP to gain a deeper insight into the meaning of responses. The approach was to use established qualitative analysis techniques of initial coding and categorising to identify themes amongst the responses to each question (Braun and Clarke, 2006).

Findings

Demographics

Demographic questions were asked at the end of the survey and were optional. This survey did not use sampling in any way and as such does not give generalisable insights to any populations. These demographics are used to show the types of respondents answering, and to see if any trends or patterns emerged when looking at the data cut by them.

Location

Nearly 80% of respondents were based in the UK. Around 85% of respondents were based in urban areas and 10% in rural areas. All rural respondents were within the UK. Two respondents did not respond (one in the UK and one not).

Gender

Gender was left as a blank text box for respondents to complete as comfortable. One respondent did not answer. The other 38 responded with Male or Female (or something which could be mapped as such, for example M or F). Two-thirds of respondents were female, which is likely due to the groups where the survey was shared (for example, Women Who Code - Data Science, Bristol Girls).

Ages

As with gender, age was a blank text for respondents to complete. These ages were then grouped together in four groups – 20-29, 30-39, 40-49 and 60+ (shown in **Figure 12**). 3 respondents did not give their age. Nearly half of respondents were in the age group 30-39, 11 were 20-29, 5 40-49 and 3 were

60+. There were no respondents aged between 50 and 59. Again, these could have been influenced by where the survey was shared.

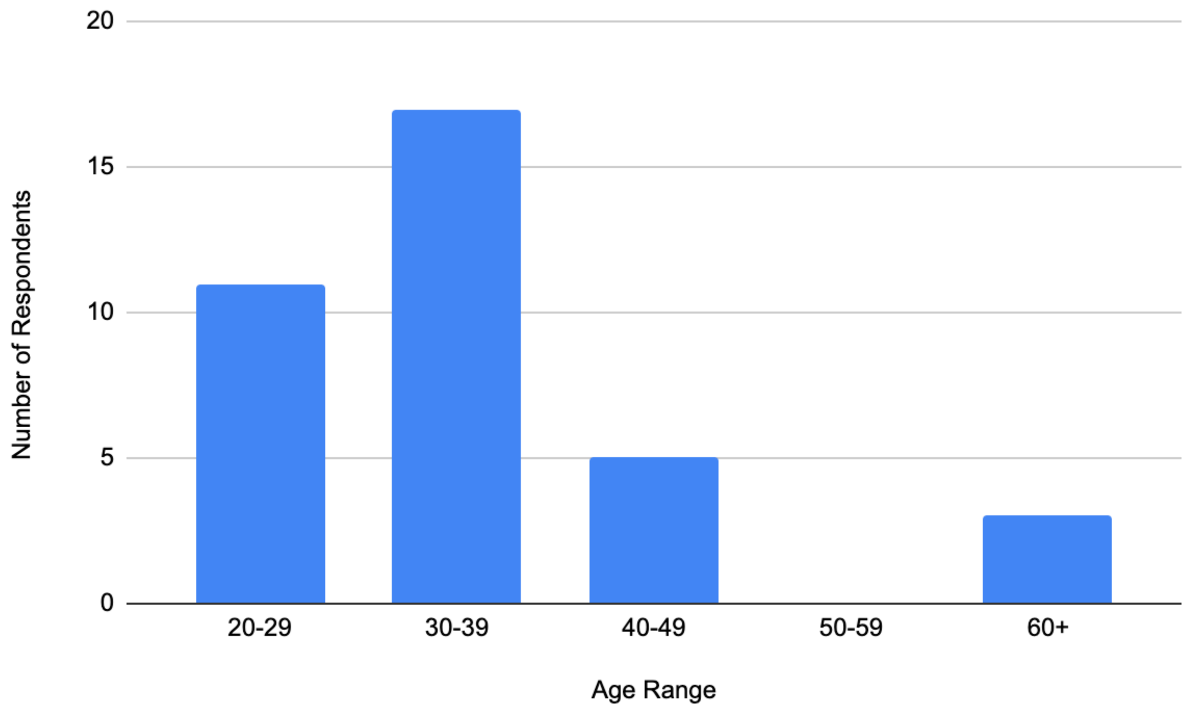


***Figure 12** - Number of survey responses per age range showing the distribution of respondents across ages. The majority of respondents were under 40. "-" indicates the respondent did not specify their age.*

Job

Respondents were also given a free text box to describe their jobs. Based on this, two categorisations were added – industry and whether the job itself was within tech or not. For industries, only industries with more than two respondents will be discussed to protect identity of respondents. The largest industry was 'Tech' which included data analysts, software developers and those who already work in one of DS, ML or AI. There were four respondents who worked in education, and a further four who were students. Three respondents were in Creative, Finance and Medical jobs.

Job titles were further split into tech (43.6%), non-tech (46.2%) and unknown (10.3%). For example, the *Education* industry category was made up of teachers and those who work for an EdTech company, these would be categorised as non-tech and tech respectively.

Current Relationship to DS, ML and AI

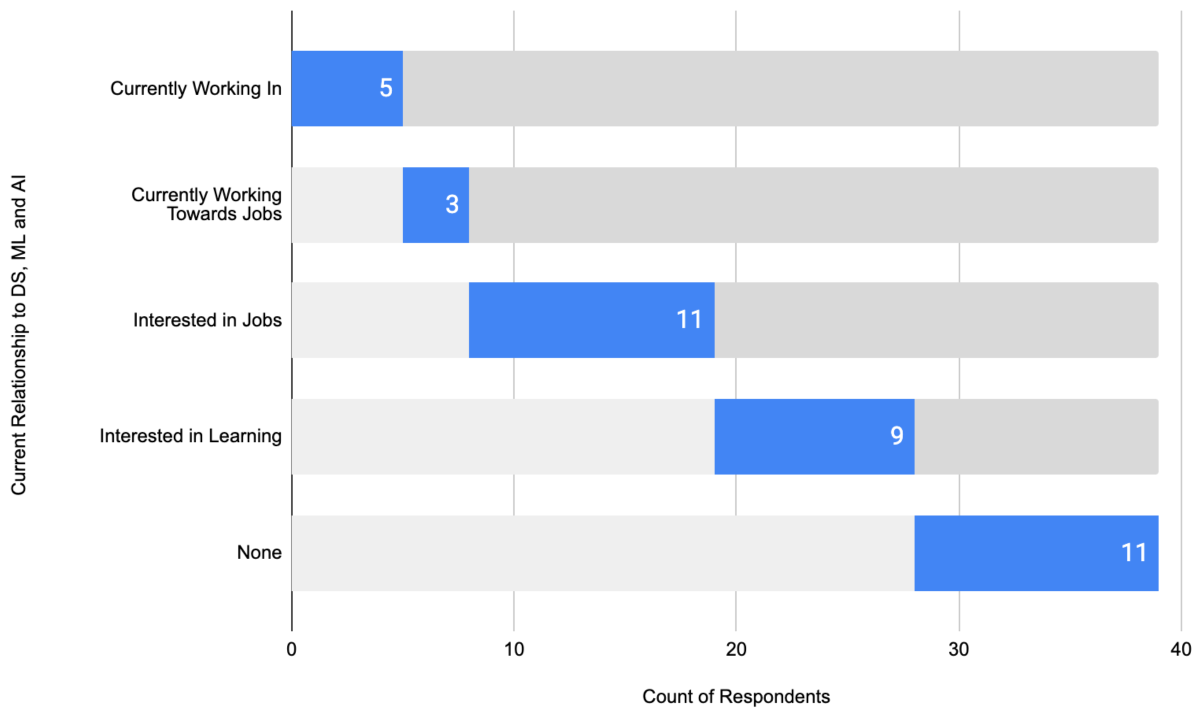


Figure 13 *– Survey respondents' current relationship to DS, ML and AI. The respondents were quite evenly spread with 8 respondents working in, or working towards, jobs in DS, ML and AI. 11 were interested in these jobs in the future and 9 interested in learning about these areas. The final 11 had no relationship with DS, ML and AI.*

A series of Yes/No questions were used to categorise and filter the respondents based on their current relationship to DS, ML and AI. If a respondent answered "Yes" to a key filtering question, they were not shown any further questions. Regarding DS, ML and AI, the respondents were asked if they currently worked in; were working towards a job; interested in a job or interested in learning about DS, ML and AI. The breakdown of responses is shown in **Figure 13**. 5 respondents were currently working in DS, ML or AI and a further 3 were working towards jobs in DS, ML and AI. 11 were interested in these jobs, 9 interested in learning and 11 were not interested in jobs or learning about DS, ML and AI.

The respondents' current relationship to DS, ML and AI was compared to their job (shown in

Figure 14). As is to be expected, every respondent who currently works in or is working towards a job in DS, ML and AI were in the tech category (rather than non-tech or unknown). Those interested in DS, ML and AI jobs had more tech than non-tech respondents. Those interested in learning about DS, ML and AI were the opposite with more non-tech than tech respondents. Only one respondent who had no relationship to DS, ML and AI was from tech – although this respondent works in a new tech-related role which may not require any coding or computer science knowledge but does require technology competence.

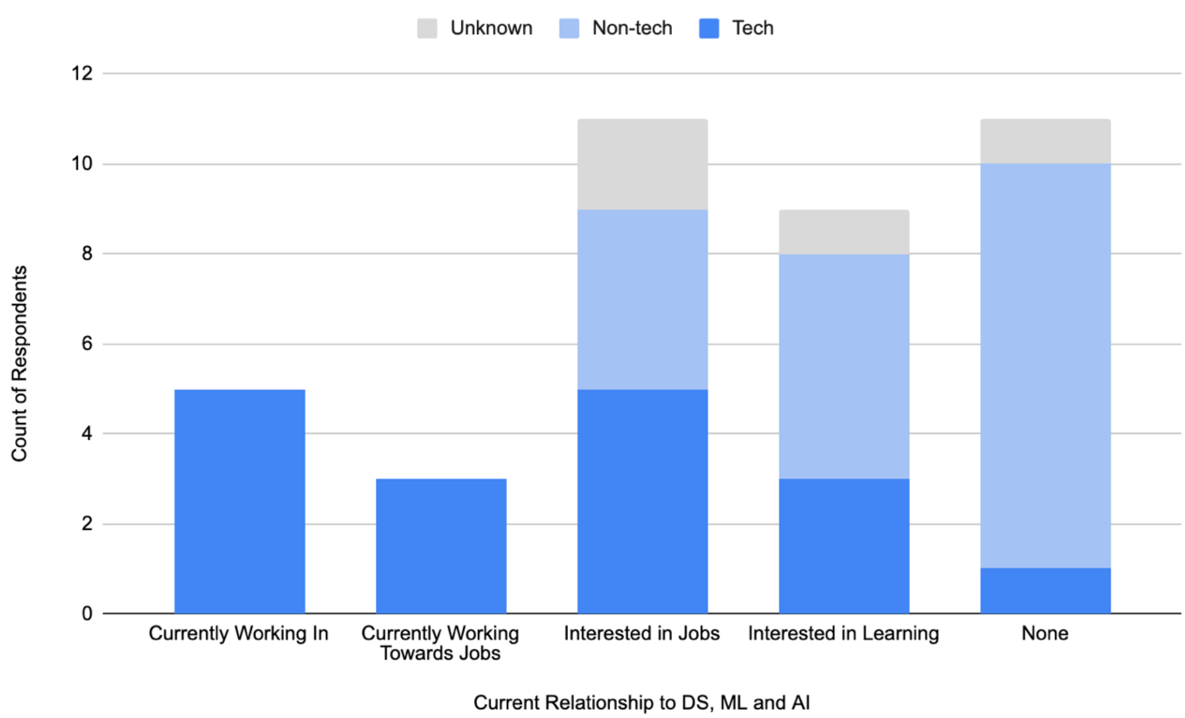


***Figure 14** – Survey respondents' current relationship to DS, ML and AI split by their job category. All of those currently working in or towards these jobs work in tech. Those interested in jobs or learning about DS, ML and AI are split between tech and non-tech. Those with no relationship to DS, ML and AI were all in non-tech roles (except one respondent).*

The respondents' current relationship to DS, ML and AI played a significant role in understanding their responses to the survey. These categories appear to be a more insightful way to analyse the responses than age or whether the respondent works in tech or not.

Requirements for DS, ML and AI Jobs

The main body of the questions aimed to understand the respondents' views of the skills, qualifications and traits needed for DS, ML and AI. As well as how these could be learnt or developed, and how difficult respondents thought this would be (the questions can be found in the Methodology section). To understand some of the characteristics of the responses, length of answers and the wording used in specific questions have been explored, beginning with people stating they do not know answers.

"Don't Know"

It was made explicitly clear, both in the survey itself and when it was shared, all answers were valuable, even not knowing the answers to the questions. Despite this, only one respondent answered they did not know the answers for all the main questions (but completed all category and demographic questions so their response was not discounted). Eight responses included at least one "don't know" answer, making up nearly 12% of all answers. Question 1a about which skills were needed had the least "don't know" answers (3), while all other questions received similar numbers of don't know responses (5 or 6). Although respondents could have answered "don't know" for each question, the majority did not give this as an answer to any question. This suggests people, regardless of their backgrounds or relationship with DS, ML and AI, have opinions and preconceptions about what is needed to work in DS, ML or AI.

Length of Answers

Taking the mean number of words per respondent per question, questions 1a and 1b (skills and qualifications) had on average 9 words; 1c – traits had 7 words; 2 – how to obtain had 11; and 3 – how difficult had 28. How difficult had more than double the average number of words (as well as characters and sentences) than all of the other questions. Having significantly more to say on how difficult the requirements (skills, qualifications and traits) are to obtain, rather than the requirements themselves or how to obtain them, could indicate this being an easier to discuss topic for the respondents. Having more to say also suggests having more opinions and thoughts on this topic.

The overall responses had a mean length of 64 words, while the median was 40 (suggesting there are some outliers at the upper end). Looking at the number of words by current relationship to DS, ML and AI (**Figure 15**) shows all these outliers are from those currently working in DS, ML or AI. All the responses in this category were longer than the responses from those currently working towards these jobs and those who have no relationship with DS, ML and AI. The median for those currently working in DS, ML or AI was more than double any of the other relationship categories and these respondents had quite a larger range in number of words. This finding is not surprising, as presumably they have been through the process of obtaining these jobs and have knowledge of the industries. Those interested in jobs in DS, ML and AI had the second highest median, and is the only relationship category to have an outlier. Those with no current relationship to DS, ML and AI had the lowest median number of words, but those currently working towards these jobs were a close second, although those with no relationship had a larger range. Those interested in learning about DS, ML and AI had quite a large range in number of words per response, which could indicate respondents are at different parts of their learning journeys which may impact how much detail they added. The pattern shown in the boxplot suggests the respondents' current relationship to DS, ML and AI has an impact on how many words respondents gave in their responses, and may also have an impact on how detailed their knowledge and opinions on the topic is.

Comparing the number of phrases found in the preprocessing to the number of words found on average (based on the median), 7 phrases were found per response. Those currently working in DS, ML and AI had on average 20 phrases per response, those with no current relationship to DS, ML and AI had 3 and all other categories had 5. Suggesting similar terminology and common phrases were used within this category. Having common language to discuss topics (which outsiders do not know) could create a barrier to others learning about or researching jobs in DS, ML and AI (consider trying to use a search engine without knowing the common terminology).

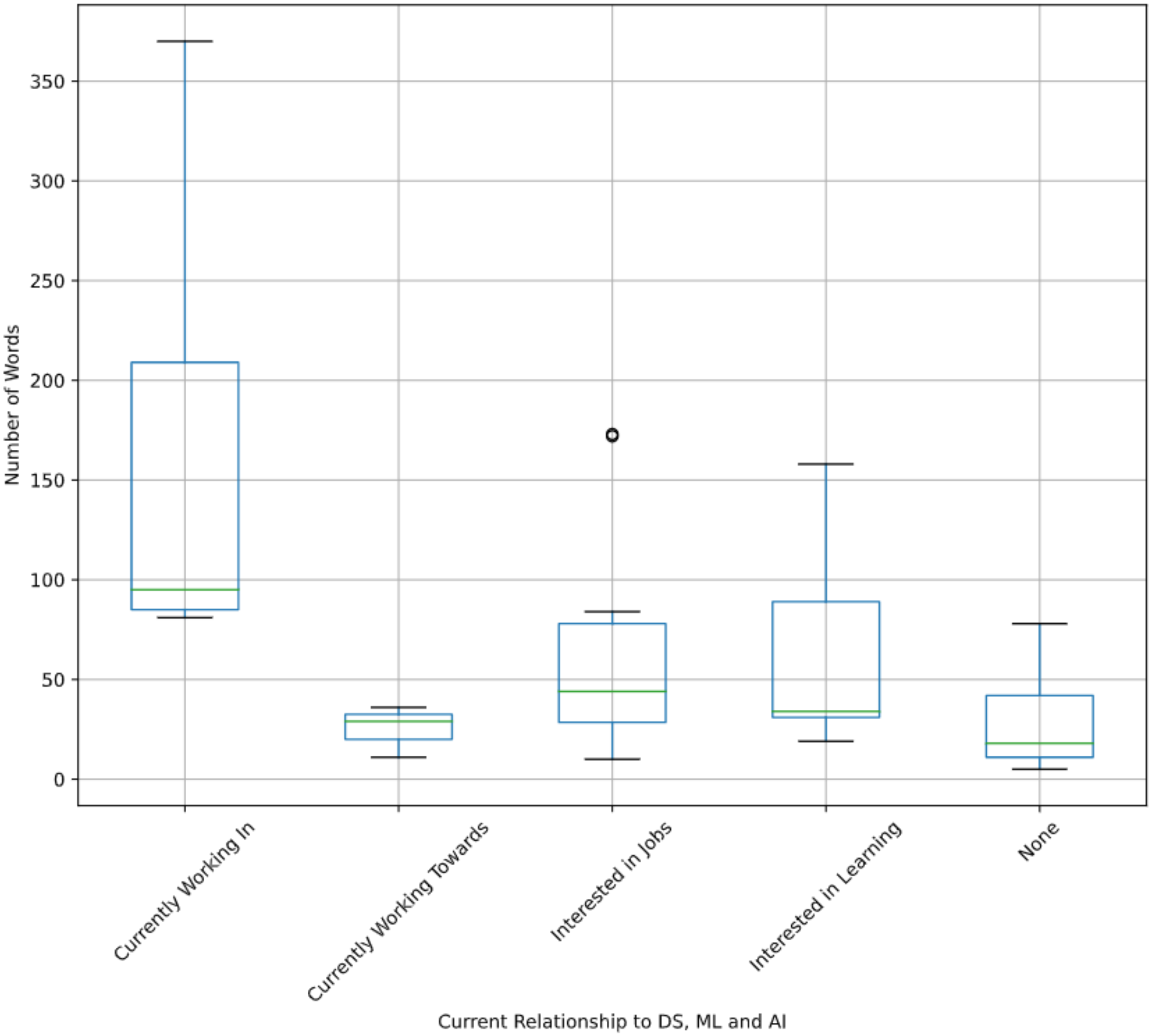


Figure 15 *– Total number of words in each survey response split by current relationship to DS, ML and AI. Those who currently work in DS, ML and AI have significantly more to say than the other 4 relationships – the lowest number of words given in this category is higher than 2 other categories (and only marginally less than another).*

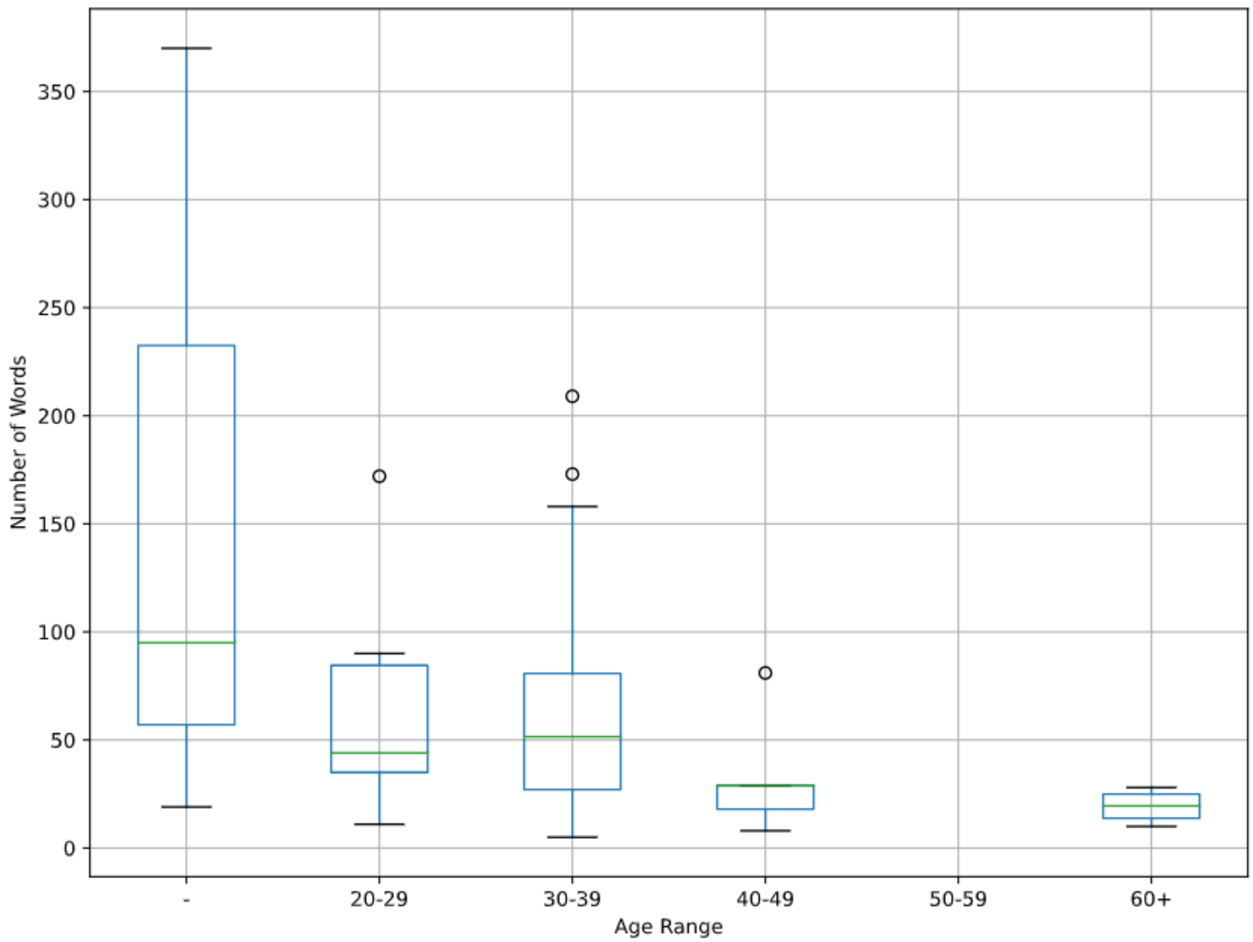


Figure 16 *- Total number of words in each survey response split by age range. The most words were given by those 30-39, on average (median), closely followed by those 20-29. Only two respondents did not give their age, one of which gave the longest answers overall.*

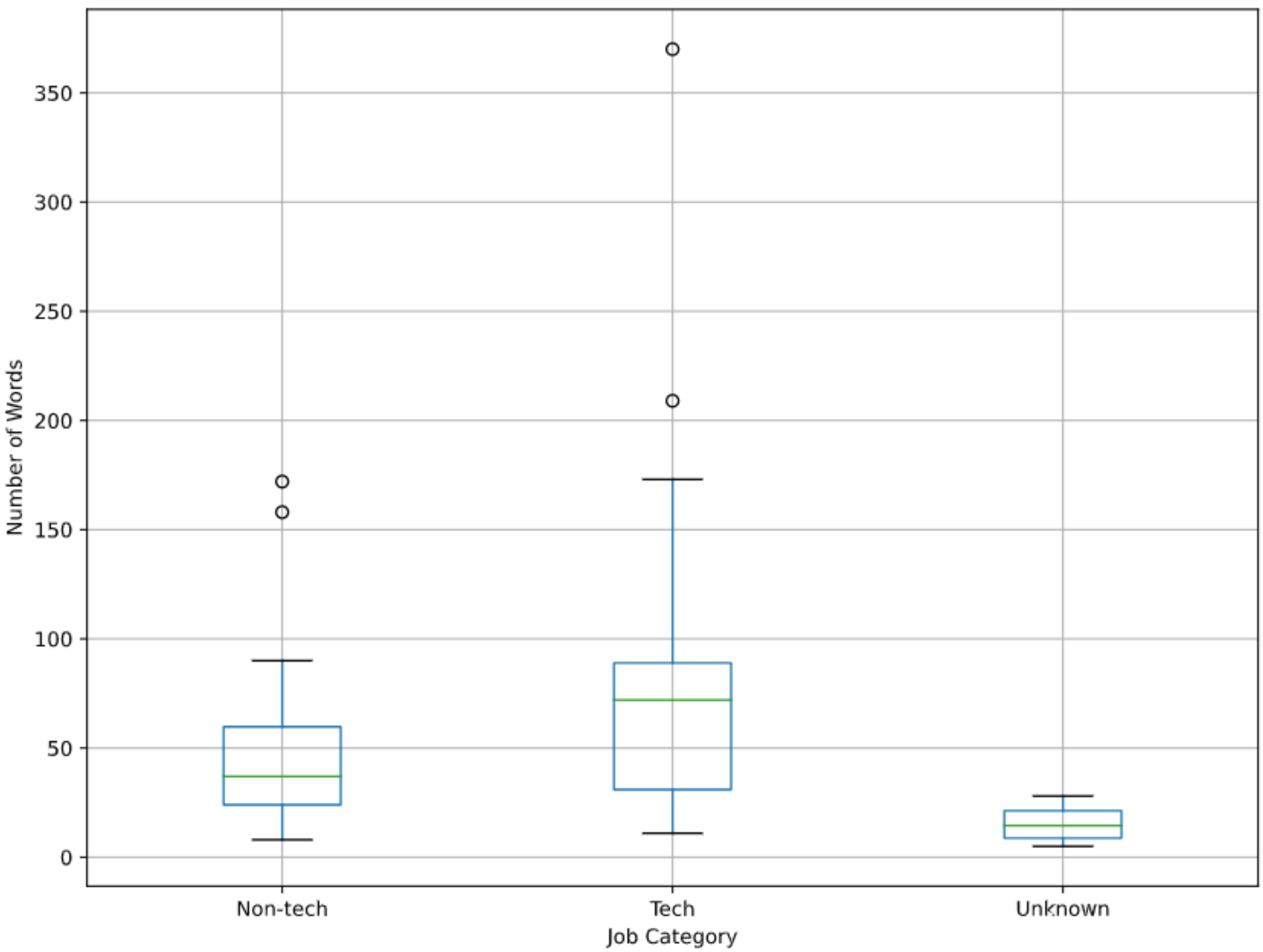


__Figure 17__ - Total number of words in each survey response split by job category. There was a large range in number of words within those with tech jobs. The tech respondents also had a higher median number of words than non-tech respondents.

When analysing the number of words per age range (shown in **Figure 16**), the most words were actually used by those who did not tell their age, although there were only 3 respondents in this group – one of which was an outlier in terms of length of answers. 30-39 was the age range with the highest median and max number of words used. 20-29 had a slightly lower median, but a much smaller range (although there was one outlier at a similar length to 30-39). 40-49 and 60+ had much smaller numbers of words used in their responses. The boxplot below suggests the age of respondents had an impact on the number of words used by respondents – specifically a divide between those under 40 having more to say than those above.

Comparing the job categories (**Figure 17**) – tech, non-tech and unknown – tech had a higher median number of words, and also some extreme outliers (one with over 350 words). Those currently working in tech may have more exposure to these areas, or may be extrapolating their knowledge of other areas, giving them more to say in response to the survey.

Choice of Words and Phrases

Figure 18 shows the words or phrases which were used 5 times or more in all of the responses. There are 37 terms used after the preprocessing steps - 15 of which are subjects (for example, code, problem solving). 9 are ways to learn or gain experience (e.g., work, online).

“Skills” was the most common word or phrase used, occurring 14 times. It is worth noting skills was combined with other words to make phrases (such as “it_skills”) and was actually used over 20 times in total. The first three questions specifically asked about skills, qualifications and traits, however skills was the only of these words which commonly occurs in responses.

“Code” (which may include uses of code, coding, codes, etc. due to lemmatization) was the next most common word. Followed closely by “work”, “learn” and “math”.

“Difficult” was also used the same number of times, but this has been analysed in the content analysis of question 3 as it was sometimes preceded by words such as “moderately” or “not” which vastly change the meaning. ‘i_think’ was also a commonly used phrase, suggesting the respondents were not confident with their answers or did not want to generalise their own opinions.

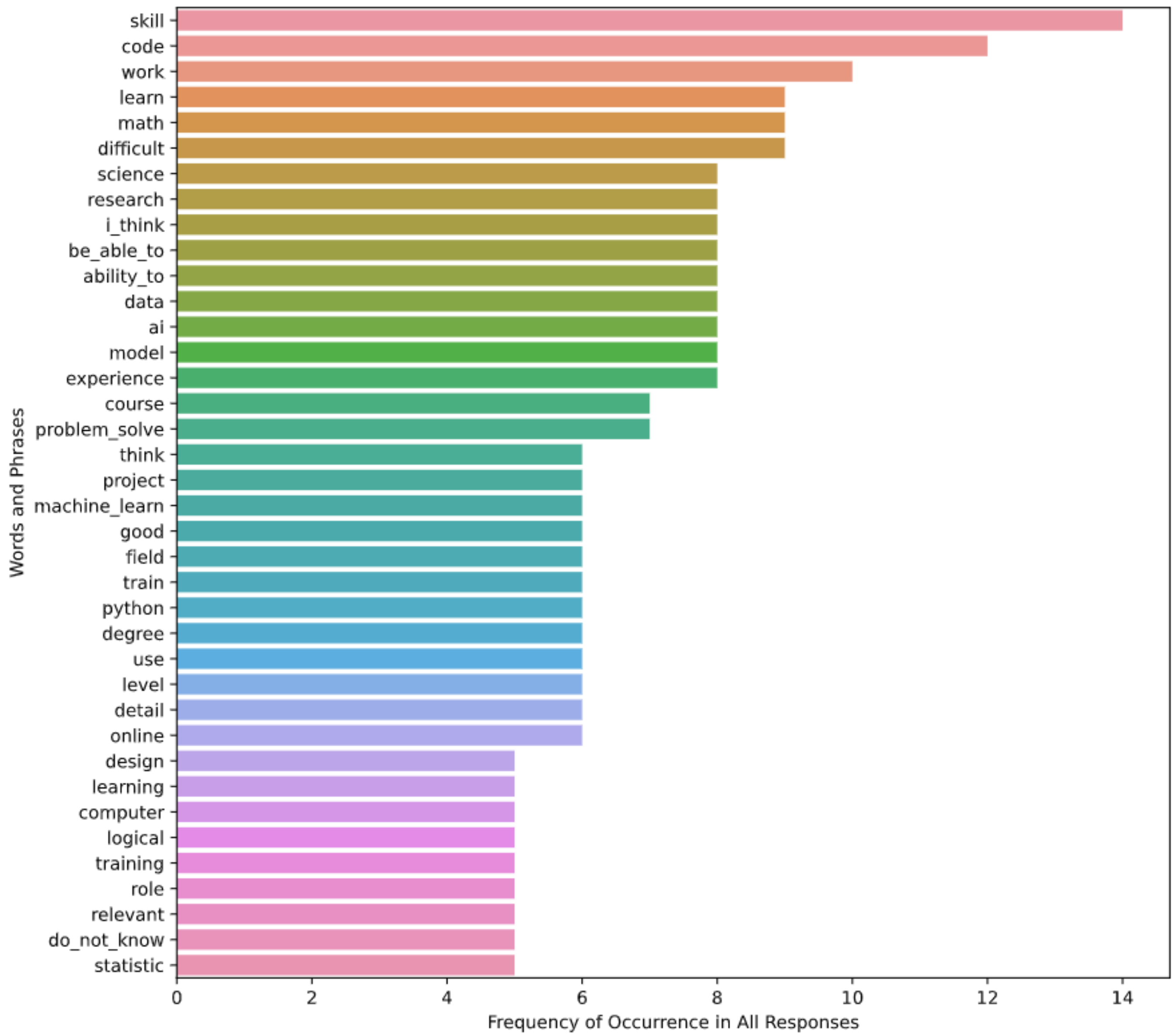


Figure 18 *- Most common words and phrases used in survey responses. "code" and "math" are two of the most common words used throughout the survey responses. The most common word and phrases were mainly technology related words and phrases, with some human elements ("problem solving", "detail", "logical").*

Other subjects made the top terms used, these were “science”, “research”, “data”, “ai” and “model”. They were closely followed by “problem_solving” which was the most common softer or human term to occur.

Despite Data Science, Machine Learning and Artificial Intelligence all being used throughout the survey, the terms were used differently throughout the responses. “Artificial Intelligence” was not used at all, but AI was used 8 times by people across all categories. “Machine Learning” was used 6 times, but not by anyone who had no current relationship to DS, ML and AI. “ML” was used twice by those currently working in DS, ML and AI. *“Data Science”* was also used by these two respondents and two others interested in DS, ML and AI jobs. “DS” was not used at all.

When the most common words and phrases were analysed for relationship to DS, ML and AI and age ranges, several of these groupings (those currently working towards DS, ML and AI jobs, those with no currently relationships to DS, ML and AI; and 40-49 and 60+ age ranges) did not have common words and phrases (occurring more than twice). These age ranges and those currently working towards DS, ML and AI jobs had small numbers of respondents (3-5) which could explain the lack of common words and phrases.

Those with no current relationship to DS, ML and AI was one of the largest grouping of respondents with 11 respondents, which shows the lack of common language and the dissimilarity of word choices in this category. All other age ranges and relationships showed some differences in the top words and phrases used. Those currently working in DS, ML and AI focused on coding but specialised words (“model” and “python”) as well as abilities and learning. Despite being the most commonly used term, “skill” was not commonly used in this category. Both those interested in DS, ML and AI jobs and those interested in learning about these areas had the word “skill” in the top two most common terms. Those interested in DS, ML and AI jobs had the word “work” as their second most common word. Followed by “online” and “train”, suggesting a focus on work experience and online training. “Science” was the most common term used by those interested in learning about DS, ML and AI followed by “skill”, “AI” and “school”. This focus on science over other subjects was also seen in the 20-29 age range. This age range also did not have “math” as a common term. However, “AI” was commonly used in the 30-39 age range, alongside “math”. One explanation for this change in subject could be the increase in coding in other subjects (e.g. bioinformatics) causing the younger generation to focus less on maths, seeing DS, ML and AI as impacting all sciences.

Sentiment of Responses

The TextBlob sentiment analysis gives a polarity score between –1 and 1 (with –1 being the most negative, 0 neutral and 1 the most positive). The sentiment scores for the responses (shown in a histogram in **Figure 19**) were largely neutral (between –0.2 and 0.2), with no responses having extreme sentiment (more than 0.8 at either end). 31 of the 39 responses had sentiment scores greater than 0.

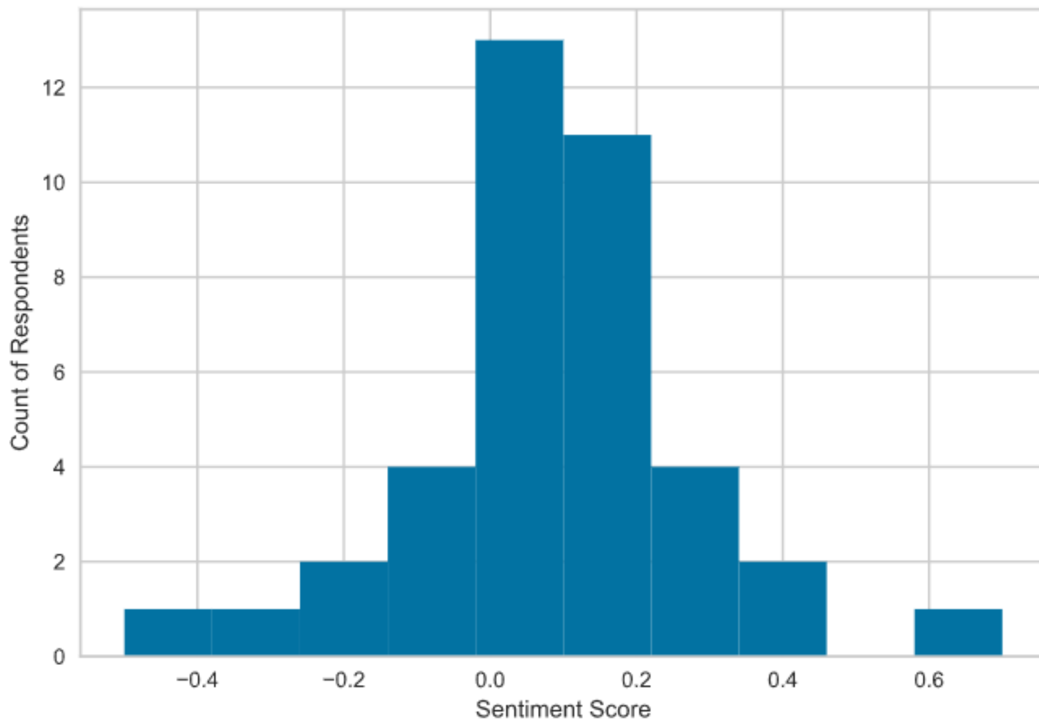


Figure 19 *– Histogram displaying overall sentiment for survey responses. The range of sentiment is -1 (negative) to +1 (positive), with 0 representing neutral sentiment. The majority of responses were slightly positive in the 0 – 0.2 range. One respondent was an outlier in terms of positive sentiment.*

Figure 20 shows a range of sentiment across the five relationships to DS, ML and AI. Those interested in DS, ML and AI jobs and those with no relationship both have outliers, with those with no relationship having quite extreme outliers at either end. The negative outlier in those with no relationship gave “Don’t know” as answers to the questions asking which skills, qualifications and traits were required and the question on how to obtain these requirements. They gave “Difficult” in response to the question on how difficult gaining these requirements would be to obtain. The positive outlier in this category was the only respondent who currently works in tech (however, in a role which is more creative than based on coding or computer science). Those with no relationship had a higher median sentiment than those currently working towards DS, ML and AI jobs and those interested in learning about these areas. This makes sense as those with no current relationship to DS, ML and AI may include a wide range of viewpoints, and both those categories could be disillusioned with their current journey. Other than one outlier, everyone who was interested in learning about DS, ML and AI had positive sentiment. It would be interesting to understand how fair along their learning journey (if even started) these respondents were, and whether their positivity was related to possibilities or ease of learning. Those interested in DS, ML and AI jobs and those currently working towards these jobs have a wide range of sentiments. Those interested in DS, ML and AI jobs had the most positive sentiment (which could be because they believe they could move jobs within the company they would for). Those currently working towards DS, ML and AI jobs were the most negative (by a significant amount) which could be explained by becoming disillusioned after deciding to work towards a job in DS, ML and AI. Finally, those who currently work in DS, ML and AI were also quite positive.

There was also a sentiment pattern across the age ranges (**Figure 21**) - 20-29 being the most positive, 30-39 slightly less positive and the biggest range of sentiment, 40-49 the least positive and 60+ more positive than 40-49 on average with a positively skewed distribution of sentiment. One suggestion for this sentiment split by age could be those in the 40-49 age range may not want to retrain or reskill as they may already have established careers, and therefore feeling more negative towards starting over in DS, ML and AI.

Sentiment also varied across job categories (**Figure 22**). All job categories – tech, non-tech and unknown – had a median sentiment greater than zero, and all less than 0.2. Sentiment was most positive in the non-tech category, although this category had an extreme negative outlier. The extreme positive outlier was within the tech category.

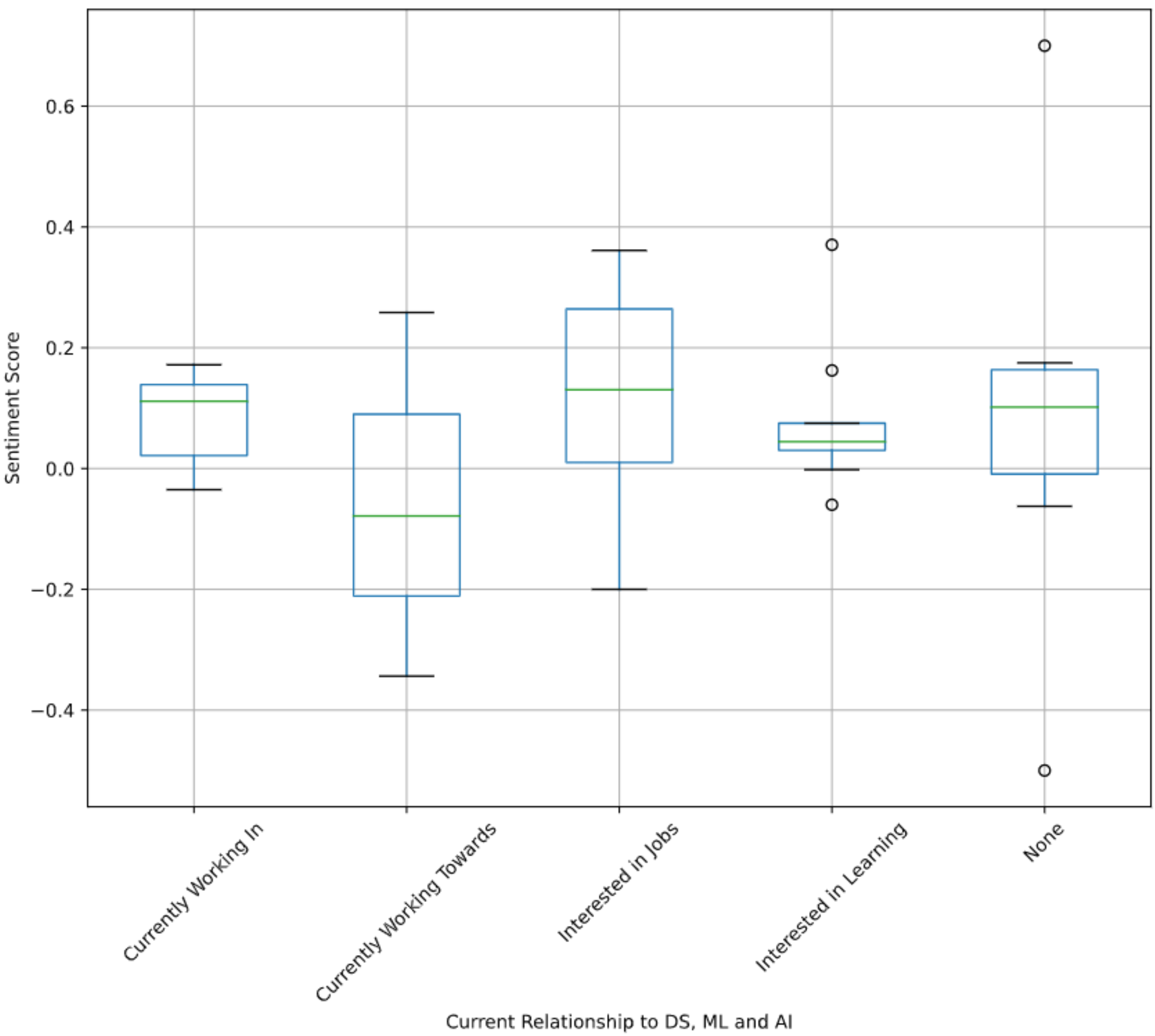


Figure 20 *- Sentiment of overall survey response split by respondent's current relationship to DS, ML and AI. Only those currently working towards these jobs had a negative median sentiment. The most positive average sentiment was from those with no relationship to DS, ML and AI, but was closely followed by those currently working in and those interested in jobs.*

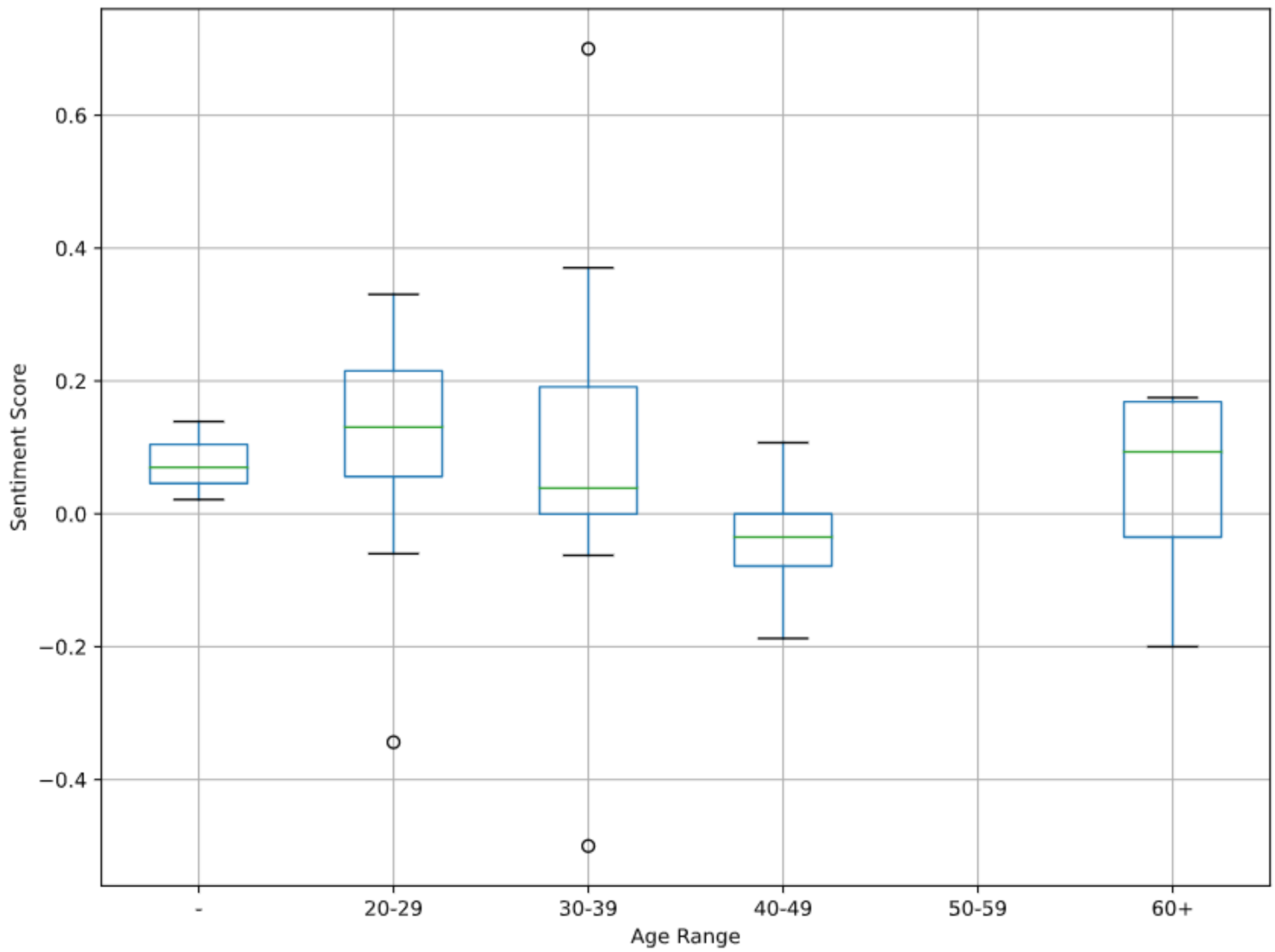


__Figure 21__ - Sentiment of overall survey response split by respondent's age range showing the varying sentiment across the age ranges. 40-49 was the only age range with average (median) negative sentiment, although only slightly. 30-39 was only slightly positive. Both 20-29 and 60+ had average positive sentiment, but 20-29 has an overall more positive range of responses (excluding one very negative outlier).

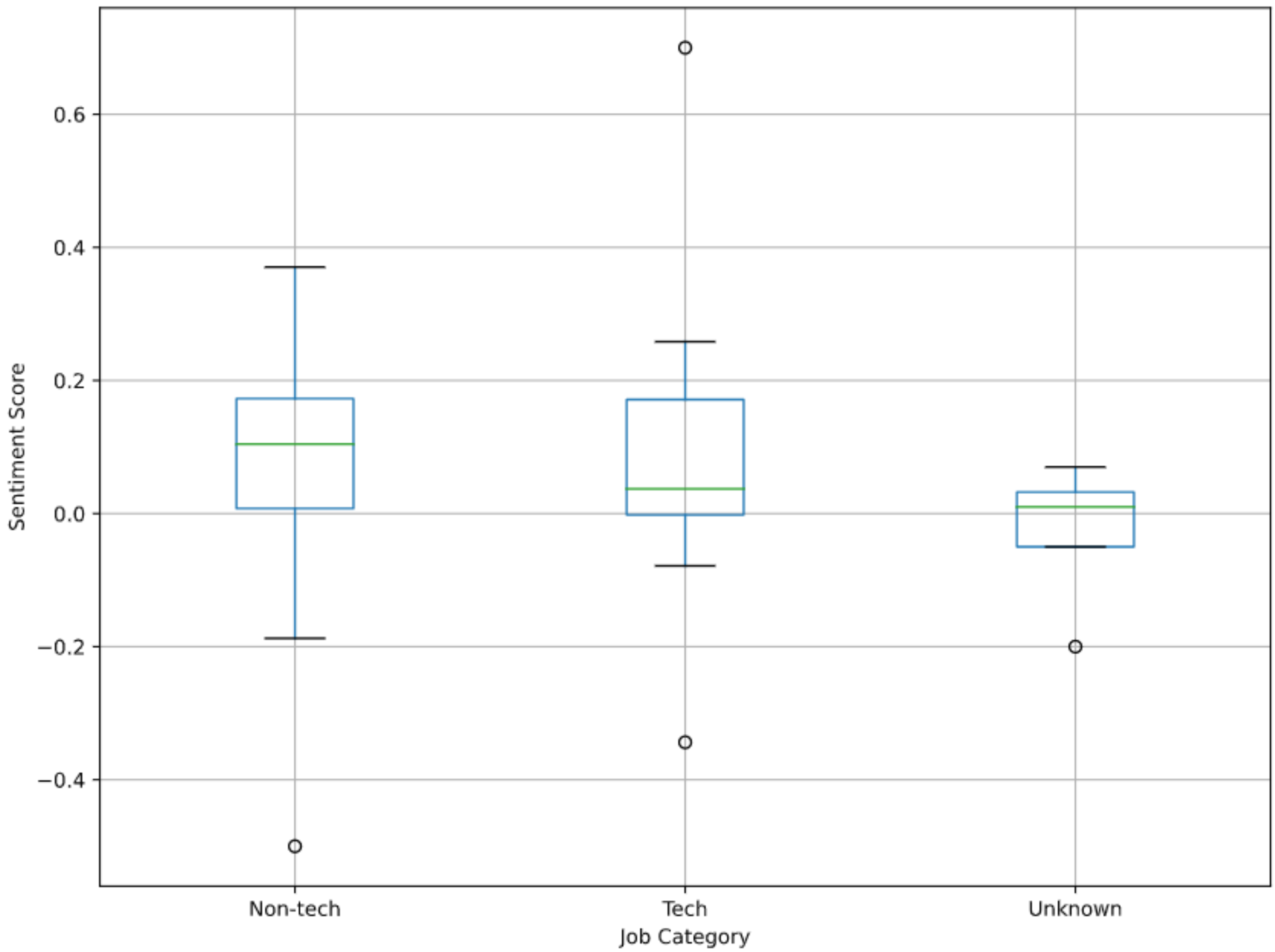


Figure 22 *- Sentiment of overall survey response split by respondent's job category. The average (median) sentiment is higher with those who have non-tech job, than tech jobs. Although it is worth noting there is a larger range of sentiment amount non-tech respondents. Both categories have outliers at extremes.*

Clusters of Thinking

When looking at the words used by respondents to discuss the requirements for working in DS, ML and AI, there were 7 groups identified by the clustering algorithm. (Note: these clusters can be seen in **Figure 11** identified by different colours). The 7 groups, or clusters of thinking, are:

1. No response
2. Short answers
3. Tech Confident Neutral Generalists
4. Tech Savvy Knowledgeable Professionals
5. Apprehensive Older Pessimists
6. Positive Younger Women
7. Removed Stereotypers

The clusters of thinking were grouped together based on their choice of wording, however patterns emerged in these groups around the demographics (age, job and current relationship to DS, ML and AI). The clusters of thinking had differences in the most common words and phrases used as well as the overall sentiment of responses and number of words (**Figure 23** and **Figure 24** respectively).

The first two clusters of thinking have been isolating due to their lack of answers, rather than common wording:

Cluster 1 - No Response

One respondent gave only "." to the questions around DS, ML and AI requirements.

Cluster 2 - Short Answers

Two respondents gave very short answers to every question - generally one word or "don't know".

The remaining 36 respondents were grouped into 5 clusters of thinking. 4 of these 5 groups had neutral sentiment – 3 of these were slightly positive and 1 slightly negative. The fifth group had moderately (greater than 0.2) positive sentiment. Analysing the sentiment, length of answers, choice of wording and demographics of the groups paints a picture of their makeup.

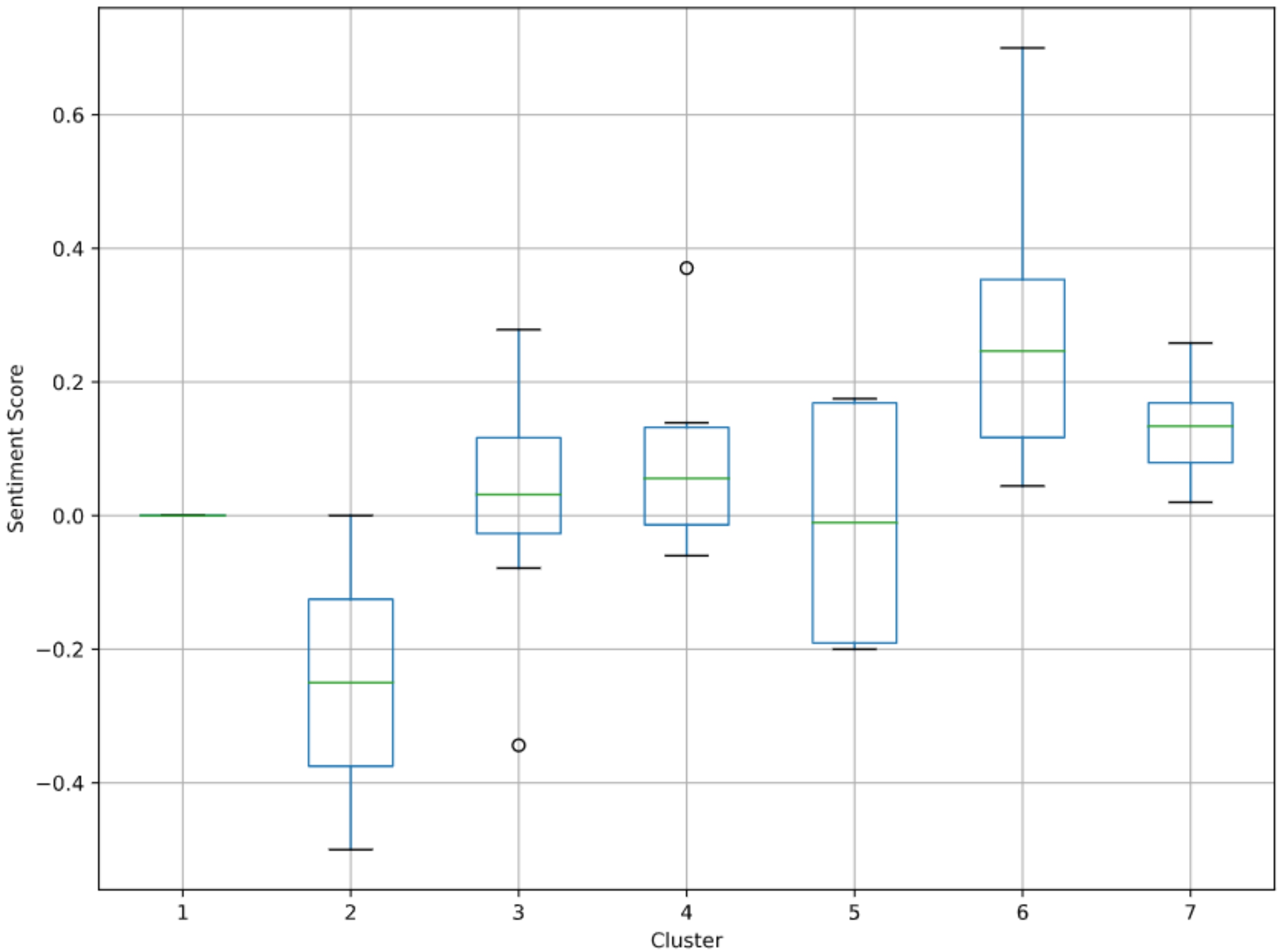


Figure 23 *- Sentiment of overall survey response split by respondent's cluster. Clusters 6 was the most positive cluster, with the highest median sentiment and all respondents have positive sentiments. Cluster 7 closely followed, but with a less positive median and overall smaller range. Clusters 3 and 4 both had a slightly positive sentiment and had respondents with positive and negative sentiment. Cluster 5 had a large range, and a just negative overall sentiment. Clusters 1 and 2 only had 1 and 2 respondents respectively.*

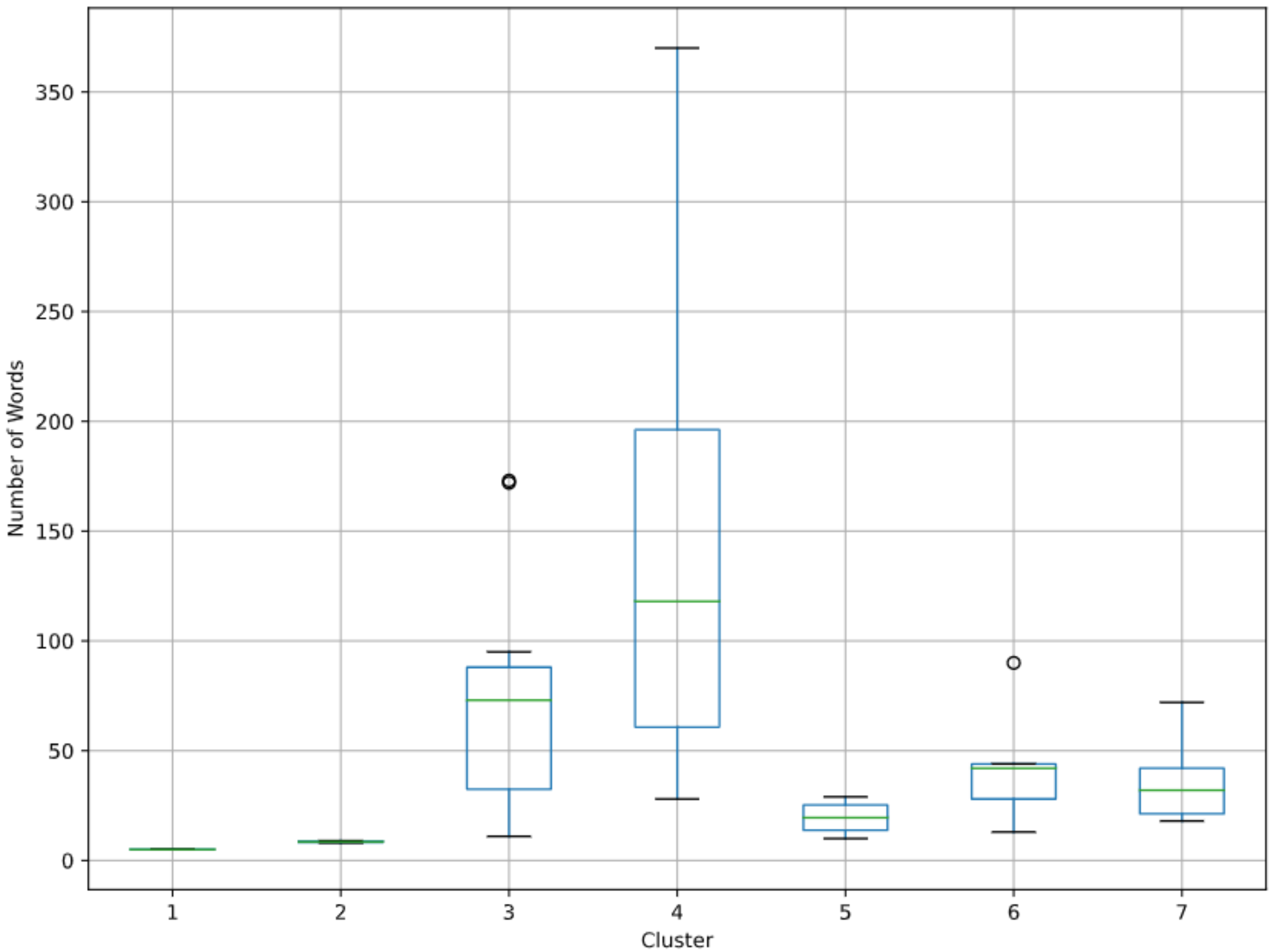


Figure 24 *- Number of words in total response split by respondent's cluster. Cluster 4 had more words per response on average than the other clusters, this cluster also had the largest range (and the response with the most words). Cluster 3 respondents used the next highest number of words, on average (median). Clusters 5, 6 and 7 all had less than 50 words per response on average but had varying ranges. Clusters 1 and 2 only had 1 and 2 respondents respectively.*

Cluster 3 - Tech Confident Neutral Generalists

Tech Confident Neutral Generalists was the largest cluster, with 14 respondents. 9 of these respondents worked in tech, 2 were students and the final 3 worked in medicine. It is worth noting two things about the jobs in this group - firstly, while students and those who work in medicine may not be expected to code, there a general expectation for them to be at least computer literate (for example, sending email, using documents and spreadsheets, being able to print and scan). Secondly, of the 9 who worked in tech, only one had a job title which suggests their role required coding. None were in the 60+ age range, with the vast majority aged 20-39. There were respondents with all current relationships to DS, ML and AI. Unlike the other clusters, there were no clear patterns or threads from examining their answers' content. The most common aspect of these responses was the use of the word "skill", this cluster accounted for 12 of the 14 occurrences. Despite being the largest cluster, the word "code" did not occur more often than in the smaller clusters. However, the word "programming" was only used by this cluster (and including these terms would shows only respondents in this cluster did not mention these skills). After cluster 4, this cluster had the longest answers – this includes particularly long answers to skills and how to obtain (12 and 15 words respectively), but only 5 words for qualifications and traits. The focus on skills could be explained by the more tech make up of this cluster. The long answers to how to obtain were focused on courses (whether university or online) and different methods of learning, often with several mentioned.

Cluster 4 - Tech Savvy Knowledgeable Professionals

Tech Savvy Knowledgeable Professionals consists of 6 respondents who were all aged 20-39 (all but one 30-39), the majority are in tech and those who are not in tech are all teachers. This cluster gave the longest answers, and seemed knowledgeable about the areas (for example, the most commonly used word or phrases in this cluster was "AI"). They also gave significantly longer answers to the traits questions than the other clusters. All mentioned computer-related qualifications. In response to how to obtain, most did not mention university, but did focus on training and certifications.

Cluster 5 - Apprehensive Older Pessimists

Apprehensive Older Pessimists had the most negative median sentiment. This cluster was made up of four respondents who were over 40. The respondents in this cluster were mostly male (all but one) and none worked in tech. The answers were the shortest of any of the 5 clusters, often respondents gave only one answer per question (when other clusters included lists and sentences in their responses) and included several "don't know" responses. Compared to other clusters there was less of a focus on coding in skills and qualifications. The traits included several "eye for detail" and "methodical" responses. In the how to obtain question, training was the main response, rather than university. The respondents also specifically said “moderately difficult” or “quite difficult” in responded to the difficulty question.

Cluster 6 – Positive Younger Women

Positive Younger Women was the most positive cluster, with all 6 responses had an above zero sentiment score. This cluster was entirely female and between 20-39 (equally split between 20-29 and 30-39). None were currently working in or towards DS, ML and AI jobs. Only one worked in tech (in a modern role which is unlikely to require coding or computer science knowledge), and the other 5 were in non-tech roles. They gave quite short answers overall, including particularly short answers to the qualifications question. In comparison to their other answers, their response to how difficult it would be to obtain these requirements was a lot longer. Their responses focused on coding and data skills, they saw lots of options for how to obtain with a focus on learning (including university). This cluster also said it would be easy to gain the necessary requirements, several stating this was due to online information and courses.

Cluster 7 – Removed Stereotypers

There were 6 respondents in the *Removed Stereotypers* group. They were the second most positive cluster, and also had all responses with an above zero sentiment score. Although the range of sentiment scores was a lot smaller than the positive younger women. There was a range of genders, ages and industries in this cluster. No one in this group currently works in DS, ML and AI. Two worked in tech, but in very different roles. The roles held by this group are not necessarily technical, however are only slightly removed (e.g. someone whose main jobs are based on people or practical skills, but some software would likely be used). The skills given by this cluster focused on IT and coding. Maths also featured in both skills and traits (“statistics” was the most commonly used term). As did intelligence. IT and coding was the main topic in the qualifications, with several respondents specifically stating degrees were required. There was no mention of university in the how to obtain question, but there was a big focus on education. There was uncertainty of the difficulty in this cluster, with several respondents highlighting barriers (including time and the need for PhDs). Overall this cluster gave the expected, stereotypical view of what is required to work in DS, ML and AI.

Taking a Deeper Dive into the Requirements

While the previous findings have looked at each survey response as a whole, additional patterns were revealed when the individual questions were analysed more deeply.

1a - Skills

The vast majority of answers to the skills question are lists of skills (separated by commas, spaces or semi-colons). 31 of the respondents listed 1-3 skills (with 11 listing only 1), one respondent listed 13 skills. 30 respondents mentioned coding or computers (including "IT skills" and "systems knowledge"). 9 mentioned maths or statistics. 15 respondents mentioned a non-technical or maths-related skills, i.e. "logical", "problem solving", "critical thinking", which will be referred to as *human* skills going forward.

Each response was transformed into separate skills, and common words which did not add any additional context (such as "understanding", "ability" and "skills") were removed. There was a total of 107 skills (words or phrases) used. Some of these were repeated, or similar and could be grouped together (for example, "coding" and "programming" or "research" and "researcher"). Grouping as such resulted in 34 skills. All skills which were used more than once are shown in a word cloud (

Figure 25). The word cloud is to scale – with "Work Life Balance" being used twice and "Coding' being used 17 times. The words and phrases used to describe skills have been further categorised into – *Tech* (purple), *Human* (green) and *Maths, Data and Science* (pink). All skills came under one of these three categories.

Both *Tech* and *Maths, Data and Science* had 19 different terms in those categories (this includes the terms in the image and ones which occurred only once which have not been included). There were 27 different words or phrases within the *Human* category. It is worth noting the categories within *Tech* are broader than those in the *Human* category – take "Computing" for example which includes four different words or phrases deemed related to a computing degree.

Tech skills were the most common listed, occurring 45 times. Although human skills were close behind occurring 38 times. *Maths, Data and S*cience skills occurred 24 times in total (with each part of this category occurring 13, 7 and 4 times respectively).

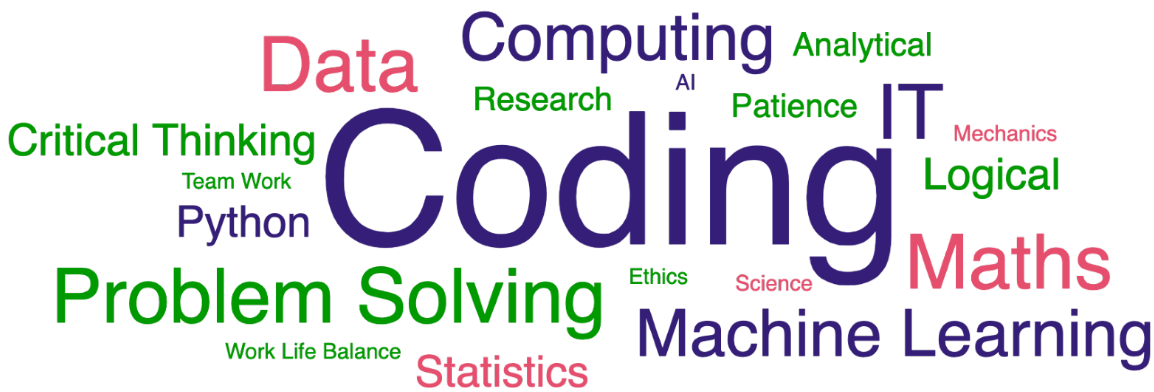


Figure 25 *- Word cloud showing skills given three or more times - size is proportional to number of times the word appeared. All skills given could be categorised into one of three categories (purple – tech; human – green; maths, data and science – pink). There are more human skills (green) in the word cloud, however the tech skills (purple) were given more frequently.*

Coding was the most common (this includes other similar phrases such programming and code). Followed by data, IT, problem solving and maths. IT and computing have been split out of IT skills were referred to specifically or as skills relating to computer hardware. Computing, as previously mentioned, referred to skills such as architecture considered related to computing degrees. Other specific technical skills, such as machine learning, AI and specifically mentioned coding languages (Python, R and SQL) remained separate categories.

The list of *Human* skills occurring more than twice: problem solving, logical, critical thinking, research, patience, analytical.

Those currently working in DS, ML and AI mentioned the most skills overall (a mean of 4.4 per respondent). All mentioned tech skills (not in ways that would necessarily have been categorised as coding, eg “architectural concepts”, “design thinking”). There was a focus on specific advanced skills. Also, a strong focus on human skills such as problem solving, deduction, etc.

Those currently working towards DS, ML and AI jobs all specifically mentioned coding or a coding language. There was a focus on maths and stats. One respondent in this category did not mention maths as a skill, but did mention it as a trait (in question 1c). As there is a lot of focus on coding and maths / stats in courses related to the three areas, this attitude from those currently learning is understandable.

In both those interested in DS, ML and AI jobs and those interested in learning about these areas mentioned a mean of 3 skills. There was a focus on tech skills with only four respondents in these two categories combined not mentioning a skill in this group. Within those interested in DS, ML and AI jobs there was a focus on coding skills. Four respondents (almost half of those who answered) did not mention any human skills (it is worth mentioning these respondents all gave such skills in response to question 1c – Traits).

Within those interested in learning about DS, ML and AI*,* all but one mentioned technical skills (their response was "mathematics"). Several mentioned "computer skills" or "IT skills" rather than coding specifically. Only three out of nine mentioned maths skills.

Every respondent with no current relationship to DS, ML and AI (who answered something other than "don't know") mentioned technical skills, except one who said "practical". Only three out of eleven mentioned maths. Only two mention human skills ("practical", "logical mind"). This is a big emphasis on the practical skills needed compared to other categories.

There are clear patterns in the respondents' thoughts on required skills with the expected focus on technical skills, such as coding and IT skills. The distinct wording (particularly around technical skills) depending on the respondent's current relationship with DS, ML and AI could further highlight the difficulty those outside these areas may face finding resources to begin learning the necessary skills. For example, an online course teaching "IT skills" is unlikely to include any programming languages.

1b - Qualifications

The responses to what qualification are needed were varied – one respondent summed it up well with their response - "from none all the way to a Phd". 5 respondents said they did not know what qualifications would be required to work in DS, ML and AI. A further 5 (including the one previously quoted) answered the qualifications question with "None' suggesting they believe no qualifications are needed. The other answers were made of two parts – the level of the qualification and the topics. Some answers included both, some one or the other.

Level

There were various levels of qualification given by respondents, these have been represented in a diagram (**Figure 26**). 16 people mentioned degrees being required (some specifically mentioning levels of degrees, e.g. undergrad, bachelors, masters). Four of these suggested more than a Bachelor's degree would be needed. These four were all from someone who was interested in DS, ML and AI jobs or interested in learning about these areas. A further respondent said a degree would be helpful, but no longer required. One respondent mentioned a BTech (this is a UK based qualification usually taken by high school students). 12 respondents did not mention any specific level, only topics or areas.

Three of the respondents who mentioned degrees also mentioned other types of qualifications. All three mentioned experience and certifications, but emphasised the practical side of these qualifications (rather than purely educational). One specifically mentioned MOOCs. Two mentioned portfolios (showing previous work or personal projects) being important.

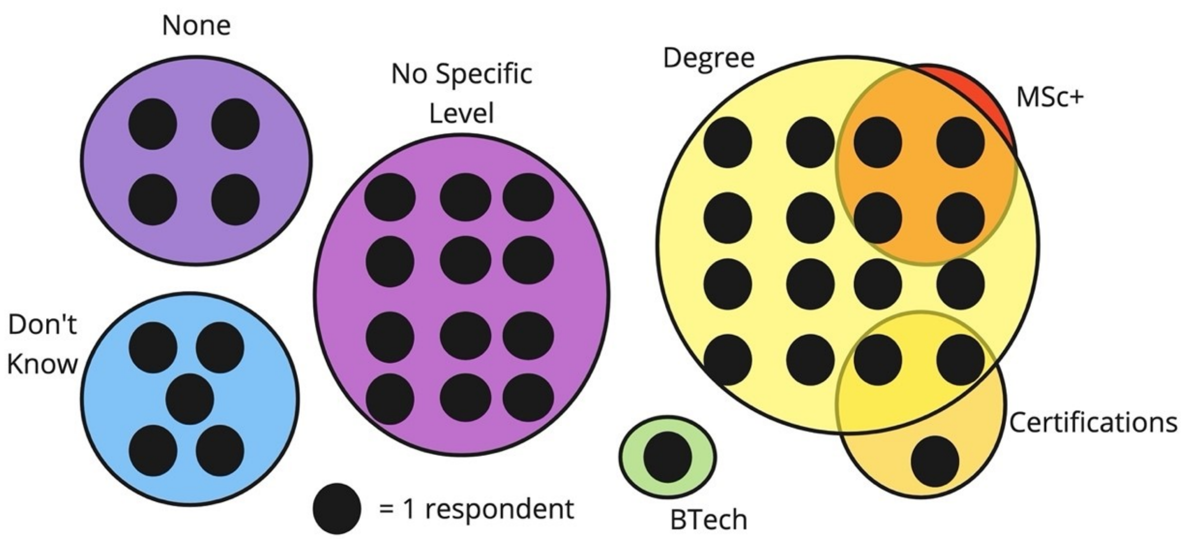


Figure 26 *- Level of qualifications given by each respondent. One black dot represents one respondent and the circles represent the category of qualification level. 12 respondents gave no specific level, 5 said "don't know" and 4 specifically said none. 16 respondents said degree (4 of which mentioned Masters and two also said certifications). 3 overall mentioned certifications and one BTech (post 16+ alternative to A-Level in UK).*

Topic

23 respondents mentioned a topic of qualifications – 10 only one, 13 more than one. The overlap in topics is shown in **Figure 27**. This diagram also shows there was a clear distinction between the topics given by those who said degrees were a requirement and those who did not. Six of those who

mentioned degrees did not specify a topic for the qualification, neither did the respondent who mentioned BTech.

The topics of qualifications were largely around maths and computers. Maths was a qualification topic given by 9 respondents, 3 who did not give a specific qualification level and 6 who mentioned degrees (indicated in the blue boxes in the diagram). A topic related to computers was given by 12 respondents (indicated in purple) – 7 who did not give a specific level and 5 who said degrees. The language used varied - of these 12, those who gave degrees all mentioned “computer science” or “computer programming”. Four of those who did not specify said “IT”, and one was very specific about computer programmes and coding languages (including “SQL, Python, Hadoop”).

Of those who specified degrees, 6 mentioned science, STEM or physics. Those who mentioned STEM, only mentioned STEM, whereas science and physics were always alongside maths. 3 specially mentioned Data Science, Machine Learning or AI degrees. Two, who also mentioned maths, mentioned statistics. Other academic subjects were mentioned – English by someone who did not specify a degree, and who gave an answer of “Maths, science and English”; also, one respondent who mentioned a degree mentioned a number of " subjects pertaining to AI - engineering, maths, psychology, linguistics, computer programming, science, design”. As well as academic subjects, more human topics were mentioned by three respondents. All whom did not specify a level of qualification and only mentioned human topics - “clear logical thinking”, “domain knowledge”, “project management, agility, communication, collaboration”.

Maths and science were mentioned more by those who specified degrees. Computer related topics were most common in those who did not mention degrees than other subjects. Those who mentioned degrees did not mention any human related topics (although they were mentioned for the vast majority of these respondents in response to the other questions).

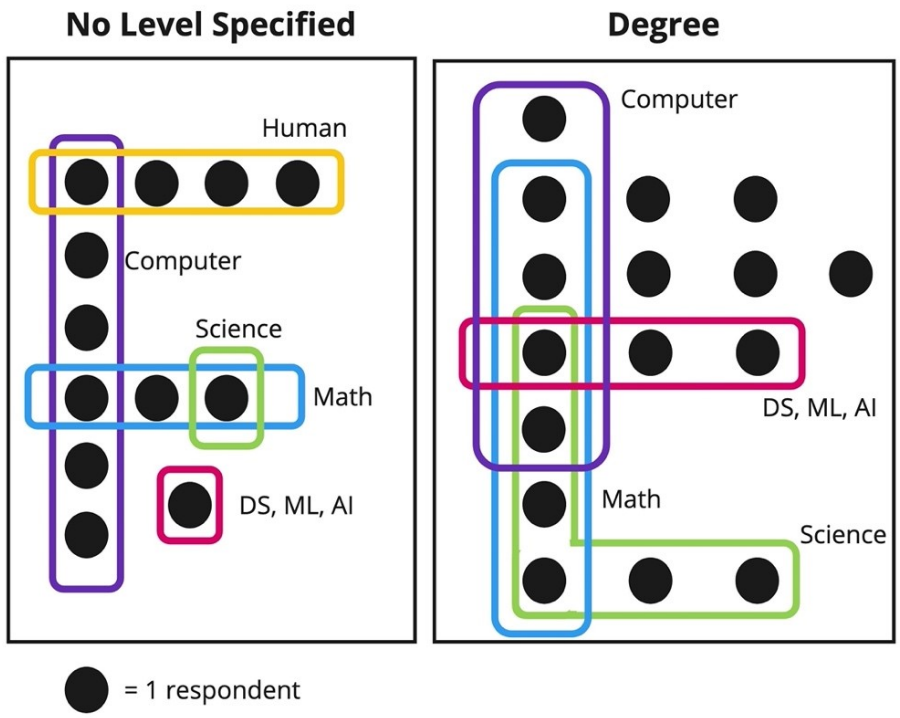


Figure 27 *- Topic of qualifications given by respondents split by the level of qualifications given. The rectangles have split the respondents based on whether they mentioned "degree" as a requirement – those who did not on the left, those who did on the right. Within the rectangles, one black circle represents one respondent and the coloured boxes indicate the topic (or subject) mentioned – where the boxes overlap shows multiple topics were given. Computer and maths related qualifications were given in both groups, however human-related qualifications were only given by those who did not specify a degree. Within those who did specify a degree there was more of a focus on science and DS, ML and AI.*

There was a divide in this answer based on current relationship to DS, ML and AI. Only one respondent who currently works in DS, ML and AI mentioned degrees, and they did not say this was a requirement ("either through a degree or certifications"). Two mentioned specific technical topics, two only mentioned human skills and one said none were needed. It might be worth noting none of this category were based in the UK, so their countries may have different requirements than within the UK market. Those who are currently working towards a job in one of these areas, who answered something other than "don't know", gave specific qualification levels (degree and BTech).

More than half of those interested in DS, ML and AI jobs mentioned degrees. One mentioned none. All but two gave specific topics, which were mostly a mix of maths, computer science and IT. One specifically mentioned a "Data Science type degree / masters".

Two of those interested in learning DS, ML and AI stated “None” for qualifications required. Only two did not specify a level. All who answered (not those who said “Don’t know” or “None”) gave specific topics, which were a mix of maths, science/STEM and computing.

Those with no current relationship to DS, ML and AI had equal numbers of degrees and not specific levels. Two did not give a topic, one gave only human topic, the rest mentioned maths or a technical topic. The technical topics mentioned were “IT” or “in one of the above” (which has been taken to mean “Data Science, Machine Learning or AI”).

While there was no one distinct answer to what qualifications are required, more than half of respondents still believed a degree to be the minimum qualification required to work in DS, ML and AI. Those who mentioned degrees, generally, specified a computer related, maths or science degree. 20 respondents (out of 39) said a qualification in a computer-related field (including DS, ML and AI), maths or science was required. This suggests there is still a stereotypical view (rightly or wrongly) of the type of qualifications needed for DS, ML and AI.

1c – Traits

Traits had the shortest answers, and five don’t know responses. One respondent said “None”. 11 gave only one trait, the most given was 7, but on average (both mean and median) two were given per respondent. This suggests respondents felt skills and qualifications were more important requirements than traits.

Most of the traits given would be considered human skills (even more so personality traits). Even those which were related to more technical skills, such as tech, data, maths, were more around thinking (eg “mathematical minded”, “tech savvy”, “data-driven thinking”). Throughout the responses there was different wording used compared with question 1a - Skills. Words such as nature, personality, mindset, thinking and interest were more common. Whereas when talking about skills, respondents used words such as understanding, skills, knowledge, training.

Looking at which traits were given together gave no real pattern. Also, traits had less obvious groupings than skills. However, there were common traits given by multiple respondents. The most common trait, mentioned 7 times, was around *detail* ("attention to detail", "detail-orientated"), this along with traits such as "patient" and "low frustration" suggest people think these types of roles could be tedious.

The other common traits, given 5 or 6 times, were Intelligent, Analytical, Learning and Curiosity. The responses around learning (including "quick learner", "willingness to fail and learn and iterate", "learning while doing") suggest learning new things on the job, and learning continually are seen as important aspects of these jobs.

Other traits mentioned more than three times include patient, logical, technical, methodical and maths.

A lot of those with no current relationship to DS, ML and AI only gave one trait. While those currently working in DS, ML and AI and those interested in these jobs gave 3 on average.

2 – How to obtain?

Six respondents did not know the answer to the question around how to obtain the skills, qualifications and traits, four of which were from the *None* category. 24 respondents mentioned some form of education (including curriculum, courses, training), most mentioned multiple types of education. 10 of these specifically mentioned university or further education and 9 specifically mentioned online learning. 14 mentioned work in some way (for example "work experience" and "on the job training"). 5 discussed research and reading, 3 suggested working on projects to learn and two specifically mentioned coding. Four respondents said an interest in or perseverance were needed to obtain the needed skills, traits and qualifications. One respondent touched on something very important to learning, the necessary conditions for successful learning: "An immersive environment for learning and discovery. Enthusiastic and nurturing teachers or educators. Time, money and resources. Access to materials and information. Strong guidance."

Only one person who either currently works in or is working towards a DS, ML and AI job mentioned university or formal education in this answer, and they only mention it as an option. There is more of a focus on self-learning and other courses. Real-world and practical experience were also mentioned several times.

Although the answers are completely different, university and higher education are also not mentioned by respondents with no current relationship to DS, ML and AI. However, "education" is mentioned several times in this category – this ranges from online courses to changing the curriculum for younger generations.

Within those interested in learning about DS, ML and AI there was more of a focus on university (with all but two respondents mentioning something related, eg "higher education"). Those interested in DS, ML and AI jobs had more of a focus on training and work experience. Although often this was mentioned as an alternative or as complementary to university education.

3 - How easy / difficult?

6 respondents gave a do not know answer to the question of how difficult or easy it would be obtain the skills, qualifications and traits. 16 specifically said "difficult", one "medium" and another "moderate". Two of these respondents only said difficult, and did not give any further context. Another did not specifically say difficult, but did state it "Would require time and a certain passion for the project". 9 of those who said it would be difficult, specifically mentioned the qualifications, with most of these mentioned the degree or masters being a lot of work. 7 mentioned difficulty getting work experience – one mentioning the need for connections, another stating "entry positions only with low salary" and one saying "you need a lot of experience to go into a role like this". Others mentioned the specific skills needed, one claiming these to be "something you are born to do rather than something you can learn". A few gave caveats, including needing a PhD as the knowledge required is deep. One respondent said "It may be easy for someone who has good school grades in related subjects and is young (18-24) but more difficult for someone who has become interested in it at a later stage and who does not have those qualifications."

6 indicated it would be easy (or "straightforward" or "accessible"), four of these were from the respondents either interested in jobs or interested in learning about DS, ML and AI. There were a few themes which emerged in these six answers. Firstly, courses are readily available online, particularly coding courses. One respondent said "There is accessible information online. While I have not personally pursued this type of career, at a glance there is guidance online on how to gain necessary qualifications" which is contradictory to what other respondents said. Another theme is the applicability or

transferability of the skills, traits and qualifications. Even within these answers, there were a lot of caveats - “is this discipline or academic field promoted to all? Is it accessible to all? It is not the world I operate in so I can’t comment on how easy it would be to get into.”; “there is a stigma with older generations and vocational types that are the barrier”; “not everyone has the right approach or mindset for it - the problem solving, the passion for the product, the curiosity to see where you can take it.”

The remaining 9 did not give a definitive answer, but gave caveats around the ease or difficulty of learning. One respondent quoted Simon Sinek “we hire people for their behaviour, the skills can always be taught”. This was someone currently working in DS, ML and AI, specifically someone who is very senior and would (based on their job title) have hiring responsibilities of these types of roles. Another respondent said the ease/difficulty was unknown but “it helps to know the right people to get in the door for an internship”. This response was from someone currently working towards a job in DS, ML and AI, which could explain their cynicism. Three of these respondents discussed there being many options, but not being sure which is the best or will translate to a job easily. One respondent summed this up well, by saying there are “a LOT of options, but not a very clear path”. Two of these three specifically mentioned online learning and bootcamps as an alternative to degrees, but both caveat about not knowing whether these make it easy to get a job or experience. One of the other respondents said it would be easier for someone with a background in science, as they would be used to research and data. Two respondent mentioned time and passion were needed, one specifically claimed it would be “straightforward if you have the right aptitude for it and the resources (time, money and materials)”. Finally, one respondent felt there was a gender and age imbalance, making it harder for young women to gain the necessary skills, qualifications and traits.

Discussion

The survey aimed to determine whether the public have an understanding of the requirements for working in DS, ML and AI; and how these requirements could be obtained. While the results of this research are not generalizable (as there was no formal sampling and the data is largely qualitative), the findings do shed light on how members of the public, including some who may not normally engage in this type of discussion see the requirements for DS, ML and AI. When considering the findings from a barriers to entry point of view, four main themes have been identified:

1. Answers Paint a Stereotypical Picture

2. Missing Other Backgrounds
3. No Clear Path
4. Cluster of Thinking

Answers Paint a Stereotypical Picture

The responses from the survey, while varied, did show a similar way of thinking towards the requirements to work in DS, ML and AI. Throughout the responses, there was a big focus on coding, maths, problem solving and education. "Problem solving" was actually mentioned at least once in response to every question. This paints a very stereotypical picture of those who work in DS, ML and AI and may go as far as creating a barrier to entry for those who do not fit this stereotype. When interviewing members of the public about their attitudes to towards general training on AI (Gemmell, Wenham and Hauert, 2021), gatekeeping by experts was identified as a blocker to the public learning about AI. There is perhaps another form of gatekeeping coming through in these responses. If the individual has created a picture of who works in DS, ML and AI as something different from themselves, this could be creating a barrier for them to enter the field. Rather than the findings of the previous report, where the gatekeeping was coming from experts, this is a form of self-gate-keeping. It could be useful to understand where this self-gate-keeping comes from – is it completely separate from the expert gatekeeping or is it entangled?

Missing Other Backgrounds

As well as painting a stereotypical picture, the responses also did not discuss other backgrounds than technologist / engineer. One respondent mentioned a list of potential degrees (including psychology and linguistics). This respondent also mentioned ethics in their skills answer, which shows a more holistic viewpoint does exist. Another respondent mentioned "potentially an interest in improving sustainability and social issues". Despite the survey not specifically asking about engineering, programming or research, there seems to be an assumption from the respondents that these are what is meant when DS, ML and AI are discussed. As can be seen in the Tweet shown in

Figure 28, these points of view are common - "Engineers wanted" was the slogan used by the UK government to recruit more people to AI and DS conversion courses.

No Clear Path

While some respondents mentioned there was a lot of information or resources online, there was no clear path laid out by any respondents. Even attending university and gaining a degree was not seen as a complete path (some thought a necessary step along the way, others disagreed).

The amount of information online was actually seen as a hindrance by some respondents, who saw the amount and lack of guidance as a blocker. A search on Coursera returned 2,678, 1,273 and 1,331 courses for “data science”, “machine learning” and “artificial intelligence” respectively. Some online courses have been designed for the general public, notably *AI for Everyone* and *Elements of AI.* It is unclear how any of these courses map directly to a job in DS, ML and AI, or what a next step to build on these would be.

Figure 28 *- Tweet*[7] *showing advert for new AI courses with the slogan "Engineers Wanted" from the UK Department for Digital, Culture, Media & Sport (DCMS). The tweet has been retweeted by Dame Wendy Hall who disagreed with the "Engineers Wanted" sentiment.*

Clusters of Thinking

While none of the responses are exactly the same, there are clear clusters of thinking. These seem to be impacted by age, whether someone currently works in tech, and their category (i.e. their current status

[7] https://twitter.com/DameWendyDBE/status/1270750435616468992

in terms interest in roles relating to DS, ML and AI). These clusters also appeared to be impacted by attitude to technology. While this wasn't explicitly asked, in some cases dislike or comfort with technology came across in the responses. These factors seemed to affect the respondents' thoughts on a number of important topics including difficulty of gaining the requirements, whether university was required and the difference between skills and traits.

Recommendations

To begin to address these potential barriers, a first step would be to make sure the other roles in DS, ML and AI (including designer, product, project manager), which may not have such a maths and coding component, are well known. Then a clear pathway to all roles could be created (including technology and engineering based ones). An interactive tool which helps people see what is required and what would be helpful. Further to this, different pathways depending on their age, current position, educational background and attitudes (towards tech, education, maths, etc) would provide new ways for others to overcome their stereotypical view of DS, ML and AI.

A campaign encouraging those from different backgrounds could also be a useful step. Part of this could address the worry around salaries and entry roles, by acknowledging the need for useful transferrable skills or non-technical skills. For example, a conversational designer for a voice assistant does not necessarily need maths and coding, but could bring their background in content writing or product design. Placing focus on domain knowledge being important (potentially more so than coding and maths which can be taught) could be an important step to alleviating these barriers.

Creating official accredited alternatives to formal education (e.g. an online badge which employers respect).

Further work

How the survey was recruited (through closed online groups) will have had an impact on who completed the survey. An interesting further study could involve expanding the survey recruitment to other groups, and including offline surveys or interviews to remove the technology barrier to participation. It could also have been useful to ask more background questions (including educational background and explicitly asking attitudes towards technology and maths).

Some further work which could be helpful to overcoming these barriers could involve additional surveys or interviews to understand the impact of educational background and attitudes to education, maths and computers. This could also involve working with participants to map out their potential routes into DS, ML and AI, and any barriers them see so these can be addressed.

Work to understand what employers are looking for, and how these requirements can be used (or overcome if they are out of touch) to help inform the above recommendations.

Conclusions

To better understand the public perception of what is required to work in data science, machine learning and artificial intelligence, an online survey was conducted. This survey aimed to be inclusive by encouraging everyone their voices mattered even if they did not know the answers. The responses were analysed in two ways. Firstly, the entire response per respondent was analysed using natural language processing methods, including sentiment analysis and clustering. Secondly, the individual questions were analysed using qualitative methods, mainly coding, categorising and thematic analysis. The findings showed there were differences in sentiment, number of words and words used based on a range of factors – age, working in tech, current relationship to the areas and attitude towards technology. The clustering algorithm revealed distinct clusters of thinking. Overall, the responses painted a stereotypical picture of someone working in DS, ML and AI – educated, good at coding, maths and problem solving. The responses (other than one) did not mention any other roles or skillsets needed in DS, ML and AI. There was also no clear path into DS, ML and AI indicated by any respondent. To overcome these barriers, a number of actions are recommended - creating pathways into DS, ML and AI for non-technologists. Also, raising the profiles of other roles in DS, ML and AI with an emphasis on those which require domain or other expertise. Finally, creating more certified alternatives to formal educations which employers respect.

Postface

The survey in this chapter aimed to better understand the public's perceptions of requirements for working in AI-related roles. The methods used allowed participants to answer in their own words, and, as such, further barriers to AI education and retraining, even for those interested in AI, came through. The survey respondents painted a stereotypical picture of someone who works in AI – good at maths and coding, degree educated, problem solving skills. They focused more on qualifications and skills than traits (which were scattered and hard to group together). Despite the type of role not being discussed, it was assumed by everyone who answered to be a technology or engineer role. It is useful to highlight this as many other roles exist related to AI. The respondents missing other backgrounds links back to the findings in Chapter 5 – there is a need to overcome preconceptions and a need for AI education for those working *with* AI. A further link can be seen in the clusters of thinking which were identified in the survey responses. Similar to the members of public in *Chapter 4: Interviews*, their life experiences (jobs, tech skills, age, etc.) impact their views and choice of wording in their responses. Further, the survey responses highlight the need for co-designing for particular communities to ensure needs are met, which includes the wording used through the education (and even to advertise) is correct. Finally, there was no one clear path into these roles which was also discussed with hiring managers in the next chapter.

Chapter 6: Survey – Hiring Managers

Preface

The previous chapter focused on the survey for members of public to understand their perceptions of the requirements to work in AI-related roles. This chapter further builds on this work by asking similar questions to those who have hiring responsibilities for these roles. The aim is to understand whether members of public and hiring managers' requirements match up, and how any gaps or issues can be addressed.

The hiring managers' survey aimed to understand the requirements to work in AI-related roles, and how someone could move into one of these roles. It further seeks to understand where the barriers presented in the previous two chapters are coming from – is it individuals themselves or are the barriers being put up by companies and experts. The hiring managers were asked similar questions to the members of public – what are the requirements and how could these be obtained. They were further asked questions to understand how their companies would play a role in retraining employees – would they provide training and how easy it would to move jobs within the company. 15 hiring managers completed the survey, providing a range of insights into this topic. The responses were analysed using qualitative methods to allow the detail and depth of the responses to come through. An example of these methods (coding, categorizing and thematic analysis) can be seen *in Appendix 3 – a – Illustration of Coding Answers to One Survey Question* and *Appendix 3 – b - Illustration of Coding Answers to One Survey Question (Zoomed In).* The analysis in this worked example resulted in the diagram in **Figure 29**.

Paper - Reaching the Baseline - Understanding Employers' Requirements for Data Science, Machine Learning and Artificial Intelligence Jobs

Authors - Laura Gemmell, Lucy Wenham*, Sabine Hauert* (*Provided supervision over the work)

This paper has been submitted to an academic journal.

Abstract

Demand for Data Science, Machine Learning, Artificial Intelligence and Robotics jobs have been increasing in recent years and this is only predicted to continue. However, people with the skills to work in these roles has not been increasing with the same velocity and companies are struggling to hire the talent they need – creating a 'Skills Gap'. Previous research shows members of the public believe there is a particular stereotype of someone who works in AI-related areas, and there is not a clear path into these jobs for someone outside this stereotype. An anonymous, online survey was designed to understand if this viewpoint is shared with hiring managers, and what can be done to create a roadmap for people to move into AI-related roles. The responses were analysed using qualitative methods, including coding, categorising and thematic analysis. This analysis identified several barriers which need to be addressed as a first step to creating a roadmap. Firstly, while there is some consensus on requirements, it is still vague and presumptuous. Companies mention a "baseline" of skills to work in these areas, but do not specify exactly what this is. Also, this baseline is more geared towards coding and maths skills, than human skills. The path into these roles is still not clear, especially for those without a STEM degree and data experience. Finally, companies are could do more to close the skills gap – providing training for new employees, and pathways for existing employees to move roles.

Introduction

Data Science (DS), Machine Learning (ML), Artificial Intelligence (AI) and Robotics jobs have increased greatly in the past few years. So much so, a skills gap has been created in these areas. Closing this skills gap requires understanding exactly what employers are looking for, and how these requirements can be obtained. To provide some insight into the requirements and how the skills gap can be closed, 15 individuals (all with hiring power in DS, ML, AI or Robotics) were surveyed. These senior experts were asked what skills, qualifications and traits they felt were needed to work in these areas. They were also asked how employees could obtain these requirements, whether their companies would provide training, and how difficult it would be for an employee to move into one of these roles.

This survey was conducted to understand if what hiring managers believe to be required and needed for working in DS, ML, AI and Robotics is the same as the public and recruiters assume it to be. The survey also aims to be a first step in creating a potential road map for people wanting to move into one of these areas.

Demand for DS, ML, AI and Robotics Skills

Based on reports from Deloitte and Accenture (Jarvis, 2020; Accenture, 2021b), demand for DS, ML, AI and Robotics skills has only increased in the UK due to COVID-19. Deloitte lists the main roles in demand (regardless of the company's experience of AI) as AI developers and engineers, AI researchers, and data scientists. Less technical roles, such as Business leaders, domain experts, and project managers, were in lower demand. What is clear from these reports is the shortage of potential employees for these roles. Accenture recommends companies retraining their own staff, giving examples of pharmaceutical company Takeda who has trained staff to use Robotics Process Automation to improve their jobs and Salesforce (a customer relationship management company) using low- or no-code platforms to allow employees to create apps despite not being technologists. Deloitte echoes the need to train current staff to use AI in their jobs. They further recommend looking in different places for talent, with a focus on university graduates.

Reports such as these often highlight the need for talent without specifying exactly what skills or traits are needed. The focus is more on role titles or roles the companies are hiring for. These roles can vary in terms of requirements, making it difficult for those interested in understanding a path for them to move into these roles.

Current Job Landscape

To illustrate the demand for these roles (focusing on the United Kingdom), keyword searches were conducted on popular job boards (Reed, Indeed and LinkedIn). These findings (shown in **Table 2**) show "machine learning" having the most job adverts on all sites, followed by "data scientist".

Both LinkedIn and Indeed allow the results to be filtered for more specific results. LinkedIn has a feature to filter on job level, with one of the pre-set levels being "Entry-level" (shown in **Table 3**). Note: this "Entry-level" setting is applied by the company writing the job advert, there are no rules as to which jobs come under this seniority categorisation (the other options are Internship, Associate, Mid-Senior, Director, Executive). Both "data scientist" and "robotics" had 42 and 45% entry level jobs respectively, whereas “machine learning” and “artificial intelligence” both only had around one third. For reference, when the same filter was applied to all jobs in the United Kingdom 43% were entry level roles.

Job Search	Reed.co.uk	Indeed.co.uk	LinkedIn
“data scientist”	869	2,335	12,158
“machine learning”	1,362	7,389	13,921
“artificial intelligence”	363	1,388	3,848
“robotics”	640	2,625	1,897

***Table 2** – Number of jobs returned for specific searches on job boards (Location: “United Kingdom” on 28/10/2021). On every platform more jobs were returned for “machine learning” than the other phrases. “Data scientist” was a close second on LinkedIn. Reed.co.uk and Linkedin followed a similar pattern, however indeed.co.uk had almost more “robotics” than the other two platforms.*

Job Search	LinkedIn - All	LinkedIn – Entry-level	% Entry-level
“data scientist”	12,158	5,523	45.43%
“machine learning”	13,921	4,510	32.40%
“artificial intelligence”	3,848	1,283	33.34%
“robotics”	1,897	800	42.17%

***Table 3** – Number of “entry-level” jobs returned for specific searches on LinkedIn (Location: “United Kingdom” on 28/10/2021). “Entry-level” is an option the job poster can choose on LinkedIn, there are no set rules for what makes a job entry-level. For reference, when the same filter was applied to all jobs in the United Kingdom 43% were entry level roles. Therefore, “robotics” roles have roughly average percentage entry level, “data scientist” slightly higher than overall, and both “machine learning” and “artificial intelligence” both have over 10% less entry-level roles.*

Qualifications

Indeed allows the job adverts to be filtered to the required qualification level (shown in **Error! Reference source not found.**). It is worth noting these qualification levels are based on Indeed's automatic detection, it is not known how accurate this is and some job adverts with qualifications may have been missed. "robotics" job adverts were substantially different than the other three - the majority of job adverts did not specify any qualifications (67%). Alevels and GCSEs also made up a greater proportion of "robotics" job adverts. GCSEs in particular accounted for 1.98% compared to 0.77%, 0.14% and 0.13% for "machine learning", "artificial intelligence" and "data scientist" respectively. "robotics" adverts had the lowest percentage requiring bachelor's degrees (only slightly less than "data scientist"), however, the percentage of job adverts requiring Master's and PhD were significantly lower than the other 3 keywords. A possible explanation for this could be some robotics related roles being more manual than the others. "machine learning" and "artificial intelligence" were, on the whole, quite similar. Both had roughly 45% of roles not specifying qualification level, and just over half requiring a bachelor's degree or higher. For both, Bachelor's degree was more commonly asked for than a Master's or PhD. "data scientist" had less than 30% of roles not specifying a qualification, and nearly 70% requiring a bachelor's degree, Masters or PhD. For DS roles only, both Master's and PhD were the requirement for a higher proportion of jobs than Bachelor's.

Skills and Traits

Further to these search results, reed.co.uk (one of the UK's largest recruitment companies) discussed a range of roles in AI with their views on what is required (Rolfe, 2020). They begin by saying

"If you're a mathematically minded problem solver with an interest in technology, a career in AI could be for you."

The article lists examples of jobs in AI - *UX Designer, Machine Learning Engineer, Research Scientist*, *Full-Stack Developer* and *Artificial Intelligence Architect*. It states a degree would be at least beneficial for all roles, however specifically for *Machine Learning Engineer, Research Scientist* and *Artificial Intelligence Architect* a Master's or PhD is required. The skills required range from specific technical skills ("graphic design", "programming languages", "big data analysis") to mathematical skills. A number of human skills or traits are also mentioned – "logic", "creativity", "attention to detail", "problem solving", "analytical

Error! Reference source not found.These finding were echoed when the OECD analysed job adverts for A I-related jobs (Squicciarini and Nachtigall, 2021) and found 30% of the skills required were related to software. This analysis also found there was a growing emphasis from 2012 to 2018 on “softer” skill, such as communication, problem solving, creativity and teamwork. A survey conducted to understand what members of the public thought the requirements were to work in DS, ML and AI (Gemmell, Wenham and Hauert, no date) again supports this view. It was found the public saw a stereotypical view of someone working in these areas (as seen on reed.co.uk) – degree education, good at maths and coding with strong problem solving skills. The survey also illustrated the public did not see one clear path into DS, ML and AI, however a degree as the most common path mentioned.

Keyword Search	**Number of Courses**
“data science”	2,874
"machine learning"	1,398
“artificial intelligence”	1,451
“robotics”	211

Table 4 *– Number of courses returned on coursera.org for related topics (searched on 05/11/2021). There were almost double the number of “data science” courses compared to “machine learning” and “artificial intelligence”; and over 10 times as many “data science” courses compared to “robotics”.*

An alternative often highlighted instead of a traditional degree are online courses. Provider of online courses, Coursera, is often seen as a useful platform to learn new skills. They offer a range of courses, from short one hour guided projects all the way to online degrees. Coursera has nearly 3,000 “data science” courses, roughly 1,500 courses for both “machine learning” and “artificial intelligence”, and just over 200 “robotics” courses (**Table 4**). DS is such a popular topic on Coursera it is its own subject, and ML is a sub-topic of DS. For both, Coursera provides a list of frequently answered questions about learning DS and ML skills. These questions include the skills and experience needed to learn DS and ML, as well as what type of people are well suited to these (Coursera, 2021a, 2021b). Coursera states the skills needed to learn DS as “basic understanding of statistics and coding”. They also describe the type of person best suited to working in DS as “analytical thinkers who enjoy coding and working with data”. The traits of someone well suited to DS were listed as “comfortable learning various coding languages”, “strong communication skills, “comfortable working against a deadline”, “work well with colleagues” and “superior organizational skills”. The typical career path of a data scientist is also described in these answers, this describes someone becoming a junior data scientist, then “after gaining some work experience, the next path for a data scientist is to earn a Master’s degree or PhD and become a senior data scientist or machine learning engineer”.

Machine learning (described by Coursera as “the intersection of computer science, data science, and algorithms and mathematical theory”) is discussed in more technical language, which could create a barrier to people learning about or feeling ML is for them. The necessary prerequisites for learning about ML, according to Coursera, are:

- “strong software engineering skills, from fundamentals like confident programming and coding ability to big picture familiarity with system design principles”
- “data modeling and evaluation to ensure that the algorithms perform well and become more, not less accurate over time”
- “a solid theoretical background in mathematics can also be invaluable”

The people “best suited for work that involves machine learning are data scientists, data engineers, mathematicians, and statisticians” according to Coursera.

These responses may create a barrier to everyone learning about DS and ML as these are skills and knowledge which everyone may not have. While courses to gain these requirements may exist on Coursera, they are not explicitly provided or linked, and as such could be difficult for people starting out.

Roadmaps

Expert are beginning to create roadmaps detailing the skills, experience and education needed to move into AI-related roles. However, these are largely aimed at professionals moving from related fields or graduates in areas such as Computer Science. One example of these is being provided by *I am AI* (I.am.ai, 2021), another by the AI Guild providing accreditation for Senior Data Scientists and ML Engineers (AI Guild, 2021). While these road maps are important for people advancing in their careers, they are extremely technical and include specialist language, potentially making them inaccessible and overwhelming for those hoping to move into these careers from other backgrounds. An excellent step in the right direction is the announcement of an online AI academy for lifelong learning as part of the UK AI Council's AI Roadmap (UK AI COUNCIL, 2021). Such an academy, including an online effort and based on community support is the type of initiative these research findings support.

This survey is a useful step towards creating a roadmap which allows others to move into DS, ML, AI and Robotics from broader backgrounds as it allows hiring managers to speak candidly about their requirements and companies' attitudes towards training and internal moves.

Methodology

Survey Design

As the intended participants of this survey are likely to be short on time and digitally savvy due to the nature of their jobs, an online survey was seen as more suitable than interviews or in-person surveys (Evans and Mathur, 2005). Freedom of expression and choice of phrasing is key to this research, so a qualitative survey was designed rather than a quantitative one (Braun *et al.*, 2020). All questions were open-ended free text boxes, rather than pre-defined choice selections, allowing respondents to elaborate, digress and contribute as they wish (Sischka *et al.*, 2020). Also, the responses were anonymous and demographic questions were optional to further encourage participation as well as candid responses.

Survey Questions

The survey consisted of some introductory categorisation questions, to determine the current relationship of the individual (and their company) to DS, ML, AI and Robotics. These questions were:

1. Does your role involve robotics, data science, machine learning or artificial intelligence?

2. Does your company work on any of the following: robotics, data science, machine learning or artificial intelligence?
3. In the near-future will your company work on any of the following: robotics, data science, machine learning or artificial intelligence?
4. Is your company interested in learning more about robotics, data science, machine learning or artificial intelligence?

These questions were shown in order, with Yes / No responses. If a respondent answered yes, they were not shown any further questions in this section.

The main body of the survey was made up of four questions, one with three parts. The aim of this section was to understand the requirements for roles in DS, ML, AI or Robotics; as well as how these requirements could be obtained and how the company would support learning or moving into these roles.

1. When thinking about roles working in these areas, are there any specific skills, qualifications or traits which are necessary? Please list as few or as many as you like.
    a. Skills
    b. Qualifications
    c. Traits
2. How do you think your employees would best learn / obtain / develop these?
3. Would your company provide these in house or would employees be expected to source their own training or experience?
4. In your opinion, how easy or difficult is it for someone to move into these roles from another non-related role?

The final section of the survey asked some optional demographic questions, including current job title, industry, size of company and location.

Survey Recruitment

As the intended participants for the survey worked in specific jobs, the survey recruitment was by invitation only. The target jobs were people who worked in a senior technology role, within a company currently or planning to use DS, ML, AI or Robotics, who had responsibility for hiring and training staff.

Analysis

The qualitative data was were analysed using qualitative analytics techniques, including qualitative coding, categorising and thematic analysis (Braun and Clarke, 2006).

Findings

Demographics

Location

2/3 of respondents were based in the UK, six of these were specifically based in London. Of those not in the UK, all but one were based in the US. All respondents, except one, describe themselves as being based in an urban area.

Company Size

Over half of respondents worked for a large company, based on the UK's definition of over 250 employees (Department for Business, 2020). These companies ranged in size from 500 to over half a million employees. Continuing to use the UK definitions of small and medium companies (less than 50 and 50-249 employees respectively), there were 4 respondents from small companies and 3 from medium.

Industry

Several respondents gave multiple industries in response to this question. The industries of the respondents included social media, education and manufacturing. Three respondents were from a consulting company. One of these described themselves as "consulting and technology", there were further two who would be classed as technology ("technology", "software"). Two respondents gave "eCommerce" as one of their industries. Two specifically said "fintech" and a further four were also related to finance and banking.

Role

11 of the respondents were in a data role, six of which worked in Data Science. One worked in robotics. The other three worked in a senior management position.

Proximity to DS, ML, AI or Robotics

The respondents were asked a series of questions to determine their current proximity to these areas. All but two currently work in a role involving one of these areas. One did not work in a role involving these, but their company did use them. The other respondents worked for a company hoping to use these areas in the near future.

Requirements for DS, ML, AI and Robotics Roles

There were 4 questions in the survey relating to hiring for DS, ML, AI and Robotics jobs directly, one which had three parts. These questions were all in the form of free text boxes allowing respondents to say as little or as much as they wanted. The shortest response (all answers combined) was 36 words and the longest 291. The median length was 106 words. These questions aimed to understand what hiring managers saw as the requirements for working in DS, ML, AI and Robotics, and how their companies might be involved in training employees. Analysing each question individually allows a deeper look at patterns and viewpoints from the hiring managers who answered the survey.

1a - Skills

For the majority of responses this question was answered as a list (separated using commas, semi-colons and new lines). When the responses were separated into the items in the lists, a total of 76 skills were given by the 15 respondents. The minimum number given was 3, and the maximum was 10. The mean number of skills given was 4, and the median was 5.

The skills have been categorised into the following themes:

- *Data*: skills related to analytics, visualisation, data science, databases and data engineering.
- *Human*: non-technical skills, sometimes referred to as "soft" skills.
- *Maths*: anything related to maths or statistics.
- *Tech*: very broad theme encompassing coding, software engineering techniques, computer science theory.
- *Business*: domain knowledge, understanding business problems.
- *Specific*: skills which relate very specifically to one of DS, ML or AI.

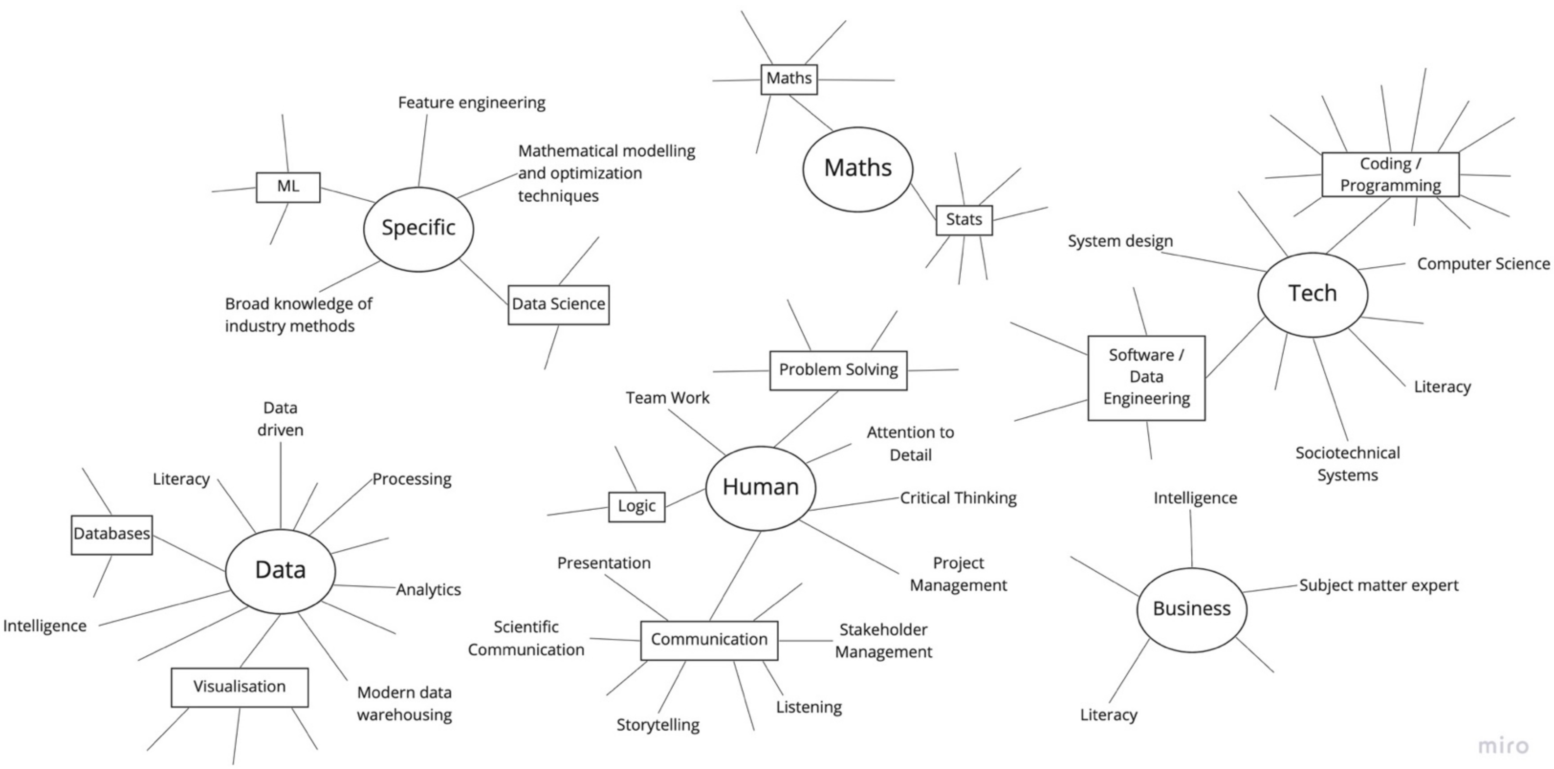


Figure 29 *- Skills map based on responses to the survey question "Which Skills are Required to Work in AI, ML, DS and Robotics?". Each line represents one mention of the skill. Lines without words at the end did not have any further specificity. Tech, human and data are the three largest skills groups. Human skills were very specific (most lines end in a word or phrases), compared to Tech skills which were vague and easily grouped together (resulting in empty lines).*

The skills and themes are represented in the form of spider diagrams (**Figure 29**). The circles represent the themes listed above, and the rectangles represent sub-themes of skills which occur more than once within these themes. The final lines (either leading to some additional text or empty) represent individual skills. The skills without text at the end did not contain more detail or specificity than the theme or sub-theme they stem from. There are more than 76 skills represented in this diagram as some 76 skills have been counted in multiple categories, for example "understanding of data/statistics/ml" has been counted as *Data, Maths* and *Specific.* Also, other skills were split into multiple skills for the diagrammatic representative, for example “data literacy + visualisation” was separated into “data literacy” and “data visualisation”.

7 skills specifically referred to DS, ML, AI or Robotics, these are under the *Specific* theme. Within this theme, the sub themes of *Data Science* and *ML* were both mentioned 2 and 3 times respectively. These 7 skills were given by 5 respondents. Half of the skills in this theme were broad (“understanding of ml”, “data science”, “understanding of data science techniques”, “broad knowledge industry methods”). The other half were about a more specific topic within this theme:

> “ability to evaluate and select appropriate ML methods for a specific project”
>
> “mathematical modelling and optimization techniques”
>
> “feature engineering”
>
> “understanding of machine learning algos and approaches (including things like accuracy and explainable AI)”

15 of these skills were related to *Data*, these were deemed different than the *Specific* skills as they were more general and could be required for more jobs than ones in these areas (for example, Data Analyst, Project Manager). 10 of the respondents mentioned at least one *Data* skill. The majority of the skills relating to *Data* were around understanding data and analytics, some of which explicitly say these words:

> “Understanding data”
>
> “background in data / analytics”
>
> “understanding of the application of data and how it can be used”
>
> “understanding of data”
>
> “Analytics”

An additional four mentioned more specific data-related skills - “data processing”, “data driven”, “data literacy” and “"data intelligence" - The ability to understand and value high quality data”. Three of the

Data skills were about data visualisation, one mentioned particular programmes - “D3, Tableau, Looker”. Database skills were mentioned twice, one respondent discussed “SQL type languages”. Related to this, another skill mentioned was “modern cloud data warehousing like BQ, Snowflake, Redshift, Azure” which are typically more related to “Data Engineering” roles than DS, ML, AI or Robotics.

Eleven skills are related to *Maths* – 5 of which mention Maths and 6 mentioned Statistics - given by 9 of the 15 respondents. The majority of these skills just indicate a vague skill in one of these areas are needed (“some knowledge”, “basic”, “experience with”, “understanding of”, “confidence”). Two are more specific - “Mathematics (Linear Algebra, Calculus)”, “statistics & experimentation methods”).

Eighteen *Human* skills were given by 10 of the respondents. Human skills can be split into further sub-themes. The largest of which was *Communication* skills which were mentioned 8 times. Three of these specifically said “communication”, others mentioned “presentation skills” and “listening”. One respondent said “storytelling” was a required skill. Another *Communication* skill given was “stakeholder management”. The final was more detailed “scientific communication - i.e., present actionable findings to a business audience who don't know/understand the scientific/technical details”. Four of the *Human* skills were “problem solving”, another two were “logic”. The other four human skills given were “project management”, “team working”, “attention to detail” and “critical thinking”.

Twenty-three *Tech* skills mentioned. These skills were given by all but one respondent (who focused on *Data* skills). Several of these were vague and could apply to many technical jobs - “technical skills”, “understanding of tech stack”, “Computer Science”, “system design”, “technical literacy”. A further three could also apply to a number of jobs and were related to engineering practices:

> “version control”
>
> “software engineering best practices”
>
> “basic software engineering skills (version control, documentation, coding)”

Another *Tech* skill was related to engineering, but specifically to data engineering:

> “engineering skills to process large amounts of data often using tools like hadoop, spark, kinesis, kafka, etc”.

Thirteen of these *Tech* skills were related to coding / programming. Most of these were general, and did not go into specifics, however three coding languages were mentioned - “Python” 5 times, “R” three times and “SQL” twice. Some skills mentioned a combination of these three languages. One respondent said Python and R, but specified SQL was also important as “so many data scientists don't know a good way to manipulate data”. One of the *Tech* skills was different than the others, focusing more on the social implications of these technologies, “understanding of sociotechnical systems”.

Finally, 5 *Business* skills were given by four respondents. These *Business* skills included: “business understanding”, “business / subject matter expertise”, “business literacy” and “an understanding of business problem”. One respondent went into greater details:

> “business intelligence - what is the value of the problem to the business, what features of the problem are most valuable, how perfectly does it need to be solved, what would happen if it isn't solved”

The “technical literacy” and “business literacy” skills were mentioned by the same respondent who added “having both is important”.

One respondent felt “The question is very broad. Each of these areas is very broad and there are 4 of them listed.” They went on to describe the core skills needed which included a range of all themes except *Specific.*

When specifically discussing DS, another respondent split the skills into three areas – “problem statement, data collection/wrangling, and solution architecture and delivery” - and described the skills needed for each.

These skills echo those mentioned in previous studies and by recruitment and education companies. There is a focus on tech, data and maths skills. It is worth emphasising that the large amount of human skills mentioned shows the requirement to work in DS, ML, AI and Robotics requires more than technical skills.

1b – Qualifications

The respondents seemed to be in two camps with regards to required qualifications – either a STEM qualification or none. This may be the cause of some vagueness and inconsistency and therefore the responses will be considered carefully through this lens. Firstly, five respondents specifically said a degree was required. One said “at least a masters in a STEM subject”, their comment was “most people in these fields” have at least a Master’s degree rather than this is definitely needed for people entering the field. The other four referred to degrees in a range of subjects. “STEM” was specified twice. The robotics respondent said an “engineering” degree but worded this as “typically helpful to create a foundation” rather than a necessity. The final respondent said “numerical, mathematical and programming orientation”. This respondent also gave an alternative or enhance on a degree - “certification provided by Amazon, Google and Azure in the Machine learning area”. Another respondent did not explicitly say a degree, but did give “science or engineering qualifications” as the requirement. The last respondent to mention qualifications did not believe a degree was needed, only high school level maths or science - “A levels in maths or science subjects, everything else can be learned”.

Two further respondents did not mention any specific qualifications but did mention the required knowledge qualifications would need to be shown. One said “deep understanding of working with data” needed to be shown, the other said “Anything showing mathematical competence to reasonably high level” would be enough.

In contrast, the remaining six respondents pointedly said no qualifications were needed. One simply stating “there are no specific formal qualifications I'd recommend at this point”. Another said “skills are more important than qualifications”. One respondent gave the caveat of no qualifications being required “if you can self teach”. The other three focused more on experience:

> “I value experience over qualifications”
>
> “I have seen a lot of great people with no certifications or degrees and other people with tons of certs that are not good. Experience is what matters most.”
>
> “I'm not a big believe[r] in qualifications, more in background. e.g. very enthusiastic hobbyist programmers often have similar technical skills to comp sci grads”

Experience was also something mentioned by the robotics respondent who said an engineering degree would be useful, as well as "past work or project experience in robotics/AI".

While some respondents expect a particular type of degree from people wanting to work in DS, ML, AI and Robotics, this was not shared by everyone. Not having clear qualification requirements may add to confusion about routes into these roles, however it also may open up the roles to candidates from other backgrounds.

1c – Traits

There were 47 traits mentioned overall which is a lot less than the 76 skills given in response to question 1a - Skills. One respondent only gave one trait, and the maximum given was 6. Both mean and median number of traits given were 3.

Trait	Number of Mentions
Technical	9
Mindset	7
Curious	4
Attention to detail	4
Communication	4
Inquisitive	3
Keen on learning	3
Balance of tech and business	2

Table 5 *– Trait mentioned by hiring managers more than once. These have been grouped together where possible.*

Nine of the traits given were not personality traits. These were focused on technology, maths or were very specific to DS, ML, AI or Robotics. Four respondents gave technical traits, two respondents gave only these technical traits, and did not mention any personality traits. One of these respondents also did not give any *Human* skills in response to the required skills questions. Some of these traits are broad - “Data engineering”, “programming”, “mathematics”, “compulsive documenting”. The other five were very specific to DS, ML and AI:

> “awareness and interest in keeping up with new machine learning techiques & methodologies”
>
> “Knowledge of processing structural and unstructural data”
>
> “experience in feature engineering and desired to have exposure to NLP, image recognition and processing”
>
> “familiarity with ML model architectures, tuning strategies and performance evaluation”
>
> “explainable ML and AI”

The remaining traits given could arguably be described as personality traits. 9 of these traits were related to mindset:

> “proactive mindset”
>
> “strong motivation to improve systems and processes”
>
> “Pragmatism”
>
> “willing to challenge group think”
>
> “willingness to experiment, fail and try something else”
>
> “scepticism so they challenge results”
>
> “broad thinker (e.g. we need people to think about the ethics of their solutions, catch inherent biases, think about how what they're building will actually be used in the real world).”
>
> “Persistant”

“open minded”

These traits suggest a particular personality, able to influence change is required for a role in DS, ML, AI or Robotics. All of these traits were given by three respondents. One respondent only gave traits from this category, accounting for five of the above quotes.

Four respondents said “attention to detail”, one expanding to say “able to see the bigger picture as well as the minute detail”. 3 respondents said “curious”, related to this a further two said “creative” and “imagination”. Three respondents gave only two traits – one of which was attention to detail and the other one of the words related to “curious”. Three further respondents mentioned inquisitively - “inquiring attitude”, “inquisitive mind regarding data”, “Inquisitive and questioning”.

Four traits given by respondents were around communication - “communication w/ team”, “persuasive”, “listening”, “ability to communicate and collaborate well with colleagues of varying technical abilities.”. Another trait mentioned three times was the need to learn - “tenacity (need to train/retrain)”, “Eagerness and ability to learn new technical skills”, “likes learning”.

Two respondents mentioned the need for a mix of technical and business traits:

> “There's a balance of people, product/business & data/math/coding skills that is quite rare to find.”

> “look at business sense and not just technical.”

Only five respondents gave traits which did not come under one of the previous categories. These traits were: “Problem Solving”, “Focus on Impact”, “project management”, “Sense of Enjoyment”, “adept”, “focused”, “friendly” and “Logical thinking”.

These traits focused more on technical traits, although the personality traits suggest a particular type of person, mainly someone who is not afraid to speak their mind, is seen as best suited to DS, ML, AI and Robotics roles.

2. How do you think your employees would best learn / obtain / develop these?

There was no clear consensus on how the requirements discussed in the previous questions would be obtained by employees, although there were common themes mentioned. The majority of respondents mentioned several options for gaining these requirements, these were often a mix of work and education.

Most respondents mentioned a mixture of formal education and work experience, some of these were vague:

> “A combination of training and work and formal education if really needed”
>
> “More practical modules at university, work on a project, learn on the job.”
>
> “Study from courses and on-the-job learning”
>
> "for the understanding of how ML works/algos generally through course work
>
> for the business specific skills on the job/through experience"

Two of the above respondents mentioned coursework or projects. Working on real life projects was also suggested by several other respondents. One was specific about working through data sets and reviewing some real-life examples:

> “On the job, working with sample data set's [sic], assigned tasks that simulate real life scenarios, working through case studies/ examples, review of real life examples”

Two respondents mentioned reading papers and working with more senior members of the team.

> “Practice, observation, co-working and pair programming, reading, online courses, part time programmes”
>
> “Previous experience (jobs/education), reading articles and research paper to stay up to date on latest developed, working with more experienced teammates”

Education was a part of these two previous responses, but not everyone saw education as important. Two respondents did not specify education at all. One saying degrees are not needed - “by doing the job - I don't think a degree is necessary”. The other focusing more on workplace-based training - "Role models Technical training and on the job coaching "

Another respondent had a different approach, they believed formal education in maths was required, but only until A-Level (UK post-16 exams). They believed coding education was useful, but could be learnt on the job, but data and business skills have to be acquired on the job.

> "For the maths side that pretty much has to be through formal education although it doesn't have to be to a high level. Top quality A-level maths is more than sufficient for most stuff. For the coding, there's an advantage to having some training or courses I think, although plenty can be learned on the job. Data intelligence and business intelligence are skills that have to be learned on the job."

Three respondents mentioned university:

> "using them everyday, coding camps help, computer science degrees are helpful but it is completely different doing this type of work in the wild."

> "university is best for the technical skills. it teaches people how to solve problems. real world experience on passion projects/work experience is necessary to know what kind of problems actually matter/are valuable to solve"

> "Some of the fundamentals (like stats) -> university or other courses (I don't rate coursera or others as I think the learning is very superficial and people don't learn how to apply their knowledge)"

The first respondent acknowledged a degree is very different to the job, they believe coding camps can help obtain the needed requirements. The other two believed a degree is the best way to learn technical skills or fundamental knowledge, such as statistics. The final respondent above, specifically calls out issues with online learning not being enough. This is in juxtaposition with the views of two other respondents who were in favour of online course providers, such as Coursera:

> "Pursuing the certifications from major platform such as Google, attend courses from DataCamp, Plurasight etc."

> "Technical skills through online courses eg. Coursera, Datacamp. Reading groups or data science community resources/blogs for knowledge sharing and keeping up with latest developments in

> the field. Communication skills by pushing themselves to collaborate as widely as possible to grow networks and practice communication in various settings."

Throughout the responses some main themes can be identified – there is a split on whether formal education is needed, continuous learning (reading, projects, etc) is expected and on-the-job experience is vital. It is also important to recognise that once again there was disagreement, lack of consensus and ambiguity across responses. This may be causing a blocker on how to create potential roadmaps into AI-related roles.

3. Would your company provide these in-house or would employees be expected to source their own training or experience?

When asked about whether companies would provide training in these areas within their company (in-house) or if employees would have to find their own training. There was a range of responses to this question – 4 said "in-house", although the detail of "in-house" training was often more through mentoring and shadowing than structured training courses or professional development. For example,

> "there should be an expectation that junior developers and data scientists will receive explicit role-related mentoring and feedback"

Only one mentioned providing in-house learning sessions. 3 respondents said the employee would have to find their own ("I would expect the employees to source their own training"), but two mentioned it would be paid for. 7 said "both" (for example, "Some in house and some self driven learning").

One theme which came through in the responses to this question was expecting employees to have a base line of knowledge or skills. This baseline was mentioned by 6 respondents who gave various reasons:

> "There would be *a level expected to start* with but further training to improve is always available"

> "We are a small company so we generally *need to hire someone with the necessary skills* and experience. However, we want people to learn and develop new skills and will support our employees toward furthering their skill set"

> "we do some ad-hoc training for people wanting to learn data but otherwise *hire for people who already know it*"

> "*Baseline expectation when joining*, with in-house courses or funded external courses to augment"

> "We would provide appropriate training as required, although *we tend to hire people with demonstrated experience in the areas we are looking for*."

> "The employee would be *expected to have a strong programming foundation* but some language/library specifics would be learned on the job, though typically not from a formal training class, just in the process of doing tasks and being mentored by more senior members of the team."

Only the final of these 6 respondents gave an indication of what these expected skills or experience were, and they focused on programming rather than any of the other skills or traits mentioned.

Throughout these answers it is not always clear and certainly not often coherent across responses, as to what the current expectation, if any, on companies to train new employees or retrain current employees in DS, ML, AI or Robotics. However, employers have expectation on the minimum requirements for hiring and moving into these roles.

4. In your opinion, how easy or difficult is it for someone to move into these roles from another non-related role?

When asked how difficult it would be to move into a DS, ML, AI or Robotics role, two respondents said it would be easy. One gave a reason - "these jobs are very in-demand". They caveated this by saying individuals needed "at least need some basic hard skills to switch, but with some personal projects and/or volunteer projects you could probably switch into this area in less than a year". They also shared an anecdote about a pharmacist they knew changing to a data science career. The other said it would be easy “with sufficient technical/coding skills and ability to easily pick up new tools and techniques”. They actually stated the main curve would be getting up to speed with the business application.

Five respondents said it would be difficult - “super hard”, “very difficult”, “hard”, “difficult”, “relatively difficult”. One gave no reasons for this perceived difficulty. Some of the reasons given by others were due to the companies, with one saying “shifts across projects and teams are limited” causing difficulty to move. Another said “employers aren't willing to go on blind faith that someone will succeed” and the onus is on the individual as there is “a lot of knowledge needed” so “individuals need to spend a lot of time proving themselves”. Another respondent mentioned “people look for experience in narrow toolset rather than recruiting for skills and aptitude”. The final respondent mentioned the “strict mathematical or coding requirements” making it difficult if an individual does not have those skills. They further commented on “most employers will be suspicious of those with neither formal training nor real-world experience in those areas and would go through rigorous technical testing through the recruitment process”.

Six respondents said the ease or difficulty would depends on various factors. Two said the ease depending on “the individual” and their combination of skills.

> “With the right attitude and some transferable skills it could be easy. With none of the aforementioned skills/ traits it would be very challenging”.

> “it's easier for people with the technical skills to move into the more business facing skills. A person without a deep understanding of calculus and solid coding skills is unlikely to be successful as an AI researcher.”

One respondent (who was specifically talking about Robotics roles) said it depended on whether the individual came from an engineering background or not – engineers “should have a decent foundation to learn the new skills needed” whereas those not from engineering “would take longer to pick up some of the new skills needed”. Another said it depends on whether the individual was moving jobs within the company or from outside. This would be due to individual having “domain knowledge and some skills”, therefore having no experience is less impactful. One said “specific qualifications” were not too hard to attain, but there is “competition for entry-level jobs and ill-informed hiring practices” making attaining a role difficult. The final respondent said it depends on “the seniority of the position”, particularly “companies should hire on potential if it is for more of a junior role. For a supervisory role, more in-depth knowledge is required.”

Two respondents did not mention whether it would be easy or difficult to move into one of these roles, but said motivation was what mattered. One said “the motivation is everything” but went on to say a lack of basic maths and science would pose a challenge. The other said individuals being “self-motivated” is what is needed for “learning new data skills”.

Overall, the answers to this question did not paint an easy way for people moving into a DS, ML, AI or Robotics role. Even moving within companies seems to require the baseline mentioned in the previous question. Therefore, the responses suggest someone from a typical STEM background or who had self-taught themselves these requirements would have an easier time moving into one of these roles.

Discussion

The aim of the survey was to understand industry experts’, in particular hiring managers’, views on the requirements needed to work in DS, ML, AI and Robotics. The survey further looked at companies’ involvement in employees obtaining these requirements and moving into a related role. Based on their current job, it can be assumed a lot of respondents were specifically speaking about DS (although they did not specify a difference). While this type of research cannot be generalised, it can provide critical qualitative detail and an interesting insight into what is required for DS, ML, AI and Robotics roles and potential barriers for individuals who wish to move into these roles. The survey responses showed a number of barriers which still need to be addressed:

1. (Vague) consensus on requirements
2. “Baseline”
3. Path is still not clear
4. Companies are not stepping up to close the skills gap
    a. Companies do not provide training
    b. Moving into these roles is not easy

(Vague) Consensus on Requirements

While the responses were not identical, there was some general consensus on what is required for working in DS, ML, AI and Robotics. These employers were looking for someone proficient at coding and good at maths (which could be proved by having a STEM degree or some certification, although this varied). Ideally someone who had experience working with data, and who could demonstrate strong communication skills and business acumen. There was a focus on how important it is to have this mix of requirements (mainly coding / data and communication / business), particularly for DS. The responses to the question on required traits in this study suggest there is a particular type of person who would be best suited to roles in DS, ML, AI and Robotics. This person is naturally technical, whose mindset challenges the status quo (which perhaps suggest someone outspoken). They are also creative with an attention to detail.

Compared to a similar study conducted with members of the public (Gemmell, Wenham and Hauert, no date), there was much more emphasis on the human and business skills required to work in DS, ML, AI and Robotics. Although there were similar human skills discussed – problem solving, logical, critical thinking. Communication skills were not mentioned by members of the public in the study at all. The members of public also had less focus on personality traits than the hiring managers.

It is worth noting in both the study conducted with the members of the public, and this survey, the surveys did not mention engineering or technology roles, but all respondents in both studies answered as if it did. In this instance, the survey itself stated "robotics, data science, machine learning and artificial intelligence jobs". However, all respondents discussed technical or engineering roles. There are roles in these areas which do not require coding (e.g. conversational designer for a chat bot, or a project manager for a data science team) which do not seem to be considered when these areas are mentioned.

"Baseline"

When asked whether training would be provided in-house, and how difficult it would be to move into a DS, ML, AI or Robotics role within the company, many respondents mentioned there would be a "baseline" of skills and experience needed. Most of these respondents do not go into specifics of what this baseline requirement actually is. Those who do give specifics all discuss technical, mathematical or hard skills suggesting this baseline refers to coding related skills, and all others (business, communication) can be trained. This raises the question, can this be reversed? I.e. should businesses be hiring those with a baseline of communication and business skills, and training for the technical side? If this was possible, it would be useful to understand what the absolute minimum requirements are (e.g. would there be a basic, or advanced, level of maths required, are there short coding courses which could demonstrate competent?) If coding and maths skills are the baseline requirement, companies could be looking in the wrong place and hiring a select group of people while missing the potential of those who do not meet the baseline. Setting the baseline to include only those with the needed technical skills those who may bring additional skills, mindsets and creativity to a team will be missed. Technical skills can be taught on the job, however the other skills – communication skills and business expertise may be harder to learn on the job. Research to further understand which skills are teachable, determining curriculums (or building on those which already exist) and hiring for those skills which are harder to teach could completely change the view of the needed baseline.

Path is Still Not Clear

Despite there being some general consensus on the requirements (particularly skills and traits, rather than qualifications), there is still not a clear path to moving in DS, ML, AI and Robotics roles. Some respondents saw a STEM degree as an absolute requirement, while others did not. Those who did not see a degree as a requirement did not give a concrete alternative which suggests having a degree, whether required or not, still remains the easiest path into these roles. Take the different responses regarding online courses provided by platforms such as Coursera – two respondents said these were sufficient to show the skills and knowledge required, however another respondent specifically said they do not consider these to be good enough. Conflicting views such as these make it difficult for those who do have degrees to know which courses (if any) will help them move into DS, ML, AI and Robotics.

Another pathway into DS, ML, AI and Robotics discussed was “experience” and “on the job” training. This feels like a “catch 22” situation – employers only hire those with baseline skills and experience, but individuals are expected to have experience and can gain the skills via on-the-job training. The companies in this study ranged from large internally known tech giants with hundreds of thousands of employees to small companies with less than 50 employees. None mentioned hiring those who do not fit the expected baseline requirements or providing in-house training for those from different backgrounds.

From these responses, it is unclear how experience or the baseline requirements are to be achieved by those not on the typical path (STEM degree, good at maths and coding, with some specific data experience).

Companies are not Stepping Up to Close the Skills Gap

Companies Do Not Provide Training - The companies who responded to this survey are not putting themselves forward to train potential employees who do not have the "baseline" skills. Once working there, however, additional training and mentoring would be provided if needed. The reasons given for this included the company being small and needing workers who have the requirements for the job already. Another reason given was time, the company did not have the time to train people. Again, if companies are only hiring those with the requirements, it does not sound easy for respondents from other backgrounds to secure these roles.

Moving into These Roles is Not Easy - The respondents did not paint an easy picture of moving into DS, ML, AI or Robotics roles, even within companies. Although this was caveated based on the respondents' backgrounds and skills, e.g. being technical and moving into a more business role would be easier than the other way around.

As previously mentioned, increasing diversity within teams increases productivity and creativity. This helps teams perform better in terms of reaching company goals (and overall improving the company's bottom line). Further, companies do not have enough of the highly technical talent they need, and this is more of an acute problem for many companies since the pandemic, where recruitment is all areas is difficult. Closing the skills gap is in the company's interest to ensure they have access to the needed talent and that they are attractive to enough potential staff. Also, increasing diversity means more voices will be involved in company decisions, particularly design or data decisions. For example, having more parents helps companies design their products for families and children.

Recommendations

Often a stereotypical view of who can work in DS, ML, AI and Robotics is painted, these responses have continued to do this but the language is subtle. There is still gatekeeping coming from these hiring managers who are hiring for experience and specific requirements. It is important for companies to explore hiring from non-typical backgrounds, both because this opens up the field to a range of candidates often missed, and it is proven diversity makes good business sense (Lorenzo *et al.*, 2018; Dixon-Fyle *et al.*, 2020). It is important companies hire from diverse backgrounds as this can greatly increase both productivity and creativity within companies (Dixon-Fyle *et al.*, 2020; Johnson *et al.*, 2022). Take for example, a team made up of computer science graduates who have taken similar career path to this point who are likely to have been taught to think about problems and their approach to problem-solving and design similarly. Those from other life, educational and career background may bring something else to this team by thinking about the problem and the approach differently.

If companies are going to insist on a “baseline” of requirements for DS, ML, AI and Robotics roles, further research to understand what exactly this means is needed. Defining an industry standard baseline at least gives those interested in these roles something to work towards. This is being worked on by various groups, including I.am.AI and the AI Guild (AI Guild, 2021; I.am.ai, 2021), but they are currently aimed at those already working in these areas, rather than those moving into DS, ML, AI or Robotics.

Companies should be involved in creating a clear path into DS, ML, AI and Robotics roles. This could be different for internal and external candidates. The path should ideally include alternatives, particularly for those who do not meet the stereotypical requirement. For example, one respondent said A-Level maths or science is sufficient, they should provide a list of requirements and pathways for someone without these qualifications. These pathways could also include acceptable courses (both free and paid), personal projects and other demonstratable experience (work or volunteer) which would be alternatives to degrees and other experience.

Conclusion

A survey was conducted with hiring managers in DS, ML, AI and Robotics to understand their requirements for hiring in these areas (skills, qualification and traits). The survey further questioned how easy it would be for employees to obtain these requirements and move into one of these roles. The responses were analysed using qualitative methods of coding, categorising and thematic analysis. Analysing the data showed there was some general consensus around the skills requirements – coding, maths and problem solving skills mixed with experience working with data. These needed to come hand in hand with communication skills and business acumen. There also was not a clear path into DS, ML, AI and Robotics as there was no consensus on what qualifications or experience were needed. What did come across though was the "baseline" requirement expected of people moving into a DS, ML, AI or Robotics role. However, this baseline was never explicitly explained. The companies surveyed did not provide initial training for obtaining these requirements, and the hiring managers did not paint an easy picture of moving into these roles. More needs to be done to create a clear path into DS, ML, AI and Robotics roles, especially for those who do not currently have coding skills or STEM degrees. Companies should play a role in this as increasing diversity is only beneficial for them. Part of creating a clear path requires companies to explain exactly what their baseline requirements are, and how these can be demonstrated.

Postface

Surveying the hiring managers revealed further barriers and cemented ones which have been revealed in previous studies. There was more of a consensus on the required skills and traits, however this was still somewhat vague. Their thoughts reinforced the views of the members of public – that working in AI related roles was for a specific person (good at maths and coding, with experience in data and business, a problem solver with good communication skills, and a strong personality). This is further added to by the hiring managers mentioning a "baseline" of skills needed to work in AI-related areas. These were very coding and technical skills, with the suggestion the other skills and traits can be taught. Having this stereotype perpetrated by both individuals and hiring managers does not make it easy for someone who does not fit this exactly to see themselves working in AI. This gatekeeping further adds to the expert gatekeeping found in the first chapter.

Again, these surveys did not suggest there was a clear path into AI-related areas. It was contradictory whether degrees were needs, and whether online courses are good enough. Similar to the "baseline", experience was often discussed as needed but as an impossible catch-22 – experience is needed to get the baseline skills but experience and baseline skills are needed to get a job.

Companies could do more to overcome the skills gap, and help people from non-typical backgrounds into AI-related roles. There is more training which could be provided by companies, both for new employees and current ones. The companies do not currently paint an easy picture of moving into AI-related roles, even internally, they could work to create a roadmap to illustrate how this could be possible.

Chapter 7: Future Co-Design

The previous three chapters have outlined the studies which were conducted as part of this thesis – a series of interviews and two online surveys. These studies highlighted a number of barriers which need to be addressed in the design of AI education to *skill the gaps*. In this chapter, I outline a community co-design plan which was created and intended to be delivered, however this was not possible due to lockdowns in 2020.

The interviews in Chapter 4 introduced the need for design with the learners' needs in mind, or better still co-designed with potential learners. These interviews also unveiled *expert gatekeeping*, a barrier which needs to be overcome to ensure AI education works for everyone. This gatekeeping was also echoed in Chapter 6's surveys with AI-related hiring managers. To ensure the experts' gatekeeping does not shape AI education, and as such add unnecessary barriers (such as the need to define AI as something complex which excludes what the public see as AI), co-design with learners is an important step. Moreover, co-design with learners and experts, where greater mutual understanding can be built and misconceptions or assumptions addressed could tackle expert gate-keeping obstacles. The surveys with MoPs in Chapter 4 also revealed another type of gatekeeping, coming from the potential learners themselves. To overcome any potential self-gatekeeping, a co-design plan aims to help co-designers reframe any pre (and mis)-conceptions they have with RAI and how these technologies impact their lives. The co-design session would build to the co-designers envisioning themselves designing RAI, and finally designing education which works for them.

The importance of gatekeeping, in terms of exclusion and power dynamics, has been seen in many STEM related areas, for example science education (Moore, 2007) and maths (Bryk and Treisman, 2010). Both science and maths were seen as required skills for working in RAI in the surveys in Chapter 5 by the public. Gatekeeping in RAI, while not a new phenomenon, does not appear to be widely covered in literature. The closest related research are examples of lack of diversity in AI, such as the research by Nesta into the gender of authors of research papers (Stathoulopoulos and Mateos-Garcia, 2019b). This gatekeeping not an inherently new or different to gatekeeping previously seen in STEM, however I argue here it is easier to see the impacts of this gatekeeping, particularly for the public. AI is a subject which often appears in the media and the public are more exposed to the impacts of AI than they are to impacts of other STEM topics. As such, the lack of diversity in AI may feel more important than the lack of diversity in mathematics as the public may see this as a GCSE topic they hated rather than something which will have consequences for their lives.

Co-design is important in areas where gatekeeping exists, as it allows an opportunity for all stakeholders to sit in the same room and have an input. Co-design, if carried out properly, aims to flatten the power dynamics and ensure all voices are recognised as important and are heard (in this case, in particular the potential learners). An example of co-design of technology allowed seniors in the USA and children in Mexico to work together on a number of digital projects (including animated films, podcasts and prototypes using BBC Microbits) (Rodriguez, 2021). Similar to the co-design plan detailed here, in Rodriguez's work "the emphasis was not on acquiring technical skills, but reflecting on the cultural, political, and economic links of digital media in the world". Through the collaboration and reflection of co-design, a deeper understanding of each other's perspectives, concerns and experiences can be gained, which would, hopefully, help reduce all kinds of gatekeeping.

The similarities between co-design and design-led thinking which is often used to create new technology products fits in well with the overall theme of technology and qualitative research throughout this thesis. Participatory Design and Co-Design have been used in education – with students, teachers and other stakeholders as designers in the process (DiSalvo *et al.*, 2017; Cavignaux-Bros, D. & Cristol, 2020).

Co-design is an established and evolving approach to research design and methodology, which has some similarities in methods but can differ in its interpretation and application (Burkett, 2012; Meynard, Dedieu and Bos, 2012). Co-design is promising for working with the public and a range of stakeholders (Evans and Terrey, 2016; Zamenopoulos and Alexiou, 2018) as well as being applicable to policy (Binder, 2011; Blomkamp, 2018). The principles of co-design outlined in the work by Zamenopoulos and Alexiou as part of the Connected Communities series (Zamenopoulos and Alexiou, 2018) were used in the plans for this co-design (and will be discussed in the next sub-section). Although as this is future work, precise details could depend on the early stages and further reading inspired by what happens in the field.

Plans for a Community Co-Design

The community co-design was originally planned to run at several community hubs around Bristol – Knowle West Media Centre, Barton Hill Settlement and local libraries. However, these ideas and sessions could be used in other settings. The intended audience was non-expert working adults from a specific community (as helping the community would be what these co-designers have in common), however anyone who wished to attend would be permitted to do so. In the planning of this co-design, it was discussed each community hub would be responsible for recruitment. As these would be pilot sessions, anyone who was free would be invited to attend and different times of day (during the day, evenings and weekends) would be trialed to find a range of participant. One community hub suggested them running a creche during the sessions to allow parents to attend. The idea was for the sessions to be iterative and reviewed / amended after each set of 5 sessions taking into account feedback and ideas raised. The 5 sessions each have a topic:

1. Examples
2. Perception
3. Impacts
4. Designing
5. Education

Each session has been split into two parts to simulate discussion. The first three sessions have specific structure and exercises inspired by the findings of the interviews in Chapter 4. These three sessions aim to both teach the co-designers about AI and gain insight into their views and understanding of AI. These sessions will function to *provoke* the co-designers to think about AI, the *things* (or resources) used to provoke have been inspired by community co-design in Seven Sisters at the future of the area above a tube station (Zamenopoulos and Alexiou, 2018). The final two sessions are less structured with open, less-formalised exercises to allow the participants to lead the co-design. These two sessions will be more focused on *projecting* and *prototyping* – allowing co-designers to create their own RAI ideas and design their own education, then to get feedback from each other and iterate their ideas if they wish. Further, each session would be recorded, and interviews conducted with co-designers to gain their feedback.

Session 1 – Examples

The initial set of interviews on AI showed the public's understanding and definition of AI is varied, and certainly differs from that of "experts". The examples given by the members of public in these interviews (shown in **Figure 7**) were vast, including both hardware and software, and ranged from very specific to vague topics. As such, it would be useful to begin each co-design session establishing what the group of co-designers think of certain examples of AI. Both exercises in this session would involve moving 10 examples of AI along the scale shown in **Figure 30**.

Everyday examples of RAI

There will be 10 examples of Robotics and AI on the table on separate cards and to spark discussion. Examples to include predictive text, maps, self-checkout. The co-designers will be asked to arrange the examples according to:

1. How often you use them
2. How useful they are
3. How "technical" they are

Controversial examples of RAI

There will be 10 examples of Robotics and AI on the table on separate cards and allow discussions to spark discussion. These will be ones which could be considered controversial, including credit scoring, facial recognition. The co-designers will be asked to arrange the examples according to:

1. How worried these make you
2. How useful they are
3. How "technical" they are

Figure 30 *– Layout of resources to be used in 'Session 1 – Examples' of the community co-design. The squares on the left represent Post-Its with examples of AI (for example, 'voice assistants' or 'recommender systems'). In this session, the examples will be given to the co-designers. Through discussion these examples will be placed on the scale on the right from least to most, in response to a number of questions (how often you use them, how useful they are, how "technical" they are). These have been left vague to spark discussion. A similar exercise will take place with "controversial" examples of AI.*

Session 2 – Perception

A barrier which was revealed in both the interviews and online survey with MoPs was the need to understand and overcome pre- (and mis)-conceptions of AI held by the public. Session 2 on perception gives an opportunity to understand the co-design groups current perceptions and where they come from.

RAI in the Media and Sci-Fi

It is important to understand where pre-conceptions come from, as such this exercise would be a chance to understand where the co-designers see RAI depicted. Understanding the news sources they use, how reliable they are (in their opinion) and how they show RAI could help overcome these pre-conceptions. **Figure 31** shows a scale which would be used to visualize how much co-designers use and trust different sources. Examples could include newspaper, Twitter, Facebook, movies, radio. These sources can be vague or specific. Using coloured Post-Its to depict the positivity, negativity or neutrality of how do these source depict RAI.

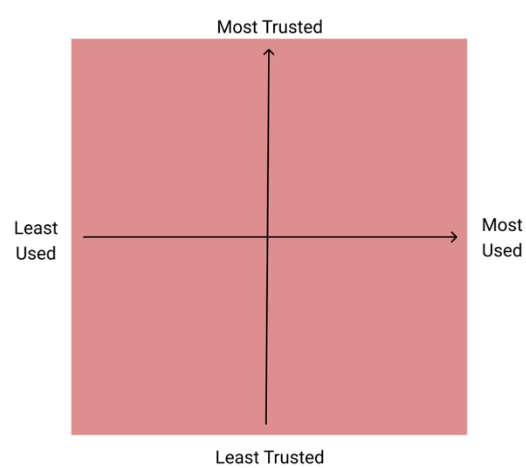


***Figure 31** – Layout of resources to be used in 'Session 2 – Perception' of the community co-design. In part 1, the group of co-designers will create Post-It notes of media sources (e.g. Twitter, the Daily Mail) with colours depicting the neutrality of the*

sources. These will then be placed on the grid above to show Use vs Trust. In part 2, the co-designers will create Post-It notes with examples of RAI from the media (e.g. "killer robots" from the news, VIKI from iRobot (film)) using colours to depict how "real" they view the technology to be. Again, the Post-Its will be placed on the grid above to show useful vs trusted for these RAI.

Demystifying - Types and Limitations of RAI

Following on from this exercise, a set of examples from media and sci-fi (for example, the "killer robot" from Terminator, the voice AI system from AI) will be suggested by the co-designers on different Post-Its (with colours indicating "realness" of the RAI, i.e. if it currently exists, nearly exists, will exist in the future or will never exist). These can then be placed (through group discussion) on a grid showing trust and use similarly to the media types (shown in **Figure 31**). The aim of this discussion is to understand the co-designers' views on which types of RAI can be trusted and which they would use.

Session 3 – Impacts

In the third session, the discussion around AI is to be reframed to focus on how AI impacts the co-designers. This could be an important step to overcoming any gatekeeping and worries.

Personal Impacts

The aim of this exercise would be to discuss the impacts of RAI on different areas of personal life. The co-designers would be asked to use different coloured Post-It notes to indicate different types of impact (e.g. good, neural, bad, unknown). These Post-It notes would then be placed in one of four categories – You, Job, Home and Hobbies (shown in **Figure 32**). If an impact did not fit in one of these categories, it could be placed outside.

Wider Impacts

The aim of this exercise would be to discuss impacts of RAI on different areas of wider life which has been split into two spheres (seen in **Figure 33**). One sphere is work related with three categories – Job, Company, Industry (shown on the left of **Figure 33**). The other is non-work related with four categories – You, Family / Friends, Community, Society (shown on the right of **Figure 33**). The aim of these spheres is to centre the thinking of the co-designers on themselves (at the centre), but also the wider impacts. Again, the co-designers would be asked to use different coloured Post-It notes to indicate different types of impact (e.g. good, neural, bad, unknown).

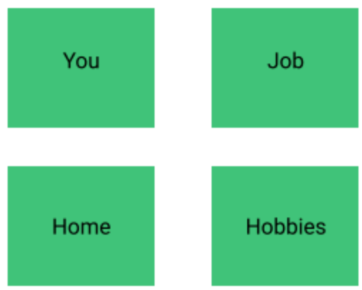


Figure 32 *– Layout of resources to be used in 'Session 3 – Impacts (Part 1 on Personal Impacts)' of the community co-design. In this exercise, co-designers will be asked to think about different RAI and how these will impact their lives. First they will write examples of RAI which touch their lives on Post-It notes, using different colours to depict different types of impact (good, bad, neutral, unknown). The co-designers will then place these Post-It notes on one of the squares above showing which part of their lives the RAI will impact – themselves (for example, health apps), their jobs (for example, auto-transcription software), their home (for example, smart assistants) and their hobbies (for example, smart booking systems for sports).*

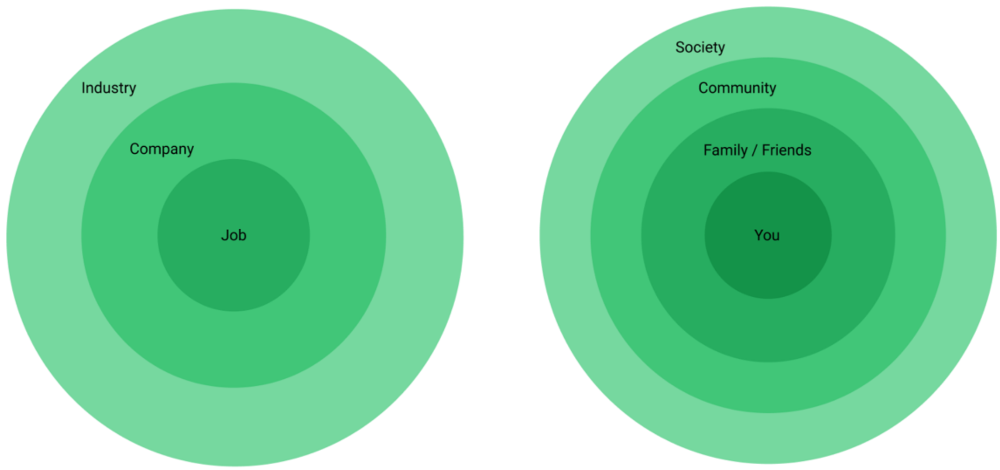


***Figure 33** – Layout of resources to be used in 'Session 3 – Impacts (Part 2 on Wider Impacts)' of the community co-design. In this exercise, co-designers will be asked to think about different RAI and how these will impact their lives (in a larger context than the previous exercise). Using the examples of RAI which they created in the previous exercise (**Figure 32**) and any other they want to add, the co-designers will show where these examples impact their lives. Firstly, on the left, how RAI impact their specific jobs, the company they work for and the entire industry they work in. Second, how does RAI impact them specifically, and widening how does RAI impact their friends / family, their community and all of society. An example of different impacts could be a parent who might not be impacted by social media algorithms, but their teenager is. The aim of this exercise is to help co-designers see how RAI touches them and their wider world, even if this is not obvious.*

Session 4 – Designing

The fourth session on designing would be slightly different than all other sessions. This session would provide an opportunity for the co-designer to think about how AI could be useful for them, if they could create it themselves. The resources for this session could include cardboard for prototyping, paper for sketching or computers for using software. The two sessions would be as follows:

1. Design a use for RAI which would be useful for you
2. Discuss each other's designs

The first session would offer a chance for co-designers to be create and explore the possibilities with RAI. The session would be free for them to use as they wish, but support would be available to guide if needed. The second session would be an opportunity to present and discuss their ideas.

Session 5 – Education

The final session would give the co-designers a chance to express what they would like to be included in an AI education. This would be broken into two sessions:

1. What do you **need** to learn / understand to exist / work with RAI?
2. What do you **want** to learn / understand to exist / work with RAI?

The needs and wants of the co-designers might be the same or very different, this would be important to understand. Allowing the co-designers to actually impact an education is vital to co-design. The plan for this session would be left blank to allow the co-designers to control the discussion and how the education was shaped.

Final Thoughts

While this co-design plan was created for community education, it could very easy be used or adapted to become a workplace education co-design.

Chapter 8: Conclusion

In this thesis, I have outlined the three studies undertaken to examine the barriers stopping people from learning about and retraining in AI. Firstly, interviewed 21 stakeholders in designing AI education – 6 members of public, 7 adult educators, 6 thought-leaders and 2 industry experts. The interviews were semi-structured and analysed using qualitative methods of coding, categorizing and thematic analysis. Next, two online surveys were created to investigate the perceived requirements to work in AI-related areas and how these could be obtained. The first survey was with for members of public, and received 39 responses. These responses were rich and analysed using both a new method I devised using NLP and qualitative methods to give a detailed picture of the public's perception of requirements. The second survey asked similar questions of hiring managers in AI-related areas. It further questioned their company's role in training and hiring people moving into these areas. Finally, some ideas for further work, including a plan and outline for a community co-design have been included.

Findings of Research

The overall finding of this research is there are barriers – preconceptions, stereotypes, gatekeeping, company attitudes– which need to be addressed to ensure no one is left behind. These barriers exist even when people are interested in learning about or retraining in AI-related areas.

One important finding of every aspect of this research was people (nearly everyone who participated in the interviews or surveys) have a lot to say about AI. This included women in a local area Facebook group, warehouse managers, IT teachers and people stopped in a park. Further to this, everyone we spoke to had their own understanding of what AI is and most had opinions on the topic. Further to this, the public are more positive than we assumed before conducting this research.

Another finding was the need to overcome stereotypes and preconceptions. These barriers come from both experts and the public (actually throughout this research the only people who did not contribute to these barriers were the educators from a council run learning centre). It has been clear people's lives – jobs, age, gender, comfort with tech and maths, etc – impact their preconceptions and stereotypes. Any efforts going forward should be mindful of this. Any educational efforts to teach the public about AI should be co-designed with the public, community interest points and local adult education centres.

A large aspect of the barriers is gatekeeping. Interestingly, in all parts of this research gatekeeping was found. Furthermore, it was actually found to be coming both from experts and from people themselves. Experts assume people cannot or would not want to learn about AI or would not be able to work in AI-related jobs. These beliefs also come from the public who assume AI training is not for them, and you must be a maths and coding person to work in these areas. It is unclear if one is causing the other, or if they are entangled. This gatekeeping needs to be addressed before more people retrain and the skills gap can be closed. This mindset also completely overlooks the other non-technical roles within AI, such as conversation designer and project manager.

A further barrier is created by the lack of a clear path to learn about or retrain in AI-related areas, particular for people who do not fit the stereotype. Some companies require degrees, others are happy with online courses. Companies state the need for baseline skills, but do not seem willing to help train employees or new hires up. Companies need to step up to address the skills gap (and increase diversity in AI-related areas). Firstly, companies should be involved and have a stake in creating clear pathways, or at the very least stepping stones, for people to move into AI-related areas. Companies also need to provide training and options for their employees to fill their skills gaps. Another potential useful step would be to hire and train those who do not meet the stereotype, but are strong in other areas (e.g. subject matter expertise, communication or business skills). Finally, education for those working *with* AI (rather than researching or coding AI) is needed. This could include warehouse workers working with robotics, or call centre workers using automated systems. Similarly, to community AI education, these industry educational efforts should be co-designed with employers and employees to ensure no one is left behind.

Reflexive Summary

An important aspect of qualitative research is the ability of the research to reflect on their research – both the research itself and on themselves as a researcher (Lichtman, 2011; Braun and Clarke, 2013). Throughout this research I personally have grown as a researcher – from a scientist who learnt the value of social science methods, to someone who seems the beauty of when qualitative and technical methods collide. Overall, I believe this research went as well as could be during the lockdown – of course, I still believe the impact and my enjoyment of the research would have been greater if the initial plan could have taken place.

The interviews study was intended to be a pilot study as a first step to a community co-design. Perhaps collecting more demographics during this research would have enhanced the findings. However, the findings of this study steered the rest of the rest and I believe they are an important piece of this puzzle.

The online studies were not as rich in data, and despite the studies having useful and significant findings, I would have preferred the opportunity to complete more interviews as being able to probe and explore the respondents' answers provides greater depth to the research. Similarly, more demographics could have been collected in this study. Despite this part of the research not being what was planned, I thoroughly believe the NLP part of the research revealed interested patterns (particularly the clusters of thinking) in the data which would have been found using only qualitative methods.

Finally, if I had greater understanding of qualitative methods when I began this research, I would have known to push back on the stipulations imposed on this research by the ethics approval in my engineering faculty, where they are less used to processing qualitative ethics involving research with people. This could allow for aspects of thicker description and a more rich qualitative data set in places, although I would still have to balance inclusion and data gathering tensions.

Significance of Work

These findings are important as the barriers identified need to be addressed before any efforts (educational or otherwise) can be effective in everyone learning about AI, increasing diversity in AI-related areas or closing the skills gap. If the barriers are not overcome, many people will be left behind as the Fourth Industrial Revolution advances and inequality caused by the digital divide will only increase.

Through this research, I have identified a number of barriers which need to be addressed. These barriers include overcoming preconceptions and stereotypes, gatekeeping and unclear pathways to learning and retraining. Importantly, the gatekeeping is coming from both individuals themselves and experts in AI-related areas.

The method of this research, mainly the qualitative methods from an engineering perspective, provides a different insight into the topic to the purely engineering perspective. Also, the research has been carefully designed, where possible, to encourage speaking with people who may not normally be included in research, and showing they have a lot to say on the topic (regardless of who they were). This highlights the importance of co-design and including the people often left behind in any educational efforts.

These barriers need to be overcome for several reasons. Firstly, the skills gap in AI-related areas is ever increasing. Retraining and moving into these roles needs to become easier, or at least more accessible, to close the skills gap. To close this skills gap, those who have not followed the stereotypical path and who are not well represented in these areas will need to be included. Increasing diversity in these industries (which will have a significant impact on the future) is an important step in creating a future which works for everyone. Furthermore, these roles are (typically) well paid and often allow flexible working arrangements (e.g. compressed hours, fully flexible hours, work from home) so they should be accessible by everyone as they can be life-changing for people, families and communities.

References

Accenture (2021a) *Artificial Intelligence - What is artificial intelligence?* Available at: https://www.accenture.com/gb-en/insights/artificial-intelligence-summary-index.

Accenture (2021b) 'Leaders wanted: Experts at change at a moment of truth', *Technology Vision*.

AI Guild (2021) *Data Careers Accreditation*, *datacareers.eu*. Available at: https://www.datacareer.eu/ (Accessed: 8 November 2021).

Alderson, P. and Morrow, V. (2011) *The Ethics of Research with Children and Young People: A Practical Handbook*. SAGE Publications. Available at: https://books.google.co.uk/books?id=ozX2i1u71isC.

Andreotta, M. *et al.* (2019) 'Analyzing social media data: A mixed-methods framework combining computational and qualitative text analysis', *Behavior Research Methods*, 51(4), pp. 1766–1781. doi: 10.3758/s13428-019-01202-8.

Andrus, M. *et al.* (2021) 'What We Can't Measure, We Can't Understand', in *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. New York, NY, USA: ACM, pp. 249–260. doi: 10.1145/3442188.3445888.

Atkins, L. and Duckworth, V. (2019) *Research Methods for Social Justice and Equity in Education*. Bloomsbury Publishing (Bloomsbury Research Methods for Education). Available at: https://books.google.co.uk/books?id=FfGEDwAAQBAJ.

Austin, Z. and Sutton, J. (2014) 'Qualitative research: getting started.', *The Canadian journal of hospital pharmacy*, 67(6), pp. 436–440. doi: 10.4212/cjhp.v67i6.1406.

Bassetti, C. *et al.* (2019) 'Co-designing for common values: creating hybrid spaces to nurture autonomous cooperation', *CoDesign*, 15(3), pp. 256–271. doi: 10.1080/15710882.2019.1637897.

Binder, T. (2011) 'LIVING THE (CODESIGN) LAB', (May).

Blomkamp, E. (2018) 'The Promise of Co-Design for Public Policy', *Australian Journal of Public Administration*, 77(4), pp. 729–743. doi: 10.1111/1467-8500.12310.

Blumer, H. (1954) ‘What is Wrong with Social Theory?’, *American Sociological Review*, 19(1), p. 3. doi: 10.2307/2088165.

Borau, S. *et al.* (2021) ‘The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI’, *Psychology & Marketing*, 38(7), pp. 1052–1068. doi: 10.1002/mar.21480.

Bostrom, N. (2006) ‘AI set to exceed human brain power. CNN Science & Space’, *CNN Science & Space*.

Bourazeri, A. and Stumpf, S. (2018) ‘Co-designing smart home technology with people with dementia or Parkinson’s disease’, in *Proceedings of the 10th Nordic Conference on Human-Computer Interaction - NordiCHI ’18*. New York, New York, USA: ACM Press, pp. 609–621. doi: 10.1145/3240167.3240197.

Bowles, J. (2014) *The computerisation of European jobs*, *Bruegel*. Available at: https://bruegel.org/2014/07/the-computerisation-of-european-jobs/ (Accessed: 2 April 2020).

Boyatzis, R. E. (1998) *Transforming qualitative information: Thematic analysis and code development.*, *Transforming qualitative information: Thematic analysis and code development.* Thousand Oaks, CA, US: Sage Publications, Inc.

Boyd, R. and Holton, R. J. (2018) ‘Technology, innovation, employment and power: Does robotics and artificial intelligence really mean social transformation?’, *Journal of Sociology*, 54(3), pp. 331–345. doi: 10.1177/1440783317726591.

Braun, V. *et al.* (2020) ‘The online survey as a qualitative research tool’, *International Journal of Social Research Methodology*, pp. 1–14. doi: 10.1080/13645579.2020.1805550.

Braun, V. and Clarke, V. (2006) ‘Using thematic analysis in psychology’, *Qualitative Research in Psychology*, 3(2), pp. 77–101. doi: 10.1191/1478088706qp063oa.

Braun, V. and Clarke, V. (2013) *Successful Qualitative Research: A Practical Guide for Beginners*. SAGE Publications Ltd.

Braun, V. and Clarke, V. (2016) ‘(Mis)conceptualising themes, thematic analysis, and other problems with Fugard and Potts’ (2015) sample-size tool for thematic analysis’, *International Journal of Social Research Methodology*, 19(6), pp. 739–743. doi: 10.1080/13645579.2016.1195588.

Brinded, L. (2017) ‘Automation killed 17,000 roles at a huge tech and services firm — but no one actually lost their job’, *Business Insider*, January. Available at: https://www.businessinsider.com/accentures-richard-lumb-davos-interview-robots-jobs-skills-leadership-training-2017-1 (Accessed: 26 February 2019).

Browne, R. (2020) ‘Facebook is creating 1,000 new jobs in the UK’, *CNBC*, January. Available at: https://www.cnbc.com/2020/01/21/facebook-is-creating-1000-new-jobs-in-the-uk.html.

Bryk, A. S. and Treisman, U. (2010) ‘Make math a gateway, not a gatekeeper’, *Chronicle of Higher Education*, 56(32), pp. B19–B20.

Budds, D. (2019) ‘New York City’s AI task force stalls’, *Curbed New York*, 16 April. Available at: https://ny.curbed.com/2019/4/16/18335495/new-york-city-automated-decision-system-task-force-ai.

Bughin, J. *et al.* (2018) ‘Notes from the AI Frontier: Modeling the impact of AI on the world economy’, *Modeling the global economic impact of AI | McKinsey*, (September), pp. 1–61. Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy [Accessed 03 April 2021].

Buolamwini, J. and Gebru, T. (2018) ‘Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification’, in Friedler, S. A. and Wilson, C. (eds) *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*. PMLR (Proceedings of Machine Learning Research), pp. 77–91. Available at: https://proceedings.mlr.press/v81/buolamwini18a.html.

Burkett, I. (2012) ‘An Introduction to Co-Design’, *Ingridburkett.Com*, pp. 1–3. Available at: http://ingridburkett.com/wp-content/uploads/2017/09/Introduction-to-Codesign-2.pdf.

Byrne, M. (2001) ‘Sampling for qualitative research’, *AORN Journal*, 73(2), p. 494. Available at: https://link.gale.com/apps/doc/A70871448/AONE?u=univbri&sid=googleScholar&xid=7ef6732c.

Cave, S. and Dihal, K. (2020) ‘The Whiteness of AI’, *Philosophy & Technology*, 33(4), pp. 685–703. doi: 10.1007/s13347-020-00415-6.

Cavignaux-Bros, D. & Cristol, D. (2020) ‘Participatory Design and Co-Design—The Case of a MOOC on Public Innovation’, in *Learner and User Experience Research: An Introduction for the Field of Learning Design & Technology*. Available at: https://edtechbooks.org/ux.

Centre for European Economic Research (2018) *Robots create jobs – new research*, *Ifr*. Available at: https://ifr.org/ifr-press-releases/news/robots-create-jobs-new-research (Accessed: 24 April 2019).

Cheng, Z. *et al.* (2012) 'Multifunctional Nanoparticles: Cost Versus Benefit of Adding Targeting and Imaging Capabilities', *Science*, 338(6109), pp. 903–910. doi: 10.1126/science.1226338.

Clark, G. (2019) *Regulation for the Fourth Industrial Revolution*. Available at: https://www.gov.uk/government/publications/regulation-for-the-fourth-industrial-revolution/regulation-for-the-fourth-industrial-revolution (Accessed: 16 July 2020).

Cohen, L., Manion, L. and Morrison, K. (2013) *Research Methods in Education*. Routledge (Education, Research methods). Available at: https://books.google.co.uk/books?id=p7oifuW1A6gC.

Cohen, L., Manion, L. and Morrison, K. (2017) *Research Methods in Education*. Taylor \& Francis. Available at: https://books.google.co.uk/books?id=9mYPEAAAQBAJ.

Coursera (2021a) *Data Science*, *coursera.org*. Available at: https://www.coursera.org/browse/data-science (Accessed: 8 November 2021).

Coursera (2021b) *Machine Learning*, *coursera.org*. Available at: https://www.coursera.org/browse/data-science/machine-learning (Accessed: 8 November 2021).

Cui, V. and Wheatcroft, L. (2021) *AI literacy – the role of primary education*, *Birmingham City University*. Available at: https://www.bcu.ac.uk/education-and-social-work/research/news-and-events/cspace-conference-2021/blog/ai-literacy-the-role-primary-education.

Delcker, J. (2019) *Finland's grand AI experiment*, *POLITICO*. Available at: https://www.politico.eu/article/finland-one-percent-ai-artificial-intelligence-courses-learning-training/ (Accessed: 26 February 2019).

Department for Business, E. & I. S. (2020) *Business population estimates for the UK and regions: 2019 statistical release*. Available at: https://www.gov.uk/government/statistics/business-population-estimates-2019/business-population-estimates-for-the-uk-and-regions-2019-statistical-release-html#definitions-and-terminology.

Devlin, K. and Belton, O. (2020) 'The Measure of a Woman', in Cave, S., Dihal, K., and Dillon, S. (eds) *AI*

Narratives. Oxford University Press, pp. 357–381. doi: 10.1093/oso/9780198846666.003.0016.

DiSalvo, B. *et al.* (2017) 'Participatory design for learning : perspectives from practice and research LK - https://bris.on.worldcat.org/oclc/988284770'. New York, NY: Routledge, Taylor & Francis Group. Available at: http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1526864.

Dixon-Fyle, S. *et al.* (2020) *Diversity wins: How inclusion matters*.

Eaton, E. (2017) 'Teaching integrated ai through interdisciplinary project-driven courses', *AI Magazine*, 38(2), pp. 13–21. doi: 10.1609/aimag.v38i2.2730.

Evans, J. R. and Mathur, A. (2005) 'The value of online surveys', *Internet Research*, 15(2), pp. 195–219. doi: 10.1108/10662240510590360.

Evans, M. and Terrey, N. (2016) 'Co-design with citizens and stakeholders', *Evidence-Based Policy Making in the Social Sciences: Methods that Matter*, (February 2017), pp. 243–262. doi: 10.46692/9781447329381.014.

Faruqe, F., Watkins, R. and Medsker, L. (2021) 'Competency Model Approach to AI Literacy: Research-based Path from Initial Framework to Model'. Available at: http://arxiv.org/abs/2108.05809.

Fast, E. and Horvitz, E. (2017) 'Long-term trends in the public perception of artificial intelligence', in *31st AAAI Conference on Artificial Intelligence, AAAI 2017*.

FCAI (2018) *Elements of Artificial Intelligence free online course*. Available at: https://www.elementsofai.com/ (Accessed: 26 February 2019).

Fereday, J. and Muir-Cochrane, E. (2006) 'Demonstrating Rigor Using Thematic Analysis: A Hybrid Approach of Inductive and Deductive Coding and Theme Development', *International Journal of Qualitative Methods*, 5(1), pp. 80–92. doi: 10.1177/160940690600500107.

Foundai (2020) *IMPROVING PUBLIC AWARENESS OF AI'S PRACTICAL BENEFITS*, *Foundai*. Available at: https://www.fountech.ai/news/improving-public-awareness-of-ais-practical-benefits (Accessed: 7 May 2020).

Frey, C. B. and Osborne, M. A. (2017) 'The future of employment: How susceptible are jobs to computerisation?', *Technological Forecasting and Social Change*, 114, pp. 254–280. doi: 10.1016/j.techfore.2016.08.019.

Fusch, P. I. and Ness, L. R. (2015) 'Are we there yet? Data saturation in qualitative research', *Qualitative Report*, 20(9), pp. 1408–1416. doi: 10.46743/2160-3715/2015.2281.

Le Gallais, T. (2008) 'Wherever I go there I am: reflections on reflexivity and the research stance', *Reflective Practice*, 9(2), pp. 145–155. doi: 10.1080/14623940802005475.

Gemmell, L., Wenham, L. and Hauert, S. (2021) 'Skilling the Gap: 21 Conversations on Designing Education for Those Left Behind as Robotics and Artificial Intelligence Advance', *Advanced Intelligent Systems*, p. 2000169. doi: 10.1002/aisy.202000169.

Gemmell, L., Wenham, L. and Hauert, S. (no date) 'Clearing the Path - Understanding How Inaccurate Assumptions Muddy the Route for People to Move into AI Jobs', *Unpublished*.

Gilster, P. (1997) *Digital Literacy*. Wiley. Available at: https://books.google.co.uk/books?id=awkoAQAAMAAJ.

Gough, B. and Conner, M. T. (2006) 'Barriers to healthy eating amongst men: A qualitative analysis', *Social Science & Medicine*, 62(2), pp. 387–395. doi: 10.1016/j.socscimed.2005.05.032.

Gov (2018) *Tech experts to provide National Centre for Computing Education*, *Gov.uk*.

Gov (2019a) *National retraining scheme*, *Gov.uk*. Available at: https://www.gov.uk/government/publications/national-retraining-scheme/national-retraining-scheme (Accessed: 2 April 2020).

Gov (2019b) *Next generation of artificial intelligence talent to be trained at UK universities*, *Gov.uk*. Available at: https://www.gov.uk/government/news/next-generation-of-artificial-intelligence-talent-to-be-trained-at-uk-universities (Accessed: 26 February 2019).

Guest, G., Namey, E. and Chen, M. (2020) 'A simple method to assess and report thematic saturation in qualitative research', *PLoS ONE*, 15(5), pp. 1–17. doi: 10.1371/journal.pone.0232076.

Guetterman, T. C. *et al.* (2018) 'Augmenting Qualitative Text Analysis with Natural Language Processing: Methodological Study.', *Journal of medical Internet research*, 20(6), p. e231. doi: 10.2196/jmir.9702.

Han, L. and Siau, K. (2020) 'Impact of Socioeconomic Status on Trust in Artificial Intelligence', *AMCIS 2020 TREOs*. Available at: https://www.researchgate.net/publication/343214673.

Hanspal, A. (2021) 'Here's why robots are actually going to increase human employment', *Weforum.com*, February. Available at: https://www.weforum.org/agenda/2021/02/world-economic-forum-automation-create-jobs-employment-robots (Accessed: 29 January 2022).

Hawking, S. (2016) *"The best or worst thing to happen to humanity" - Stephen Hawking launches Centre for the Future of Intelligence*, *cam.ac.uk*. Available at: https://www.cam.ac.uk/research/news/the-best-or-worst-thing-to-happen-to-humanity-stephen-hawking-launches-centre-for-the-future-of (Accessed: 3 February 2022).

Hingston, P., Combes, B. and Masek, M. (2006) 'Teaching an undergraduate AI course with games and simulation', *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 3942 LNCS, pp. 494–506. doi: 10.1007/11736639_61.

I.am.ai (2021) *AI Expert Roadmap*, *i.am.ai*. Available at: https://i.am.ai/roadmap/ (Accessed: 8 November 2021).

IBM Cloud Education (2020) *Artificial Intelligence (AI)*.

Ingargiola, G. *et al.* (1994) 'A Repository that Supports Teaching and Cooperation in the Introductory AI Course', *ACM SIGCSE Bulletin*, 26(1), pp. 36–40. doi: 10.1145/191033.191048.

Jarvis, D. (2020) *The AI talent shortage isn't over yet*, *Deloitte*. Available at: https://www2.deloitte.com/us/en/insights/industry/technology/ai-talent-challenges-shortage.html (Accessed: 4 November 2021).

Johnson, P. C. *et al.* (2022) 'Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation?', *Technological Forecasting and Social Change*, 179, p. 121636. doi: 10.1016/j.techfore.2022.121636.

Kabir, M. (2019) 'Does artificial intelligence (AI) constitute an opportunity or a threat to the future of medicine as we know it?', *Future Healthcare Journal*, 6(3), pp. 190–191. doi: 10.7861/fhj.teale-6-3.

KPMG (2018) *How the UK can win the AI race: What we know, what the public think and where we go from here*. Available at: https://assets.kpmg.com/content/dam/kpmg/uk/pdf/2018/09/how-the-uk-can-win-the-artificial-intelligence-ai-race.pdf.

KPMG (2021) 'Socio-Economic Background Pay Gap Report 2021', (September).

Krafft, P. M. *et al.* (2020) 'Defining AI in Policy versus Practice', in *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. New York, NY, USA: ACM, pp. 72–78. doi: 10.1145/3375627.3375835.

Kvale, S. (2008) *Doing Interviews*. SAGE Publications (Qualitative Research Kit). Available at: https://books.google.co.uk/books?id=x7lXd08rD7IC.

Lankshear, C. and Knobel, M. (2008) 'Introduction', in *Digital Literacies: Concepts, Policies and Practices*, pp. 1–16.

Leeson, W. *et al.* (2019) 'Natural Language Processing (NLP) in Qualitative Public Health Research: A Proof of Concept Study', *International Journal of Qualitative Methods*, 18, p. 160940691988702. doi: 10.1177/1609406919887021.

Lero (2018) *Lero , The Irish Software Research Centre : RED Line*.

Li, C. *et al.* (2020) 'Research on Artificial Intelligence Customer Service on Consumer Attitude and Its Impact during Online Shopping', *Journal of Physics: Conference Series*, 1575(1), p. 012192. doi: 10.1088/1742-6596/1575/1/012192.

Libai, B. *et al.* (2020) 'Brave New World? On AI and the Management of Customer Relationships', *Journal of Interactive Marketing*, 51, pp. 44–56. doi: 10.1016/j.intmar.2020.04.002.

Lichtman, M. (2011) *Understanding and Evaluating Qualitative Educational Research*. 2455 Teller Road, Thousand Oaks California 91320 United States: SAGE Publications, Inc. doi: 10.4135/9781483349435.

Lloyds Bank (2021) 'Essential Digital Skills Report 2021'.

Long, D. and Magerko, B. (2020) 'What is AI Literacy? Competencies and Design Considerations', in

Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. New York, NY, USA: ACM, pp. 1–16. doi: 10.1145/3313831.3376727.

Lorenzo, R. *et al.* (2018) *How Diverse Leadership Teams Boost Innovation*. Available at: https://www.bcg.com/en-us/publications/2018/how-diverse-leadership-teams-boost-innovation.

Luckin, R. (2017) 'Towards artificial intelligence-based assessment systems', *Nature Human Behaviour*, 1(3), p. 0028. doi: 10.1038/s41562-016-0028.

Makridakis, S. (2017) 'The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms', *Futures*, 90, pp. 46–60. doi: 10.1016/j.futures.2017.03.006.

Manchester, H. and Cope, G. (2019) 'Learning to be a smart citizen', *Oxford Review of Education*, 45(2), pp. 224–241. doi: 10.1080/03054985.2018.1552582.

Manyika, J. *et al.* (2017) 'Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation', *McKinsey Global Institute*, (December), pp. 1–160. doi: 10.1002/lary.20616.

Marshall, M. N. (1996) 'Sampling for qualitative research', *Family Practice*, 13(6), pp. 522–526. doi: 10.1093/fampra/13.6.522.

Matthews, B. and Ross, L. (2010) *Research Methods: A Practical Guide for the Social Sciences*. Pearson Longman. Available at: https://books.google.co.uk/books?id=7s4ERAAACAAJ.

Mccarthy, J. (2004) 'What is Artificial Intelligence?', pp. 1–14.

Meynard, J.-M., Dedieu, Benoit and Bos, A. P. (Bram) (2012) 'Re-design and co-design of farming systems. An overview of methods and practices', in Darnhofer, I., Gibbon, D., and Dedieu, Benoît (eds) *Farming Systems Research into the 21st Century: The New Dynamic*. Dordrecht: Springer Netherlands, pp. 405–429. doi: 10.1007/978-94-007-4503-2_18.

Moore, F. M. (2007) 'Language in science education as a gatekeeper to learning, teaching, and professional development', *Journal of Science Teacher Education*, 18(2), pp. 319–343. doi: 10.1007/s10972-007-9040-0.

Morgan, L. (2020) *Why AI literacy is critical, even for non-technical employees*, *Search Enterprisse AI*.

Available at: https://searchenterpriseai.techtarget.com/feature/Why-AI-literacy-is-critical-even-for-non-technical-employees (Accessed: 30 November 2021).

Moritz, B. and Stubbings, C. (2019) ‘Preparing everyone, everywhere, for the digital world’, *PricewaterhouseCoopers*, p. 9. Available at: https://www.pwc.com/gx/en/upskilling/pwc-upskilling-preparing-everyone-everywhere-for-a-digital-world.pdf.

Mubarak, F., Suomi, R. and Kantola, S. P. (2020) ‘Confirming the links between socio-economic variables and digitalization worldwide: the unsettled debate on digital divide’, *Journal of Information, Communication and Ethics in Society*, 18(3), pp. 415–430. doi: 10.1108/JICES-02-2019-0021.

Naqshbandi, K. *et al.* (2019) ‘Codesigning technology for a voluntary-sector organization’, *Human Technology*, pp. 6–29. doi: 10.17011/ht/urn.201902201606.

National Health System (2018) ‘A Health and Care Digital Capabilities Framework’, *HEE.nhs.uk*, pp. 1–30. Available at: https://hee.nhs.uk/sites/default/files/documents/Digital Literacy Capability Framework 2018.pdf.

Ng, D. T. K. *et al.* (2021) ‘AI Literacy: Definition, Teaching, Evaluation and Ethical Issues’, *Proceedings of the Association for Information Science and Technology*, 58(1), pp. 504–509. doi: 10.1002/pra2.487.

Noble, L. (2018) *Marks & Spencer creates Data Science Academy using Apprenticeship levy*, *HRD Connect*. Available at: https://www.hrdconnect.com/2018/08/03/marks-spencer-creates-data-science-academy-using-apprenticeship-levy/ (Accessed: 26 February 2019).

Nowell, L. S. *et al.* (2017) ‘Thematic Analysis’, *International Journal of Qualitative Methods*, 16(1), p. 160940691773384. doi: 10.1177/1609406917733847.

O’Neil, C. (2016) *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. USA: Crown Publishing Group.

OECD (2015) *Inequalities in Digital Proficiency: Bridging the Divide*.

OECD (2018a) *Education at a Glance 2018*. OECD (Education at a Glance). doi: 10.1787/eag-2018-en.

OECD (2018b) *Finland - Overview of the education system (EAG 2018)*.

OECD (2019) *Employment Outlook 2019: The Future of Work.*, *OECD*. Available at: https://www.oecd.org/employment/future-of-work/ (Accessed: 2 March 2020).

OECD (2021) *OECD Skills Outlook 2021*. doi: https://doi.org/https://doi.org/10.1787/0ae365b4-en.

Office for Students (2020) *Postgraduate conversion courses in data science and artificial intelligence*, *Office for Students*. Available at: https://www.officeforstudents.org.uk/advice-and-guidance/skills-and-employment/postgraduate-conversion-courses-in-data-science-and-artificial-intelligence/ (Accessed: 5 May 2020).

ONS (2019a) *The probability of automation in England: 2011 and 2017*, *ons.gov.uk*. Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/theprobabilityofautomationinengland/2011and2017 (Accessed: 2 March 2020).

ONS (2019b) *Which occupations are at highest risk of being automated?*, *ons.gov.uk*. Available at: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/whichoccupationsareathighestriskofbeingautomated/2019-03-25 (Accessed: 2 March 2020).

Open University (2019) *The UK skills shortage is costing organisations £6.3 billion*, *open.ac.uk*. Available at: http://www.open.ac.uk/business/apprenticeships/blog/uk-skills-shortage-costing-organisations-£63-billion (Accessed: 4 February 2020).

Oppenheim, A. N. (2000) *Questionnaire Design and Attitude Measurement*, *The British Journal of Sociology*. London; New York; New York: Bloomsbury Publishing.

Ouchchy, L., Coin, A. and Dubljević, V. (2020) 'AI in the headlines: the portrayal of the ethical issues of artificial intelligence in the media', *AI and Society*. Springer London, 35(4), pp. 927–936. doi: 10.1007/s00146-020-00965-5.

Oyebode, O., Alqahtani, F. and Orji, R. (2020) 'Using Machine Learning and Thematic Analysis Methods to Evaluate Mental Health Apps Based on User Reviews', *IEEE Access*, 8, pp. 111141–111158. doi: 10.1109/ACCESS.2020.3002176.

Pangrazio, L. (2016) 'Reconceptualising critical digital literacy', *Discourse*. Routledge, 37(2), pp. 163–174. doi: 10.1080/01596306.2014.942836.

Parsons, S. and Sklar, E. (2004) ‘Teaching AI using LEGO Mindstorms’, *AAAI Spring Symposium - Technical Report*, 1, pp. 8–13.

Perrault, R. *et al.* (2019) *Artificial Intelligence Index 2019 Annual Report*. Available at: https://hai.stanford.edu/sites/g/files/sbiybj10986/f/ai%5C_index%5C_2019%5C_report.pdf.

Prentice, C., Dominique Lopes, S. and Wang, X. (2020) ‘The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty’, *Journal of Hospitality Marketing & Management*, 29(7), pp. 739–756. doi: 10.1080/19368623.2020.1722304.

PwC (2020) *New World, New Skills.*, *PwC Global*. Available at: https://www.pwc.com/gx/en/issues/upskilling.html (Accessed: 5 May 2020).

PwC (2021) *Hopes and fears 2021*, *PwC Global*. Available at: https://www.pwc.com/gx/en/issues/upskilling/hopes-and-fears.html (Accessed: 29 November 2021).

PWC (2017) ‘Will robots really steal our jobs ? An international analysis of the potential long term impact of automation Key findings : impact of automation’.

Raspberry Pi (2021) *The AI Effect*, *FutureLearn*. Available at: https://www.futurelearn.com/info/courses/introduction-to-machine-learning/0/steps/262221 (Accessed: 4 February 2022).

Rodriguez, D. (2021) *Designing an Intergenerational Third-Space to Develop Critical-Digital-Literacy LK - https://bris.on.worldcat.org/oclc/1264655139*. University of Bristol TA - TT -. Available at: https://research-information.bris.ac.uk/en/studentTheses/068cfa22-6151-4ed3-991d-253df8fc06b5.

Rolfe, A. (2020) *Jobs in Artificial Intelligence (AI)*, *reed.co.uk*. Available at: https://www.reed.co.uk/career-advice/jobs-in-artificial-intelligence-ai/ (Accessed: 5 November 2021).

Roy, K. *et al.* (2015) ‘Sampling Richness and Qualitative Integrity: Challenges for Research With Families’, *Journal of Marriage and Family*, 77(1), pp. 243–260. doi: 10.1111/jomf.12147.

Royal Society, T. (2019) *Dynamics of data science skills How can all sectors benefit from data science talent?*, *The Royal Society*.

Saunders, B. *et al.* (2018) 'Saturation in qualitative research: exploring its conceptualization and operationalization', *Quality and Quantity*. Springer Netherlands, 52(4), pp. 1893–1907. doi: 10.1007/s11135-017-0574-8.

Schank, R. C. (1987) 'What is AI anyway?', *The Foundations of Artificial Intelligence*, 8(4), pp. 3–13. doi: 10.1017/cbo9780511663116.003.

Schouten, A. (2020) *AI Literacy 101*, *Towards Data Science*. Available at: https://towardsdatascience.com/ai-literacy-101-what-is-it-and-why-do-you-need-it-73238ec7c2db (Accessed: 29 November 2021).

Schwab, K. (2017) *The Fourth Industrial Revolution*. New York, NY, USA: Crown Publishing Group.

Silver, D. *et al.* (2016) 'Mastering the game of Go with deep neural networks and tree search', *Nature*, 529(7587), pp. 484–489. doi: 10.1038/nature16961.

Sischka, P. E. *et al.* (2020) 'The Impact of Forced Answering and Reactance on Answering Behavior in Online Surveys', *Social Science Computer Review*, p. 089443932090706. doi: 10.1177/0894439320907067.

Smith, A. and Anderson, M. (2017) 'Automation in Everyday Life', *Pew Research Center*, p. 78.

Snodgrass, L. (2017) 'Academics can't change the world when they're distrusted and discredited', *The Conversation*. Available at: https://theconversation.com/academics-cant-change-the-world-when-theyre-distrusted-and-discredited-77420.

Squicciarini, M. and Nachtigall, H. (2021) 'Demand for AI skills in jobs'. doi: https://doi.org/https://doi.org/10.1787/3ed32d94-en.

Stathoulopoulos, K. and Mateos-Garcia, J. C. (2019a) 'Gender Diversity in AI Research', *SSRN Electronic Journal*, (July). doi: 10.2139/ssrn.3428240.

Stathoulopoulos, K. and Mateos-Garcia, J. C. (2019b) 'Gender Diversity in AI Research', *SSRN Electronic Journal*, (2018). doi: 10.2139/ssrn.3428240.

Strauss, A. L. (1987) *Qualitative analysis for social scientists.*, *Qualitative analysis for social scientists.*

New York, NY, US: Cambridge University Press. doi: 10.1017/CBO9780511557842.

Suri, H. (2011) 'Purposeful Sampling in Qualitative Research Synthesis', *Qualitative Research Journal*, 11(2), pp. 63–75. doi: 10.3316/QRJ1102063.

Terry, G. and Braun, V. (2011) '"I'm committed to her and the family": positive accounts of vasectomy among New Zealand men', *Journal of Reproductive and Infant Psychology*, 29(3), pp. 276–291. doi: 10.1080/02646838.2011.592976.

The Royal Society (2017) *Machine learning: the power and promise of computers that learn by example*, *Report by the Royal Society*. doi: 10.1126/scitranslmed.3002564.

Touretzky, D. *et al.* (2019) 'Envisioning AI for K-12: What Should Every Child Know about AI?', *Proceedings of the AAAI Conference on Artificial Intelligence*, 33, pp. 9795–9799. doi: 10.1609/aaai.v33i01.33019795.

UK AI COUNCIL (2021) 'AI Roadmap', pp. 1–22.

Varghese, S. (2019) 'In Finland, prisoners are being taught crucial AI skills', *Wired*, October. Available at: https://www.wired.co.uk/article/finland-ai-prisons.

Vega, E. S. (2019) 'Designing Women : Essentializing Femininity in AI Linguistics Designing Women : Essentializing Femininity in AI Linguistics'.

WEF (2018) *The Future of Jobs Report*, *Weforum.com*.

Wharton, A. and Burris, V. (1983) 'OFFICE AUTOMATION AND ITS IMPACT ON WOMEN WORKERS', *Humboldt Journal of Social Relations*. Department of Sociology, Humboldt State University, 10(2), pp. 112–126. Available at: http://www.jstor.org/stable/23262321.

World Economic Forum (2016) *The Global Risks Report 2016 11th Edition*.

Wyse, D. *et al.* (2016) *The BERA/SAGE Handbook of Educational Research*. SAGE Publications. Available at: https://books.google.co.uk/books?id=ioiwDQAAQBAJ.

Yudkowsky, E. and Bostrom, N. (2011) 'The ethics of artificial intelligence', *Cambridge handbook of artificial intelligence. Cambridge University Press, Cambridge*. Available at:

https://scholar.google.com/scholar_lookup?title=The ethics of artificial intelligence&pages=316-334&publication_year=2011&author=Bostrom%2CN&author=Yudkowsky%2CE (Accessed: 29 November 2021).

Zamenopoulos, T. and Alexiou, K. (2018) *Co-design As Collaborative Research. Connected Communities Foundation Series*. Bristol: Bristol University/AHRC Connected Communities Programme.

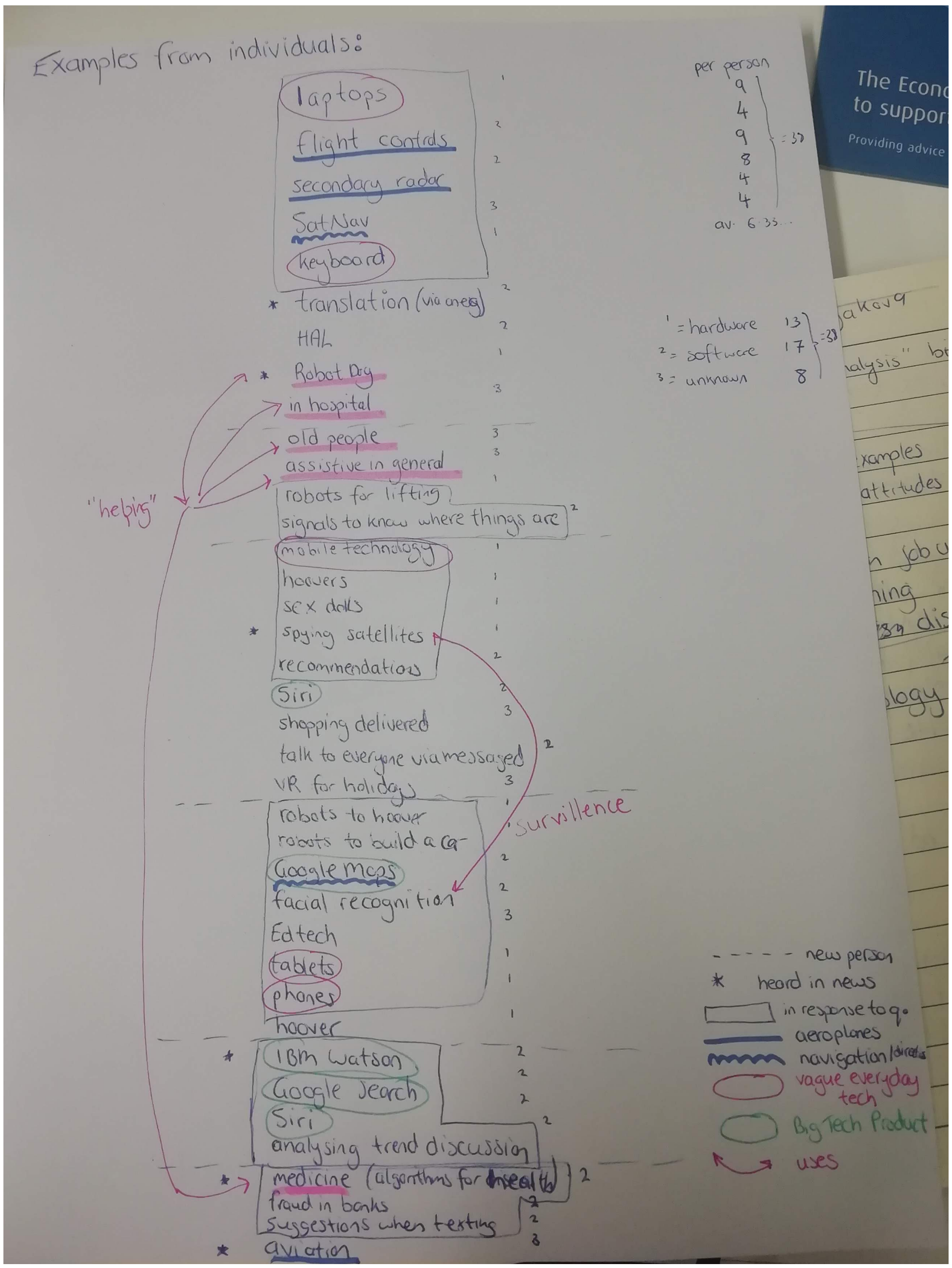
Zhang, B. and Dafoe, A. (2019) ‘Artificial Intelligence: American Attitudes and Trends’, *SSRN Electronic Journal*, (January). doi: 10.2139/ssrn.3312874.

Zimmerman, M. R. (2018) *Teaching AI: Exploring New Frontiers for Learning*.

Appendices

Appendix 1 – Illustrations of Code "Examples of AI"

Moving from Code to Category / Theme. The output of this analysis is the diagram in **Figure 7**.



Appendix 2 – Illustration of Coding Answers to One Survey Question

Colours indicate beginning to draw out categories / themes. The output can be seen in **Figure 26** and **Figure 27**.

age	cat	Qualifications	level	topic_1	topic_2	topic_3	topic_4	topic_5	topic_6	topic_7	Count of Topics
20-29	Interested in Learning	Qualifications in maths or science (undergraduate degree level)	degree (undergrad)	math	science						2
20-29	Interested in Learning	Software engineer, human factors expert	not specific	software enginee	human factors expert						2
-	Currently Working In	domain knowledge	not specific	domain knowledge							1
40-49	Currently Working In	project management, agility, communication, collaboration	not specific	project management	agility	communication	collaboration				4
30-39	None	I don't know	-								0
30-39	Interested in Learning	Ideally degree level qualifications in subjects pertaining to AI - engineering, maths, psychology, linguistics, computer programming, science, design etc. Practical qualifications i.e. certification in electrical engineering or computer sciences. Experience of building or designing AI or components that would be combined to make AI.	degree (undergrad)	engineering	maths	psychology	linguistics	computer progra	science	design	7
30-39	None	Maths, science and English	not specific	maths	science	english					3
30-39	None	IT/maths	not specific	it	maths						2
30-39	None	Degree level physics / maths?	degree (undergrad)	physics	maths						2
-	Currently Working In	Background in computer science, either through a degree or certifications. Practical implementation projects as part of a portfolio are extremely important. MOOCs are a great way of learning new content - to scout talent, I think the key is to find talent that can build on this knowledge and develop the mindset towards approach AI/data science/ML problems.	degree (undergrad)	computer science							1
40-49	Currently Working Toward	not sure	-								0
20-29	Interested in Job	Degree in maths, physics or computer science, machine learning	degree (undergrad)	maths	physics	computer scienc	machine learning				4
40-49	Interested in Job	It qualifications	not specific	it							1
40-49	None	Degree	degree (undergrad)								0
30-39	Interested in Job	BSc in an appropriate field	degree (undergrad)								0
30-39	Interested in Job	Data Science type degree / masters	degree (undergrad)	data science							1
30-39	Interested in Job	I think a degree is certainly helpful, but probably not required at this point. Microcredentials and certifications might be a replacement, but more of a focus on portfolios and experience.									0
20-29	Currently Working In	N/A	None								0
20-29	Interested in Learning	MSc in a relevant field	MSc								0
60+	Interested in Job	Maths	not specific	maths							1
30-39	Interested in Learning	Computing	not specific	computing							1
60+	Interested in Job	Above basic IT skills, above average coding skills.	not specific	it	coding						2
30-39	Interested in Learning	None	None								0
20-29	Interested in Job	Degree qualified	degree (undergrad)								0
30-39	Currently Working In	data science: SQL, Python are definite must-haves in today's job marker; Hadoop, Scala, Perl; AI/ML - I mean, I built a prototype for ML in ruby. It's possible it's just not commonly accepted and it's harder to hire for folks outside of Python. It's more important to be able to decompose a business problem and understand what possible algorithms come together for each piece of the problem for ML.	not specific	data science	SQL	Python	Hadoop				4
20-29	Currently Working Toward	Minimum Bachelor's in CS, CSE, Math, Statistics or relevant coursework	degree (undergrad)	CS	CSE	maths	Stats				4
30-39	Interested in Job	BSc minimum, probably post graduate qualifications in some form of computer science/maths & statistics	degree (undergrad)	computer scienc	maths	stats					3
20-29	Currently Working Toward	BTech	btech								0
20-29	None	IT	not specific	it							1
30-39	None	..	-								0
20-29	Interested in Job	From none all the way to a Phd	None								0
20-29	Interested in Learning	Degree in a STEM subject or similar	degree (undergrad)	STEM							1
-	Interested in Learning	Level 4 AAT is highest, currently studying CIMA accountancy	-								0
30-39	Interested in Learning	None	None								0
30-39	Interested in Job	Degree in STEM	degree (undergrad)	STEM							1
40-49	None	Degree	degree (undergrad)								0
60+	None	Degree in one of the above	degree (undergrad)	data science	machine learning	ai					3
30-39	None	Don't know	-								0
60+	None	Clear logical thinking	not specific	clear logical thinking							1
											1.333333333
											1

Appendix 3 – a – Illustration of Coding Answers to One Survey Question

Colours indicate beginning to draw out categories / themes. Output can be seen in **Figure 29**.

skills	Industry	data_role	ds_ml_ai	Current job (please provide as much detail as you are comfortable with, for example status / role / tenure)	skills										count of skills given
Data driven, attention to detail, background in data / analytics, understanding of the application of data and how it can be used	Payments, fintech, eCo	No	No	VP Product & Implementation	Data driven	attention to detail	background in data / analytics	understanding of the application of data and how it can be used							5
Mathematics (Linear Algebra, Calculus), Logic, Computer Science	eCommerce	Yes	No	Director of BI and Analytics, 2 y	Mathematics (Linear Algebra, Calculus)	Logic	Computer Science								4
coding (often Python or R), problem solving, storytelling, visualization (D3, Tableau, Looker), modern cloud data warehousing like BQ, Snowflake, Redshift, Azure, engineering skills to process large amounts of data often using tools like hadoop, spark, kinesis, kafka, etc, business understanding, project management skills, software engineering best practices, version control	Education	Yes	No	Data Lead	coding (often Python or R)	problem solving	storytelling	visualization (D3, Tableau, Looker)	modern cloud data warehousing like BQ, Snowflake, Redshift, Azure	engineering skills to process large amounts of data often using tools like hadoop, spark, kinesis, kafka, etc	business understanding	project management skills	software engineering best practices	version control	11
The question is very broad. Each of these areas is very broad and there are 4 of them listed. The core skills are databases, statistics & experimentation methods, coding (usually in python), database skills (usually SQL type languages), and business/subject matter expertise, scientific communciation - i.e. present actionable findings to a business audience who don't know/understand the scientific/technical details	Consumer internet/soc	Yes	Yes	Data Science Manager, (roughl	databases	statistics & experimentation methods	coding (usually in python)	database skills (usually SQL type languages)	business/subject matter expertise	scientific communciation - i.e. present actionable findings to a business audience who don't know/understand the scientific/technical details					7
- understanding of sociotechnical systems - basic software engineering skills (version control, documentation, coding) - understanding of data/statistics/ml - ability to evaluate and select appropriate ML methods for a specific project	Technology	No	No	Senior developer advocate, 1.5	understanding of sociotechnical systems	basic software engineering skills (version control, documentation, coding)	understanding of data/statistics/ml	understanding of data/statistics/ml	understanding of data/statistics/ml	ability to evaluate and select appropriate ML methods for a specific project					7
Mathematical confidence, some statistical knowledge, coding ability in one language, Team working skills, communication skills, presentation skills	consultancy	Yes	Yes	Chief DS, 6 years in industry, 1	Mathematical confidence	some statistical knowledge	coding ability in one language	Team working skills	communication skills	presentation skills					7
coding, problem solving, stakeholder management, listening	fintech	Yes	Yes	head of data science	coding	problem solving	stakeholder management	listening							5
Strong coding skills eg. Python, R, SQL Problem-solving Data visualisation Communication	Insurance	Yes	Yes	Data Science Manager	Strong coding skills eg. Python, R, SQL	Problem-solving	Data visualisation	Communication							5
experience with statistics, mathematical modelling and optimization techniques, data science, data processing, feature engineering, programming languages such as Python and R	Consulting and Techno	Yes	Yes	Data Science Manager	experience with statistics	mathematical modelling and optimization techniques	data science	data processing	feature engineering	programming languages such as Python and R					7
Technical and business literacy (having both is important), basic statistics, data literacy + visualisation, understanding of machine learning algos and approaches (including things like accuracy and explainable AI); for technical roles python / R but also SQL (so many data scientists don't know a good way to manipulate data)	Consulting	Yes	No	Advanced Analytics consultant	technical literacy	business literacy (having both is important)	basic statistics	data literacy	visualisation	understanding of machine learning algos and approaches (including things like accuracy and explainable AI)	for technical roles python / R but also SQL (so many data scientists don't know a good way to manipulate data)				6
Understanding data, good use of programming, working understanding of data science techniques/statistics	Banking	Yes	Yes	Data Scientist	Understanding data	good use of programming	working understanding of data science techniques/statistics	working understanding of data science techniques/statistics							5
It's a really cross-skill area. There are very broadly 3 aspects of a data science project in industry - problem statement, data collection/wrangling, and solution architecture and delivery. For delivery you need coding skills, and some basic maths. For solution architecture you need broad knowledge of industry methods, understanding of the tech stack, and an understanding of the business problem For data collection, you need coding skills, some basic maths, and "data intelligence". The ability to understand and value high quality data. This is the skill I often find lacking in otherwise technically gifted researchers. For problem statement, you need business intelligence - what is the value of the problem to the business, what features of the problem are most valuable, how perfectly does it need to be solved, what would happen if it isn't solved.	Software	No	No	CEO	coding skills	some basic maths	broad knowledge of industry methods	understanding of the tech stack	an understanding of the business problem	coding skills	some basic maths	"data intelligence" - The ability to understand and value high quality data	business intelligence - what is the value of the problem to the business, what features of the problem are most valuable, how perfectly does it need to be solved, what would happen if it isn't solved		10
Problem solving Analytics Coding	Financial services	Yes	No	Leadership role in data product	Problem solving	Analytics	Coding								4
Programming skills, maths skills, logical thinking, technical skills, critical thinking	Technology company	Yes	No	Commercial Analytics Manager	Programming skills	maths skills	logical thinking	technical skills	critical thinking						6
Strong programming skills especially Python, good communication, system design	Manufacturing	No	No	In between roles, previous was	Strong programming skills especially Python	good communication	system design								4

Appendix 3 – b - Illustration of Coding Answers to One Survey Question (Zoomed In)

Data driven	attention to detail	background in data / analytics	understanding of the application of data and how it can be used						
Mathematics (Linear Algebra, Calculus)	Logic	Computer Science							
coding (often Python or R)	problem solving	storytelling	visualization (D3, Tableau, Looker)	modern cloud data warehousing like BQ, Snowflake, Redshift, Azure	engineering skills to process large amounts of data often using tools like hadoop, spark, kinesis, kafka, etc	business understanding	project management skills	software engineering best practices	version control
databases	statistics & experimentation methods	coding (usually in python)	database skills (usually SQL type languages)	business/subject matter expertise	scientific communciation - i.e. present actionable findings to a business audience who don't know/understand the scientific/technical details				
understanding of sociotechnical systems	basic software engineering skills (version control, documentation, coding)	understanding of data/statistics/ml	understanding of data/statistics/ml	understanding of data/statistics/ml	ability to evaluate and select appropriate ML methods for a specific project				
Mathematical confidence	some statistical knowledge	coding ability in one language	Team working skills	communication skills	presentation skills				
coding	problem solving	stakeholder management	listening						
Strong coding skills eg. Python, R, SQL	Problem-solving	Data visualisation	Communication						
experience with statistics	mathematical modelling and optimization techniques	data science	data processing	feature engineering	programming languages such as Python and R				
technical literacy	business literacy (having both is important)	basic statistics	data literacy	visualisation	understanding of machine learning algos and approaches (including things like accuracy and explainable AI)	for technical roles python / R but also SQL (so many data scientists don't know a good way to manipulate data)			
Understanding data	good use of programming	working understanding of data science techniques/statistics	working understanding of data science techniques/statistics						
coding skills	some basic maths	broad knowledge of industry methods	understanding of the tech stack	an understanding of the business problem	coding skills	some basic maths	"data intelligence" - The ability to understand and value high quality data	business intelligence - what is the value of the problem to the business, what features of the problem are most valuable, how perfectly does it need to be solved, what would happen if it isn't solved	
Problem solving	Analytics	Coding							
Programming skills	maths skills	logical thinking	technical skills	critical thinking					
Strong programming skills especially Python	good communication	system design							

Appendix 4 – a – Ethics Approval for Interviews (Chapter 4)

Study Details

Legacy Ethics Tool ID

87002

Applicant username

lg17706

Faculty

Faculty of Engineering

Department

Aerospace Engineering

Submitted on behalf of

Is this a student project?

Postgraduate PhD

Supervisor username

sh14565

Project Title

Leaving No One Behind: Educating Those Most Impacted by Artificial Intelligence

Estimated start date

01/06/2019

Duration (months)

6

Lead questions to determine the correct ethics review route

L1. Does your research involve any of the following?

- Medical Devices, ionising radiation, drugs, placebos or other substances to be administered to participants.
- Human Blood or Tissue Samples (Tissue means any relevant material consisting of or including cells - for definition of 'relevant material', please see Human Tissue Authority website at http://www.hta.gov.uk/ - this link opens in a new window
- Adults (over 16) who lack capacity to consent for themselves including participants, who will be retained in the study following loss of capacity.
- Recruiting or using client data from NHS patients, nursing home/independent hospital/clinic or medical agency patients, users of social care services or prisoners. For more details on definitions please see 'Does my project require review': http://www.nres.nhs.uk/applications/approval-requirements/ethical-review-requirements-for-ethical-review-under-legislations/ (this link opens in a new window)

L2. Does your research involve any of the following?

- Animals (either use or observation)
- Has or will your research be submitted to another ethics committee? (if so please provide details of the committee and dates (submission/approval/provisional approval etc).

L3. Does your research involve any of the following?

- Working or travelling overseas
- Trials outside the UK
- Pregnant research subjects
- Conception/Contraception
- Children under 5
- More than 1500 research subjects
- Genetic Engineering
- Hepatitis/CJD/HIV & AIDS related research

L1_v2 - Does your research involve any of the following?

- Medical devices, ionising radiation, drugs, placebos or other substances to be administered to participants.
- Adults (over 16) who lack capacity to consent for themselves including participants, who will be retained in the study following loss of capacity.
- Recruiting or using client data from NHS patients, nursing home/independent hospital/clinic or medical agency patients, users of social care services or prisoners. For more details on definitions please see 'Does my project require NHS review': http://www.nres.nhs.uk/applications/approval-requirements/ethical-review-requirements/requirements-for ethical-review-under-legislation/ (this link opens in a new window).

No

L2_v2 - Does your research involve any of the following:

- Human Blood or Tissue Samples (Tissue means any relevant material consisting of or including cells - for definition of 'relevant material', please see the Human Tissue Authority website at http://www.hta.gov.uk/ - this link opens in a new window.

No

L3_v2 - Does your research involve any of the following:

- Animals (either use or observation)

No

L4_v2 - Does your research involve any of the following?

- Has or will your research be submitted to another ethics committee?

No

L5_v2 - Does your research involve any of the following?

- Working or travelling overseas

No

L6_v2 - Does your research involve any of the following?

- Trials outside the UK
- Pregnant research subjects
- Conception/Contraception
- Children under 5
- More than 1500 research subjects
- Genetic engineering
- Hepatitis/CJD/HIV & Aids related research

No

Project Outline

Brief Project Outline (up to approximately 300 words)

The entire PhD project aims to create an educational framework for teaching Artificial Intelligence (AI) to people usually missed out by other initiatives, such as higher education and workplace retraining. This stage of the project is an initial set of interviews to study attitudes and requirements of key stakeholders - thought leaders and government, learning companies, companies whose workforce is likely to be affected by AI and, most importantly, individuals who will be the target of such education. The interviews are semi-structured to allow the conversations to be more in-depth and explore topics we had not thought of.The interviews will not be recorded.

Checklist questions to determine level of review

1. Does the research involve human participants?

Yes

1a. Does the research involve participants who are particularly vulnerable or unable to give informed consent?

Examples of vulnerable participants or those unable to give informed consent are children, people with learning difficulties, patients, people experiencing emotional distress or mental illness, people living in care or nursing homes, and people recruited through self-help groups, participants in a dependent or unequal relationship with the researcher(s) or research supervisor.

No

1b. Will it be necessary for participants to take part without their knowledge and consent at the time?

Examples include the covert observation of people.

No

1c. Will the research involve actively deceiving participants?

Examples include deliberately falsely informing participants, withholding information from participants or misleading participants in such a way that they are likely to object or show unease when debriefed about the study.

No

1d. Will the research involve discussion or collection of information on sensitive topics?
Sensitive topics under the Data Protection Act 1998 include:

The racial or ethnic origin of the data subject;

- Their religious beliefs or other beliefs of a similar nature;
- Whether they are a member of a trade union (within the meaning of the Trade Union and Labour Relations (Consolidation) Act 1992);
- Their physical or mental health or condition;
- Their sexual life;
- Their commission or alleged commission by them of any offence;
- Any proceedings for any offence committed or alleged to have been committed by them, the disposal of such proceedings or the sentence of any court in such proceedings.

If the research is in relation to any of the sensitive topics listed under the DPA 1998 then the legal issue requiring such scrutiny in such cases that 'explicit consent' must be obtained.

No

1e. Does the research involve invasive procedures?
Invasive procedures may include:

- Administration of drugs placebos, or other substances (e.g., drinks, foods, food or drink constituents, dietary supplements) to study participants;
- Biological samples from participants be obtained;
- Pain or more than mild discomfort likely to result from the study.

No

1f. Does the research involve scans or x-rays of research participants?

No

1g. Does the research involve photographs, videoing, recording or similar of research participants?

No

1h. Will financial inducement (other than reasonable expenses and compensation for time) be offered?

No

1i. Will the study involve the use or storage of information about living people whose personal identity could be discovered from that information?

No

1j. Does the study risk causing psychological stress or anxiety or other harm or negative consequences beyond that normally encountered by the participants in their life outside research?

No

2. Does your research involve the analysis of secondary datasets or unpublished data?

3. Will the research involve politically and culturally sensitive funding sources?

Examples include the defence sector, projects with potential environmental effects and other internationally regulated or protected industries. For more information, please follow the link to the 'Research Governance and Integrity Policy': http://www.bris.ac.uk/red/support/governance/RGI.pdf (this link opens in a new window).

No

4. Will the research involve politically, culturally or socially sensitive topics?

For more information, please follow the link to the Faculty of Arts Ethics Committee Guidance Note (PDF 78kb) (this link opens in a new window).

No

Supporting Information

Supporting information
(up to approximately 300 words)

Please provide any additional information in relation to your study such as adhering to a particular SOP or confirming if your study is a service evaluation/audit as opposed to research.

Approved

Approved

Approval date

21/05/2019

Archived

No

Escalated

No

Upload Study Documents

Amended Request

Consent Form

Documents

Type	Document Name	File Name	Version Date	Version	Size
Consent Form		interviewee-consent-form.docx	20/05/2019		16.0 KB

Debriefing Sheet

External Ethics Approval

Full Ethics Application

Insurance Details

Letter of Access

Participant Information Sheet

Documents

Type	Document Name	File Name	Version Date	Version	Size
Parental / Guardian Information Sheet		87002-revised-pis.pdf	23/05/2019		156.5 KB

Peer review

Protocol

Questionnaire/Survey

Documents

Type	Document Name	File Name	Version Date	Version	Size
Questionnaire		phd-stage-1-interview-questions.pdf	09/05/2019		103.0 KB

Recruitment Advertisment

Research site approvals

Topic Guide

Other

Appendix 4 – b – Participant Information Sheets for Interviews (Chapter 4)

Participant Information Sheet

Project title: Leaving No One Behind

I would like to invite you to take part in my research project. Before you decide whether or not to participate, I would like you to understand why the research is being conducted and what it would involve for you. Talk to others about the study if you wish. Please ask me questions if anything is unclear.

What is the purpose of the project?
I am studying for a research degree (PhD) at the **University of Bristol**. The current focus of this research is to *study attitudes to new technology and training*. By participating in this interview, you will provide data which will be of great value in better understanding these issues.

Why have I been invited to participate?
I am inviting as many people as possible to participate in this stage of my research. For this stage, interview participants have been split into categories:

- Government / companies – to understand their position on new technology and retraining.
- Adult education companies – to understand what retraining is already taking place.
- Individuals – to understand how people feel about retraining, and what they would need to make retraining for them successful.

Do I have to take part?
All participation in this research is voluntary. I will describe the study and go through the consent with you before you participate and answer any questions you might have. If you agree to take part, I will then ask you to sign the consent form. You are free to withdraw at any time, without giving a reason.

What will happen to me if I take part and what will I have to do?
The interview is of no fixed length and you are free to go into as much or as little detail as you wish. However, interviews are not expected to last more than 10 minutes. During the interview, you will be asked questions relating to your personal experiences with new technology, particularly Artificial Intelligence. If there are any questions you do not feel comfortable answering, please say so and we will move on. The interview will not be recorded but notes will be taken throughout. This is to help ensure that your responses are represented as accurately and openly as possible.

What are the possible disadvantages and risks involved in taking part in the project?
While there are no disadvantages or risks involved in taking part, some of the questions may relate to your work history (and what tasks you have carried out for employment). The aim of these questions is to understand if attitudes change based on industry, we can continue the interview without spending a lot of time on these questions if you so wish.

What are the possible benefits of taking part?
I am hoping this research will go on to inform the creation of a retraining scheme, which I am hoping to launch in the future. I hope that participants in this study will go on to see the benefits from such a scheme.

Will my participation in this project be kept confidential?
Anonymity and confidentiality will be retained throughout. No one will be able to identify you from the data collected in this interview. The data collected with be sorted in a password protected file on a secure server and will not be saved for longer than necessary.

What will happen to the results of the research project?
The research will be written up for my Doctoral Thesis and could also be used in publications and presentations. You will not be identified as an individual in any of these. If you would like to be kept up to date with the results, please send me an email and I will be happy to.

Who is organising and funding the research?
My research is part of the FARSCOPE PhD programme at the University of Bristol. It is funded by the Engineering and Physical Sciences Research Council (EPSRC).

Who has reviewed the study?
The Faculty Research Ethics Committee has reviewed this study.

Further information and contact details
Please feel free to contact me with any questions, comments or concerns: laura.gemmell@brl.ac.uk

If you have any concerns related to your participation in this study please contact the Faculty of Arts Research Ethics Committee - Liam McKervey, Research Governance and Ethics Officer (Tel: 0117 331 7472 email: Liam.McKervey@bristol.ac.uk)

Appendix 4 – c – Consent Form for Interviews (Chapter 4)

University of BRISTOL

Interviewee Consent Form

I am studying for a research degree (PhD) at the University of Bristol. The current focus of this research is *to study attitudes to new technology and training*. By participating in this interview, you will provide data which will be of great value in better understanding these issues.

Voluntary Participation
All participation in this research is voluntary. If you choose to participate you may change your mind and withdraw from the interview at any time. If for any reason you decide not to continue, the data you have already provided will not be used.

During and After Interview
The interview is of no fixed length and you are free to go into as much or as little detail as you wish. During the interview, you will be asked questions relating to your personal experiences with new technology, particularly Artificial Intelligence. If there are any questions you do not feel comfortable answering, please say so and we will move on. The interview will not be recorded but notes will be taken throughout. This is to help ensure that your responses are represented as accurately and openly as possible.

Confidentiality and Anonymity
The research will be written up for my Doctoral Thesis and could also be used in publications and presentations. Anonymity and confidentiality will be retained throughout.

Please feel free to contact me with any questions, comments or concerns:
laura.gemmell@brl.ac.uk

………

Voluntary Consent of Interviewee

- I have read the above and give my voluntary and informed consent to be interviewed by Laura Gemmell for this research.
- I give permission for notes to be taken on the interview.
- My anonymity and confidentiality will be respected.
- I reserve the right to withdraw from this research at any time.

Signed:	Name:	Date:
………………………………………………………………	……………………………………………	…………………………

THANK YOU VERY MUCH FOR YOUR SUPPORT WITH THIS RESEARCH

Laura Gemmell

If you have any issues or complaints about this research, please contact Liam McKervey at the University of Bristol. Address: *1 Cathedral Square, Bristol, BS1 5DD*. Email: *liam.mckervey@bristol.ac.uk*. Telephone Number *(0117) 42 84051*.

Appendix 4 – d –Interview Questions (Chapter 4)

Institutions / Government / Thought Leaders

Aim - to gain traction for the project, and to understand if there are any papers or projects that have been missed or are coming soon.

Intro - I'm a PhD researcher studying AI education, particularly for people usually missed initiatives like higher education and in-work training schemes. At this stage I am just carrying out initial research into what is needed for such a framework to be successful, and as you/your company are industry-leaders in AI I'd like to get your input from the beginning. I've read your work X (give a little summary of it, especially key points on attitudes and education).

1. What do you think the biggest challenge in making such an educational scheme work will be?
2. Further to the work published, is there any work/papers due to be published that will be relevant?
3. Is there any place I could present my findings where there would be or interest in these ideas or people I should contact regarding this project?

Companies That Will Be Affected

Aim - understand what is going on in these industries, with regards to AI.

Intro - I am conducting an initial pilot study into attitudes around new technology and training. I am interested in understanding how companies will be affected by by new technologies. One of the new technologies we are interested in is Artificial Intelligence (or AI). check understanding of artificial intelligence first - if no: It is in the news quite a lot at the minute, however there isn't really a proper, agreed-upon definition of what it is. Some examples of AI include content recommendation, like when Amazon recommends something else to buy, or Netflix recommends somethings else to watch based on what you've previously watched. Another example is chatbots that pop up on websites and voice assistants (like Siri or Alexa).

1. Do you think AI will be used in your company / industry?
    a. In what way?
    b. Why?
2. Do you think any part of your workforce will be impacted by these changes?
3. Do you have, or are you in the process of planning, any schemes in place for staff with regards to these technologies / the future to empower them or retrain them?
    a. What are they?

Learning Companies

Aim - understanding of how we can retrain their typical students, or how they are already retraining people in coding/ data science / AI.

Intro - I'm doing my PhD on AI education, particularly I'm hoping to create an education programme or framework aimed at people usually missed initiatives like higher education and in-work training schemes. At this stage I am just carrying out initial research into what is needed for such a framework to be successful, and I'd be keen to chat to you about your typical students and how AI education would work for them.

1. Describe your typical student.
    a. In terms of education, and jobs.
2. Have you had to change how or what you teach based on technological advances?
3. How would we teach your typical students about topics such as Artificial Intelligence?
    a. How much do you think they would be able to access and understand?
    b. What would the challenges be?
4. What else should be considered when designing this type of education?

Individuals

Aim - begin to work out a baseline for how to start planning where and how to pitch an educational retraining framework. Ask - Would you be willing to do a quick interview please? It will only take around five minutes. It is an initial study into attitudes around new technology and training.

Intro - One of the new technologies we are interested in is Artificial Intelligence (or AI). It is in the news quite a lot at the minute, however there isn't really a proper, agreed-upon definition of what it is. Some examples of AI include content recommendation, like when Amazon recommends something else to buy, or Netflix recommends somethings else to watch based on what you've previously watched. Another example is chatbots that pop up on websites and voice assistants (like Siri or Alexa).

1. Have you ever used anything like this?
    a. Can you think of any other examples of AI that you have used or heard of?
    b. What do you think about these? (Are they useful? Do they work?)
2. Do you mind if I ask you a question about work?
    a. What sort of work have you done? (Example, working in a shop, working in an office)

    b. What tasks do carry out in this type of work? (Example, using a till, interacting with customer, using a spreadsheet)
3. What do you think the benefits could be of this type of technology? (in both work and your everyday life)
4. What do you think the challenges could be?
5. Would you be interested in getting some training or learning more about AI?
    a. Why?
    b. Would you be interested in training to help you:
        i. Use AI in everyday life
        ii. Understand how AI works
        iii. Build something with AI
        iv. Work with AI
    c. Do you think this type of training exists?
        i. Where?

Appendix 5 – a - Ethics Approval for Online Surveys (Chapter 5 & 6)

University of BRISTOL

Faculty of Engineering Research Ethics Committee

Upon completion this application form should be uploaded as an attachment, together with documents referred to in the application, to your online ethics submission. This form should be completed in conjunction with the guidance form.

	Questions 1-12 **Contact Information and Study Details**
1.	**Title of the research:** Skills needed to work in artificial intelligence related fields.
2.	**Applicant details:** Student Name or Principal Investigator: Laura Gemmell Job or Course Title (UG or PG): FARSCOPE PhD (PG) Contact number: [redacted] Email: laura.gemmell@bristol.ac.uk
3.	**Details of Supervisor (if applicant is a postgraduate or undergraduate student)** Name: Sabine Hauert Title: Associate Professor Contact number: +441174559206 Email: sabine.haurt@bristol.ac.uk
4.	**Other investigator(s) involved, with job title:**
	Lucy Wenham, Lecturer (School of Education)
5.	**Source of funding:**
	EPSRC via FARSCOPE CDT Programme
6.	**Start Date and Project Duration:**
	Start Date: April 2021 Duration: 9 months
7.	**Where will the study take place?**
	Online using surveys.

8.	**Background and aims of the study:**

Background

Education around artificial intelligence (AI) and robotics is not often aimed at the general public (with a few notable exceptions, such as Finland's online Elements of AI course). In a previous study (Gemmell *et al,* 2021) we found members of the public saw AI training as not for them and not easy to access despite them being interested in learning more. This study also found experts in AI held certain gatekeeping believes regarding which skills where necessary to learn about AI, including maths and coding. We propose an online qualitative survey to investigate the perception (both of the public and employers) around which skills, qualifications and traits are required for roles related to AI.

Aim

This study aims to understand what skills, qualifications and traits both the public and employers believe necessary for jobs in fields related to AI. Further to this, we hope to gain an understanding of how people believe these skills could be learnt and how easy they think learning these skills is. We will compare whether the public and employers have similar or varying views on these topics.

References

Gemmell *et al.* (2021) 'Skilling the Gap: 21 Conversations on Designing Education for Those Left Behind as Robotics and Artificial Intelligence Advance', *Advanced Intelligent Systems*, p. 2000169. doi: 10.1002/aisy.202000169.

9.	**Outline the design of the study and list the procedures to which the participants will be subjected, the anticipated testing time and any treatments administered:**
	Participants will be sent a link to the survey (a Google Form). Either directly for business or via a network for members of the public. The wording of the consent form and questions are in the word document *survey_questions* also uploaded. The survey will contain a consent form with relevant information, participants can choose whether to proceed or not. They will be asked a number of yes or no questions to determine their interest in AI. Followed by several free text questions specifically about skills. Members of the public will be asked to give their email address if they wish to participate in the next stage of the research (optional). Demographic questions (location, age, gender and job for members of the public, location, company size, industry, job level for business) will be included to better understand the results. The responses will be anonymous. If any members of the public choose to give their email address, this will be separated from the data and not used in any analysis. The responses will be analysed using a mix of methods, including coding and thematic analysis to find themes within the answers and natural language processing methods (such as sentiment analysis and named entity recognition). All data will be processed and analysed in line with both the University of Bristol RED guidelines.
10.	**Does your study involve the collection or use of any human tissue or exudate? If yes, what is the material to be collected?**.
	Yes ☐ No ■
	If yes, please explain:

	Tissue Act Advisor that collection and storage of this material will be undertaken under an appropriate licence?
	Yes ☐ No ☐
11.	**Will the research involve working with animals?**
	Yes ☐ No ■
	If yes, please identify how you will address any animal welfare issues and whether you have undertaken ethical review elsewhere (e.g. zoo or national park authorities). Please also see the relevant guidance.
12.	**Has this study been subjected to peer review?**
	Yes ☐ No ■

	Questions 13-22 **Recruitment and Informed Consent**
13.	**Who will be recruited to participate in this study?**
	Members of public: any member of the public can complete the survey. Ideally those interested in learning about AI will be recruited. Business: businesses who operate in a data heavy field or those who will face near-future changes due to data and AI will be recruited.
14.	**Are there any potential participants who will be excluded? If so, what are the exclusion criteria?**
	Members of public: no participants will be excluded. Business: will be excluded if the field is unrelated and unimpacted by AI, but this will occur in conversations prior to the survey link being sent.
15.	**How many participants will be recruited?**
	As many as possible. The survey will remain open for at least one month.
16.	**How will the participants be recruited?**
	Members of public: Survey links will be shared in online communities (e.g. Women Who Code, Women in AI) and to students of Adult Education centres via the educators. Recruitment will be self-selected and voluntary. Business: links will be sent to participants directly once they have expressed an interest in participating. Potential companies will be contacted (both through contacts and directly).
17.	**How will informed consent be obtained from all participants or their parents/guardians prior to individuals entering the research study?**
	The first part of the survey will be a consent form which must be approved before participation.
18.	**How long will potential participants have to decide whether to give consent?**
	As long as they wish, although they cannot continue with the survey without consenting.
19.	**Will participants be kept informed of new information that becomes available during the study which may influence their continued participation**?
	No, as we will not be collecting contact details from all participants. The participants will be provided with a link to Laura's research profile and will be able to check back to this if they wish.

20.	**Will the study involve actively deceiving, or withholding information from, the participants?**
	Yes ☐ No ■
	If YES, explain why it is necessary to use deception and state how you will ensure that the participants are provided with sufficient information at the earliest stage, and how you intend to ameliorate possible distress caused by the deception, including a plan for subject debriefing.
21.	**Will participants be made aware that they can withdraw from the study at any time without having to give a reason for doing so?**
	As the survey is anonymous and not linked to any identifying details, participants will not be able to withdraw. However, they have the option to not continue with the form at any point throughout.
22.	**Describe potential risks (physical, psychological, legal, social) arising from these procedures:**
	Asking about jobs can be upsetting for some people, the specific question about current job will be optional.
22b.	**Is there likely to be any risk to the investigator during this study?**
	Yes ☐ No ■
	If yes, please explain how this will be minimised However, as the survey will be open and online, there is a risk that upsetting material could be viewed and analysed. The impact this could have on mental health has been considered, and a plan created if this arises (involving contacting the mental health services at the University of Bristol).
22c.	**Is there likely to be any risk eg. legal, adverse publicity, to the UoB?**
	Yes ☐ No ■
	If yes, please explain

	Questions 23-32 **Outcomes and Data Protection**
23.	**How will participants be informed about the outcome of the study?**
	As we are not collecting contact information (unless the participant wishes to participate in the next stage of research), we will not be informing them individually. We will share the outcome through all of the recruitment channels to be shared.
24.	**How will the results of the study be disseminated and reported?**
	Published in peer reviewed journals and conferences, and as part of a PhD thesis.
25.	**Is any payment other than reimbursement of expenses to be made to participants?**
	Yes ☐ No ■
	If YES, outline the reason for this and the amounts involved.
26.	**Will personal data, beyond that recorded on the consent form, be used in the research?**
	Email address will be collected for those who wish to participate in the next stage of the research. These will not be stored with the survey response data.
27.	**Will the participants be audio-taped or video-taped?**
	No.
28.	**What arrangements have been put in place to ensure confidentiality and security of data gathered in the study? Will the data be stored in hard copy or electronically, and where will it be held?**
	Email addresses will only be collected from those who want to participate in the next part of the study. These will be removed from the data set and saved separately. The email address will be saved and used in compliance with GDPR. The data will be sorted within ARDS electronically and will anonymous ensuring no individual or company can be identified using this data.
29.	**Has this proposal been seen by or submitted to another ethics committee?**
	No

30.	**Do any of the investigators have any actual or potential conflict of interest in this study?**
	No.
31.	**Is there any other relevant information you would like to make known to the committee?**
	No.
32.	**How will the data be made available at the end of the project?** You must declare your level of access, see Data Access appendix
	To ensure reproducibility, the data will be made open in the anonymous way described in question 28.
33.	**Have you read and understood the guidelines for completing this form (see last page)?**
	Yes ■ No ☐

	Appendices
	Informed Consent
	Obtaining informed consent from parents does not obviate the need to obtain informed consent or assent from children participating in research. Assent means that the child shows some form of agreement to participate in the research without necessarily comprehending the nature of the research sufficiently to give full informed consent. Investigators working with infants should take special effort to explain the research to the parents and be especially sensitive to any indication of discomfort or avoidance in the infant. It is good practice to ask participants on the consent form to confirm their consent to keep and make use of the data they have contributed. This allows someone, who for example becomes unhappy about their participation in the research, to prevent their data being used. The researcher should keep signed copies of consent forms securely and separately from the research data. For a questionnaire study, the researchers should consider if the questionnaires can be returned anonymously, in which case a consent form may not be necessary since consent is implied by the subject choosing to participate in the study. Under these circumstances, an information sheet is still required.
	Data Access
	Research funders and publishers increasingly require researchers to find a way to provide access to their research data, even if that data initially includes personal information. The University of Bristol requires you to assign an expected access level to your research data, your selection will be checked and signed off by the Ethics Committee. If you intend to create multiple datasets with different anticipated access levels you should select the most restrictive access level you expect to use. The four access levels are: •Open – my data can be made openly available through a data repository •Registration required – my data should only be available to bona fide researchers, on request •Controlled – any access requests for my data should be referred to committee for review on a case-by-case basis •Closed – my data should not available for sharing If, during the course of your research, you believe that your nominated access level will no longer be appropriate you should inform your Faculty Ethics Officer. You must also ensure that you get the appropriate level of consent from participants at the start of the project to allow for onward use. If you need more information about this please see the guidance on sensitive data http://data.bris.ac.uk/research/storage-and-security/sensitive-data/ or contact data-bris@bristol.ac.uk Guidance on access levels Open – this level can be assigned where consent has been given by participants to make their anonymised data publicly available through a repository, in addition the risk assessment of re-identification of this anonymised data has been classed as low. These data sets can be made openly available through data repositories, including the Bristol Research Data Repository. Registration required – this level can be assigned where consent has been given by participants to make their anonymised data available to bona fide researchers on request, within the terms of participant consent and the risk assessment of re-identification of the anonymised data is low. If the data is deposited with the University of Bristol Research Data Repository requests will be facilitated by the Research Data Service. Controlled – this covers cases where historical consent for sharing is very limited and/or the risk assessment of re-identification is classed as medium to high. If the data is deposited with the University of Bristol Research Data Repository the Research Data Service will forward on requests to a Data Access Committee who will work with you as the PI to decide if/what data is appropriate to be made available. Closed – this covers data that is not available for sharing (except by regulators) because of ethical, IPR, prior exclusive agreements or other constraints. This should only be assigned if you have got prior agreement from the funder that they are willing to allow the data to be completely closed.

Before submitting this form, please refer to the checklist below.

(Do NOT include a copy of this checklist with your application)

Checklist

In assessing all applications, the Faculty Committee for Ethics will ask the following questions:

1. Do the likely benefits of the research outweigh the risks (if any) to the participants?
2. Are there possible risks to participants greater than they would normally encounter in their life outside research? If so, are adequate safeguards in place to minimise any harm?
3. Are there possible risks to investigators?
4. What degree of discomfort, distress or deception, if any, is foreseen?
5. Is the study adequately supervised and is the principal supervisor responsible for the project clearly identified, adequately qualified and experienced?
6. Are appropriate procedures (e.g. information sheet) in place for informing participants about the research study?
7. Are there proper procedures for obtaining consent from the participants or, where necessary, their parents or guardians?
8. Please attach (where appropriate)
    - Recruitment adverts / messages / forms
    - Information sheet / transcript
    - Consent form
    - Debriefing sheet / transcript
    - Questionnaire
    - Any other relevant material (e.g. an unpublished questionnaire enquiring about possibly sensitive topics or collecting personal data).

Links to useful guidelines concerning ethics of research involving human participants

ESRC Research Ethics Framework
http://www.esrc.ac.uk/ESRCInfoCentre/Images/ESRC_Re_Ethics_Frame_tcm6-11291.pdf#search='esrc%20research%20ethics%20framework

National Research Ethics Service (NRES)
http://www.nres.npsa.nhs.uk/

Medical Research Council Guidelines on Good Research Practice
http://www.mrc.ac.uk/pdf-good_research_practice.pdf

Appendix 5 – b - Questions for Online Surveys with Public Including Consent Form (Chapter 5)

Survey title: Skills Needed for Working with Artificial Intelligence

----

The goal of this research is to find out what **skills people think are needed for working with artificial intelligence**. Your thoughts and opinions are valuable, whether you know absolutely nothing about artificial intelligence or are an expert.

Your voice is important to this discussion so please respond in your own way, in your own words, as short or as long as you wish.

Your contribution is anonymous and data storage and ethics conform to the University of Bristol guidelines. Your participation is voluntary and you are free leave the survey at any time without providing an explanation before submitting. As the survey is not collecting identifying information, once submitted we cannot remove your responses.

If you have any issues or complaints about this research, please contact Liam McKervey at the Unversity of Bristol. Address: 1 Cathedral Square, Bristol, BS1 5DD. Email: research-governance@bristol.ac.uk, Telephone Number (0117) 42 84051.

The research will be written up for my Doctoral Thesis and could also be used in publications and presentations. Anonymity and confidentiality will be retained throughout. Direct quotes may be used in research outputs but nothing which could identify individuals. Supplying demographic information is optional, and will not be used in any research outputs if this could identify any individuals (or if the demographic group has less than four individuals).

If you wish to find out more about my research, here is a link:

https://research-information.bris.ac.uk/en/persons/laura-gemmell

7. I am happy to proceed with this survey
    a. Yes
    b. No – stop survey

Please answer the following questions about your interest in roles relating to artificial intelligence.

8. Do you currently work in a data science, machine learning or artificial intelligence job?
    a. Yes – skip to Main
    b. No
9. Are you currently working towards a data science, machine learning or artificial intelligence job?
    a. Yes – skip to Main
    b. No
10. Are these types of jobs something you would be interested in?
    a. Yes – skip to Main
    b. No
11. Is learning about artificial intelligence something you would be interested in?
    a. Yes
    b. No

The following questions are about data science, machine learning and artificial intelligence skills and jobs. In all of these questions, please give as much or as little detail as you like. If you do not know, that is a useful response.

12. When thinking about roles working with artificial intelligence, are there any specific skills, qualifications or traits which are necessary? Please list as few or as many as you like.
    a. Skills
    b. Qualifications
    c. Traits
13. *(Based on responses to first 5 questions, different wording will be used) Either:*
    a. How are you learning / developing / obtaining these? Please give any specific details.
    b. How might you learn / develop / obtain these? Please give any specific details.
14. In your *experience / opinion*, how easy or difficult is it to gain the necessary skills, qualifications and traits for these roles? Can you say a little bit about why you gave this answer?

Co-design interest:

15. (Optional) We are going to design a curriculum to make gaining the needed skills easier, we hope to co-design this with potential students. If you would be interested in participating in the co-design, please leave your email address:

Please note, any email addresses provided in response to this question will be stored separately and not linked to the responses to other questions in the survey. This ensures responses are anonymous. Email addresses will only be used to contact those interested in participating in the next stage of this research.

Please provide demographic information to help with our research. All questions are optional.

16. (Optional) Are you based in the UK?
    a. Yes
    b. No
17. (Optional) Region / Country
18. (Optional) Would you describe your location as rural or urban?
19. (Optional) Gender
20. (Optional) Age
21. (Optional) Current job

Appendix 5 – c - Questions for Online Surveys with Hiring Managers Including Consent Form (Chapter 6)

Survey title: Skills Needed for Working with Artificial Intelligence

----

The goal of this research is to find out what **skills are needed for working with artificial intelligence**. You have been asked to complete this survey as you, your department, company or industry have been deemed as already or potentially impacted by advances in artificial intelligence.

Any opinions or views on the topic are valuable to our research, so please give as much or as little detail as you wish.

Your contribution is anonymous and data storage and ethics conform to the University of Bristol guidelines. Your participation is voluntary and you are free leave the survey at any time without providing an explanation before submitting. As the survey is not collecting identifying information, once submitted we cannot remove your responses.

If you have any issues or complaints about this research, please contact Liam McKervey at the Unversity of Bristol. Address: 1 Cathedral Square, Bristol, BS1 5DD. Email: research-governance@bristol.ac.uk. Telephone Number (0117) 42 84051.

The research will be written up for my Doctoral Thesis and could also be used in publications and presentations. Anonymity and confidentiality will be retained throughout. Direct quotes may be used in research outputs but nothing which could identify individuals. Supplying demographic information is optional, and will not be used in any research outputs if this could identify any individuals (or if the demographic group has less than four individuals).

7. I am happy to proceed with this survey
    a. Yes
    b. No – stop survey

Please answer the following questions about your interest in roles relating to artificial intelligence (for the sake of this survey artificial will also refer to robotics, machine learning and data science).

8. Does your role involve robotics, data science, machine learning or artificial intelligence?
    a. Yes – skip to Main

    b. No
9. Does your company work on any of the following: robotics, data science, machine learning or artificial intelligence?
    a. Yes – skip to Main
    b. No
10. In the near-future will your company work on any of the following: robotics, data science, machine learning or artificial intelligence?
    a. Yes – skip to Main
    b. No
11. Is your company interested in learning more about robotics, data science, machine learning or artificial intelligence?
    a. Yes
    b. No

The following questions are about robotics, data science, machine learning and artificial intelligence skills and jobs. In all of these questions, please give as much or as little detail as you like. If you do not know, that is a useful response.

12. When thinking about roles working with artificial intelligence, are there any specific skills, qualifications or traits which are necessary? Please list as few or as many as you like.
    a. Skills
    b. Qualifications
    c. Traits
13. How do you think your employees would best learn / obtain / develop these?
14. Would your company provide these in house or would employees be expected to source their own training or experience?
15. In your opinion, how easy or difficult is it to gain the necessary skills, qualifications and traits for these roles? Can you say a little bit about why you gave this answer?
16. In your opinion, how easy or difficult is it for someone to move into their roles from another non-related role?

Please provide demographic information to help with our research. All questions are optional.

17. (Optional) Are you based in the UK?
    a. Yes
    b. No
18. (Optional) Region / Country
19. (Optional) Would you describe your location as rural or urban?
20. (Optional) Company Size
21. (Optional) Industry
22. (Optional) Current job

Appendix 6 – Code for NLP (Chapter 5)

Code for the NLP in Chapter 5 can be found in the following Github repository.

Appendix 7 – Ethics Email

Re: 118028 - Eng Checklist Ethics App(Id nr.: 1112389)

From: Megan Wood-Smith <megan.wood-smith@bristol.ac.uk>
Sent: 27 April 2021 14:29
To: Laura Gemmell <laura.gemmell@bristol.ac.uk>
Cc: Sabine Hauert <sabine.hauert@bristol.ac.uk>
Subject: 118028 - Eng Checklist Ethics App(Id nr.: 1111994)

Dear Laura,

Ref: 118028
Title: Skills needed to work in artificial intelligence related fields.

Thank you for submitting your ethics application. Your application has been preliminary reviewed by the Faculty of Engineering Research Ethics Committee Chair who provided the following feedback:

'The consent form does not adequately inform participants: "In completing the survey, you are agreeing to this data being used in my thesis, academic journals and other publications" does not explain what data will appear, if direct quotes will be used this should be explicitly pointed out and no demographic data should be made public that contains less than four participants. The participants should be told they can leave the study at any time without giving an explanation and should be given a contact for research governance if they want to complain about the study. There should be more careful explanation about supplying the email address; this is done in the application but not in the questionnaire itself, this needs to explain that the email address will be separated from the questionnaires, not shared with anyone and deleted by some date provided. Finally, this application does not cover the interviews; this will require a subsequent application.'

Please revised your study documents to address the above comments, highlighting or track-changes for ease of review. Please forward your revised documents to me and I will facilitate a review with the Chair.

If you have any questions please let me know.

All the best,
Megan

Appendix 8 – Transcript for Video in Methodology for Chapter 4

This Cross disciplinary thesis involved both applying methods from qualitative research to the design of AI education, and the development of bespoke techniques in natural language processing. The aim was not to advance the methodology, but to use existing methodologies adapted to the questions asked in each chapter of the thesis. This is a common approach in engineering where the method is often included in the individual chapters. Here I will elaborate on the method for chapter 4, the stakeholder interviews, which is the part of the thesis closest to social science practice.

I decided the research questions in this chapter were most suited to an interpretivist, qualitative, exploratory research study according to social science literature such as “Research methods in education” by Cohen et al (Cohen, 2017). As an engineering doctoral student, it was important I also explore how qualitative research has been used in engineering. Human aspects and accompanying qualitative methods have a long and evolving history in engineering. Earlier papers, such as “Qualitative methods in empirical studies of software engineering" published in 1999 (Seaman, 1991), consider how qualitative methods can be combined with more established methods in this field. A particularly useful more recent paper, “Qualitative methods for engineering systems: Why we need them and how to use them” published in 2017 (Szajnfarber, 2017), specifically considers good qualitative research in engineering. This approach aligns with my choices and thinking. The paper suggests appropriate situations to use qualitative methods. The ones that apply here are “understudied phenomena”, and “can’t extract from context”.

Further a direct from the paper - “Was the choice to execute a qualitative study well justified? If understanding of the phenomenon is mature and/or the phenomenon can be extracted from its context, other research tools are likely more appropriate” Based on this statement, I believe the choice of a qualitative study was well justified. The process described in this paper is the one I followed. In particular they recommend careful consideration of the selection of cases to ensure depth and inherent variability, they also stress drawing on complementary types of data for triangulation, which fits with me considering 4 different groups of stakeholders. They recommend using established methods of data collection and analysis, which fits with my choice of semi-structured interviews and a thematic approach.

“Most engineers are familiar with the positivist and postpositivist perspectives, which assume that there is an absolute truth.” this is a direct quote from the book Qualitative Research Basics: A Guide for Engineering Educators (Van, 2008). It is very unusual for engineers to consider epistemology, most do not even know they are positivist. An exception is the field of engineering education where it was reassuring for me to read definitions of interpretivism. The authors of this book further go on to say, “Much qualitative research is based on an interpretivist perspective, which states that truth is contextual, depending on the situation, the people being observed, and even the person doing the observation.” which fits nicely with my research.

In selecting my sample, as is so often the case, I had to balance several factors such as richness, anonymity, and inclusion. Qualitative research seeks rich elaboration of the categories so we understand what demographics are involved. But there is always a balance in the field.

I focused on four groups of participants, these were thought leaders (which refers to anyone who is deemed an expert on a topic – for example, due to their job, publications, talks or books.), industry experts, adult educators, and members of the public. The first three categories of stakeholders all used purposive sampling, starting with an initial contact, and then snowball sampling. It is the member of public group of participants that required the most careful design in order to access the less heard voices.

As an engineering PhD student, I’ve been instructed by the engineering ethics board to blur categorical information and demographics with 3 or less participants (this email can be found in the appendix). Not including such information is common in areas such Human Robot Interaction, which is the more qualitative branch of robotics, and the name of a top conference in the area. A recent review of HRI papers published in 2022 showed that of 236 studies in HRI, 139 didn’t comment on recruitment methods, 118 failed to report incentives, and 62 lacked gender data (Cordero, 2022). The existence of this paper indicates a spotlight is now being shone on this area in engineering, it is possible the engineering ethics (such as the restrictions which I was subject to) will need to be updated as we learn effectively through interdisciplinary research.

There was also consideration of balancing the desire to gather rich data and the inclusive goals of reaching out to access voices less heard in research. In considering this balance, after much thought, the decision was made to not record interviews and not appear too intrusive about personal details. All this was intended to create a more relaxed, open and un-intimidating tone and context for greater inclusion. It is precisely those who may be put-off by academia and the trappings of much formal research, whose voices are most sought here. There are two extracts of data from this research worth revisiting when reflecting on the strengths and weaknesses of my methodological design when it relates to sampling.

A direct quote from one of my participants, "I'm interested in diversity. Universities, AI, engineering. There is a white, euro-centric, middle class focus to everything. There is a culture dimension not being addressed. Need more diversity to make sure these things work for everyone. Good data is also a problem. For this you need cooperation [interviewer: what do you mean?] Like in this study, why would I be honest if this doesn't have my interests at heart? AI fails to balance culture and class. There is not wide enough participation. Good luck on PhD from your very comfortable position of privilege." The quote highlights the potential negative impacts of asking further demographics when you're trying to access unheard voices.

Further my reflective journal, which I used after every interview, shows several experts and members of the public expressed the lack of recording and anonymity was an important aspect in their decision to participate. Anonymity here was not only that they could not be identified, but they felt personal details were intrusive and off putting.

Given this, I didn't ask participants about their demographics, other than job. They had a variety of jobs (including warehouse worker, retired engineer, teacher, social media manager, childminder trainer and first-aider). If they volunteered other demographics. I noted it down. For example, two interviewees gave their ages throughout their interviews as "nearly 20" and 78. It has been assumed all other interviewees fall within this age range.

Rather than providing any other details of the individuals, which would go against my ethics approval, I can elaborate on the setting in which the members of public were interviewed as it was carefully chosen. The location was a park in a North East London Borough. This Borough includes some wards in the top 10% most deprived areas of the UK. The specific park is located in one of these wards. Having lived and worked in this area for several years I was integrated into the community. This led to me being invited to a community event. On investigating, I realised this would provide an ideal context to reach out to a rich socio-culturally diverse range of participants. The park is within a mile of multiple cultural centres, including mosques, synagogues, and Christian churches. While ethically I can't give the details on individual specifically, across the 6 participants, and based on my conversations I felt they reflected the diversity of the area.

If I were to conduct this research again, under difficult ethical constraints as engineering embraces a richer approach to qualitative research learning from social sciences, I would revisit whether or not to ask for further personal characteristics. This would remain a complex ethical choice given my desire to access the least heard voices. It may be I would encourage at the end of the interview those who wished to to provide further information. One option which feels like a good fit for this research would be asking participants to self-describe.

Appendix 9 – References for Video in Methodology for Chapter 4

Cohen, L., Manion, L. and Morrison, K. (2017) *Research Methods in Education*. Taylor \& Francis. Available at: https://books.google.co.uk/books?id=9mYPEAAAQBAJ.

Seaman, C. B. (1999) 'Qualitative methods in empirical studies of software engineering', *IEEE Transactions on Software Engineering*, 25(4), pp. 557–572. doi: 10.1109/32.799955.

Szajnfarber, Z. and Gralla, E. (2017) 'Qualitative methods for engineering systems: Why we need them and how to use them', *Systems Engineering*, 20(6), pp. 497–511. doi: 10.1002/sys.21412.

Van, N. *et al.* (2008) 'Rigorous Research in Engineering Education NSF DUE-0341127'.

Cordero, J. R., Groechel, T. R. and Mataric, M. J. (2022) 'A Review and Recommendations on Reporting Recruitment and Compensation Information in HRI Research Papers', in *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, pp. 1627–1633. doi: 10.1109/RO-MAN53752.2022.9900744.