Group 6

Apprentices of automation: adapting career paths to ever-smarter machines

Abstract

We examine the effects of automation on a number of professional sectors, and the degree of uncertainty this creates in the people affected. We then look at whether or not they make decisions accordingly, and if so, what the nature of these decisions are. A mixed method was chosen, incorporating a quantitative survey and qualitative interviews. The survey investigated 107 students' decisions regarding future career prospects and if they intend to develop skills relevant to automation. The interviews were conducted with 11 individuals working in fields affected by automation, or in which they have knowledge of the development of this technology. Our guiding hypothesis is that people's knowledge and perceptions about automation in their present or future careers influence the sort of decisions they might make to adapt themselves. We also hypothesise that knowledge and perception in turn might be influenced by certain individual factors. So far, literature on the topic of automation has focused on the concrete effects of technological developments on professional sectors themselves as opposed to the actual perceptions and adaptation of individuals. We therefore hope that this research will work as an impetus for further research on people's reactions in the context of rising uncertainty regarding this technological shift. This could have implications for social policy directions linked to job protection and adaptability.

Key words: automation, occupational choice, future, uncertainty, individual perceptions

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Introduction

In a technological age in which automation, robotics, and artificial intelligence (AI) are making their way into the professional world in an increasing number of sectors, the future seems uncertain in many ways. Our aim in doing this project is to gain a deeper insight into the ways in which this affects people's decisions regarding their professional future, and how certain demographic factors may play on these perceptions. The research questions that guided our methodological journey were the following:

1) How do the recent developments in automation affect professions and how does this shape people's perceptions and decisions about the future of their careers?
2) What factors might influence people's degree of certainty regarding their future in the context of the increasing prevalence of automation technologies?

This paper starts off with a review of the literature, followed by a justification of our methods, and the analysis of survey and semi-structured interview results, from which we finally draw a conclusion.

Literature Review

In seeking to find out about the ways in which individuals react to the rise of automation in terms of perceptions of their own professional future and decisions made accordingly, we reviewed the following literature on the effects of automation on the labour market, which we have grouped into three main topics. This pool of research was used as a basis on which to ground our own research, but we also hope to bridge any identified gaps in the literature.

I. The general effects of automation on professions: a review of the jobs and sectors most affected

In an effort to quantify the proportion of jobs likely to be affected by automation in the US, Frey and Osborne (2013) developed a probabilistic algorithm using nine skill variables estimating the degree of computerisation of various occupations. These were derived from the 2010 Occupational Information Network online database (O*NET), and were related to three 'bottlenecks' of computerisation: "level of perception and manipulation, creativity, and social intelligence" (Frey and Osborne 2013:32-33). Their key findings were that 47% of occupations in the US will be at high risk of automation in the near future, especially in the categories of transportation and logistics, office and administrative support work, and production occupations, services, sales and construction (2013:41). Note a potential self-selection bias in 'high-skilled' workers' potentially overrepresented survey answers (Handel, 2016:160), meaning that 'lower-skilled' workers' job insecurity might be under-represented.

An analysis of the effects of automation in the UK based on the Office for National Statistics' survey of labour force, and Frey and Osborne's reported predictions (2013; 2014) was conducted by Deloitte (2015). According to this research, jobs with the lowest probability of automation included those with the least routine required, "high level cognitive or social skills" and "significant manual dexterity" (Deloitte, 2015:3). At the opposite end of the spectrum, those with the highest probability of being automated "were largely administrative in nature or involved routine manual activities" (ibid). Another aspect of the findings pointed to a growth in the number of people working in jobs less likely to be computerised were expected to grow, such as "caring, leisure, and other service occupations" (ibid). This was in accordance with Frey and Osborne's idea of the three 'bottlenecks' of automation mentioned above (Deloitte, 2015:7).

II. An outlook on the longer term: will more or less jobs be created?

While the above makes clear that many jobs can be automated, the equilibrium impact of automation remains unclear. While jobs may be lost, the concept of creative destruction posits that new jobs will at the same time be created. In trying to assess the degree to which automation replaces occupational roles, Willcocks and Lacity (2016a) analysed four case studies of Robotic Process Automation (RPA) in the US, UK and Canada. RPA refers to automation of "swivel chair" service tasks, such as transferring data from one software to another, as for example from e-mails and spreadsheets to Enterprise Resource Planning systems (Willcocks and Lacity 2016a: 66). They found that automation did not result in layoff of internal staff, but at most in job wastage (Willcocks and Lacity, 2016b: unpaginated). This is concordant with some of our interviews, in which it seemed that those already working in a certain profession were made to change tasks but not asked to leave the company.

The Pew Research Center in collaboration with Elon University (2017) conducted a wide canvassing of experts and members of the public with an interest on developments in technology, asking whether they thought educational and training programmes would successfully adapt to the 'jobs of the future' (Rainie and Anderson, 2017:3), from which five themes were deduced (p.7). While some were hopeful, concerns also arose regarding the replacement of more jobs than would be created, and the socio-economic negative impacts this would entail for the workforce (p.22).

Applying the "technological unemployment" theory postulated by John Maynard Keynes in the 1930s to present-day findings on automation reported by diverse sources, Petropoulos (2017: unpaginated) looked at both positive and negative impacts of automation on employment. On the negative pole, a 'displacement effect' may take place where workers lose their jobs (e.g. the introduction of automobiles had laid off horse-related-job workers), whereas on the positive pole, there may be a 'productivity effect' where more job opportunities are created. An example of the productivity effect is the reduction in the number of bank clerks following the introduction of Automated Teller Machines. Whereas this replaced a number of bank clerks, the cost-reduction also allowed for the opening of more bank branches, and therefore more employees. Similarly, self-checkout machines in supermarkets and fast food stores might not completely replace cashiers as machinery errors still occur calling upon human cognitive skills, something which was reported in some of our interviews with supermarket staff.

In contrast, a study by Acemoglu and Restrepo states. that for every industrial robot introduced in the US economy, between 3 and 5.6 workers may lose their jobs, and introducing one more robot per thousand employees may reduce wages between 0.25-0.5% (2017:35). Whereas the worries raised by some of our interviewees did not directly relate to robots per se, some (such as taxi drivers) did worry about technological advances in their jobs allowing for the replacement of traditional techniques by cheaper ones.

III. Adapting to this trend: which skills will we prioritise?

In terms of adaptation to the rise in automation, the hopeful themes found by the Pew Research Center revolved around new platforms of learning and training (notably online, making it more accessible for many), new skills to be prioritised ('21st-century skills' harder to replace), and new forms of credentialing (Rainie and Anderson, 2017:7*)*. Most respondents deemed the most valuable skills in an age of increasing technology as "human" skills, such as "emotional intelligence, curiosity, creativity, adaptability, resilience and critical thinking" (p.13). Moreover, many believed that skills used for working in the development of robotics and AI itself would become primordial, although others acknowledged that this might lead to an overload of programmers, not all of which would be able to work in the sector (p.14). Amongst those most pessimistic however, a number of respondents mentioned that technological advancements would not leave many skills left to learn once most jobs were replaced, and that shifts in training mechanisms were both difficult to fund and harder for individuals to engage in (pp.17-22).

Also mentioned was the rise in individualised self-learning (e.g. through online courses), and the increasing availability of coding and programming classes (p.15). This served as a starting point for our survey of students' decisions regarding future careers, in which many reported developing certain computational skills for their future prospects.

Finally, Susskind and Susskind analysed trends in automation and developed theories about their origins. They hypothesised that within 10 to 20 years, all professions will display these trends, leading to a "post-professional" society in which people will be trained for skills rather than jobs (2015:263). Accordingly, only a small fraction of individuals (out of classified into 12 sectoral categories) will continue to work as they previously did since their expertise and talent cannot be automated (p.264).

Most of the literature we reviewed conveyed similar results regarding the occupational sectors most affected by automation, and skills said to guarantee more safety were generally divided into 'human' skills less likely to be automatable, and programming and computing skills useful for the generation of automation technologies. However, given the ever-increasing development of technology and the shift towards better-performing artificial intelligence, the literature is composed mainly of predictions or to-date effects of automation, which are continually changing. Individuals' perceptions of these changes are evolving and therefore have yet to be documented, and the aim of our research is therefore to explore these responses in an age of uncertainty.

Methodology

Survey

The survey conducted was in an online format, being shared extensively on international social media platforms to maximise the outreach and demographic of undergraduate students responding. The first part of the survey asked a number of different questions, ranging from key indicators such as gender and household income level to questions on future career choices, and the importance assigned to several factors while making such a choice. The second part asked about the choices regarding programming and coding courses, and explored the reasons why the responders do or do not learn or plan to learn any such skill. The third part of the survey, after providing basic definitions of automation and artificial intelligence, asked respondents to rate their understanding of the recent developments in the two categories, the degree of positive or negative impact they thought such developments would have in their chosen prospective career, and how much importance they attached to such impact while (1) choosing the career in the first place and (2) choosing to learn (or not learn) a programming or coding skill.

Qualitative interviews

An important part of our research was composed of semi-structured qualitative interviews with working individuals or prospective workers. This allowed us to ask about specific topics based on pre-existing knowledge, while taking the form of a conversation, with flexibility in adapting our questions to the flow of the discussion (Mason, 2002:62-63). Since our aim was to delve into individuals' own perceptions and experiences, this method allowed them to voice their beliefs and attitudes, with less constraint than specific close-ended questions (Savage, 2010:186). We acknowledge that no data is ever fully objective, interpretation being an ongoing process involving the choice of topic, questions, sample and analysis. We therefore do not claim that our findings are generalizable, but rather that they provide an in-depth window of understanding into the views of our participants.

Our interview sample was composed of one teacher, two tube drivers, three taxi drivers, two retail supermarket workers, one interpreter, one prospective solicitor, one prospective investment banker, and a computer-engineering student. Interviews were conducted in person in locations convenient for our interviewees or over the phone, and were all-bar-three recorded with the informed consent of respondents. Confidentiality and anonymity were protected and ensured through consent forms signed by both parties. Interview data was coded using hybrid thematic analysis incorporating an *a priori* approach based on prior research, with an inductive one (to a greater extent) based on participants' answers (Feredey and Cochrane, 2006). The initial coding of interviews led us to identify three prominent themes: 'Degree of automation', 'Temporal estimations of automation', and 'Role of institutions in professional security'.

Analysis

Survey

Note: For key demographics of our sample see Appendix.

The survey was completed by 106 respondents and had an almost proportionate mix of genders, income levels, and countries of origin. However, bias concerning the pool of respondents, specifically about being restricted (albeit to a small extent) by the socio-economic and cultural backgrounds of extended friend circles of the researchers is an acceptable concern. It is therefore advisable to treat this as survey not of undergraduate students of all possible international demographics, but rather as a somewhat more restricted pool of undergraduates with a certain degree of international exposure - perhaps more aware of global culture, trends and developments than an average undergraduate. This, though restrictive, is still a very varied and influential demographic to study.

From the survey, it has been found that around 44.3 % of students learn some form or programming or the other *electively* (as opposed to being obligated to due to degree regulations). Comparing sector-wise, the difference between percentages of students learning such programming for each sector has been found to be significant at the 5% significance level, with those in the banking, finance and consultancy sector being most likely, and those in the politics, civil services and diplomacy sector being least likely to learn it. (see Figure 1)

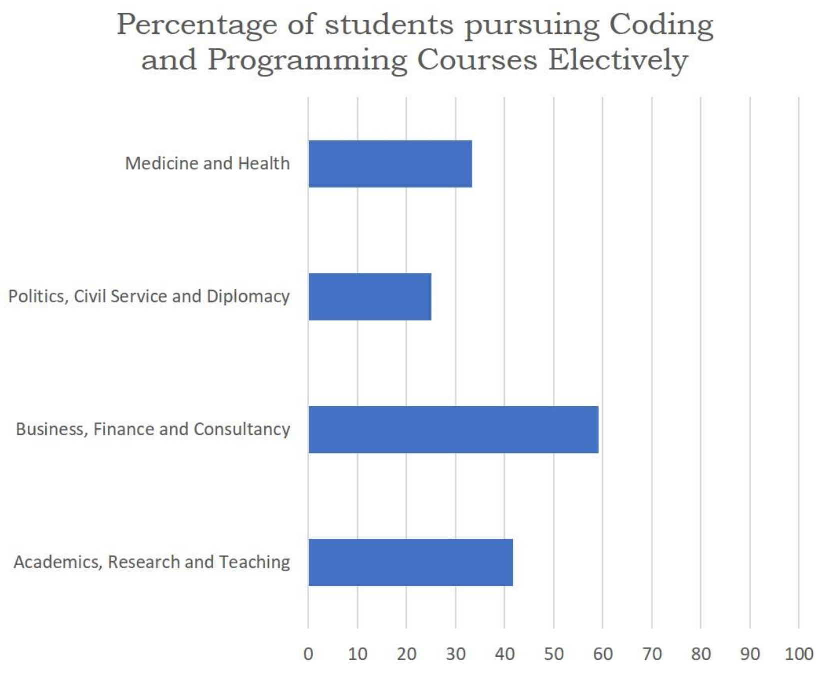

Figure 1.

When asked about why they choose to learn it, “strengthening future career” is found to be the most important reason across all sectors of intended future careers, with the highest mean value being computed for those intending to work in banking, finance and consultancy sectors (The value is assigned from a scale of 1 to 5, with 1 being “Not important” and 5 being “Extremely important”). Another interesting point to note might be the fact that when those who do *not* learn any programming are asked why they choose not to learn it, those in the banking, finance and consultancy sector are significantly more likely than any other sector to state the only reason being that they are “not skilled enough”, and least likely to say because it is “not relevant to their career” or that they are “not interested”. (see Figures 2 and 3)

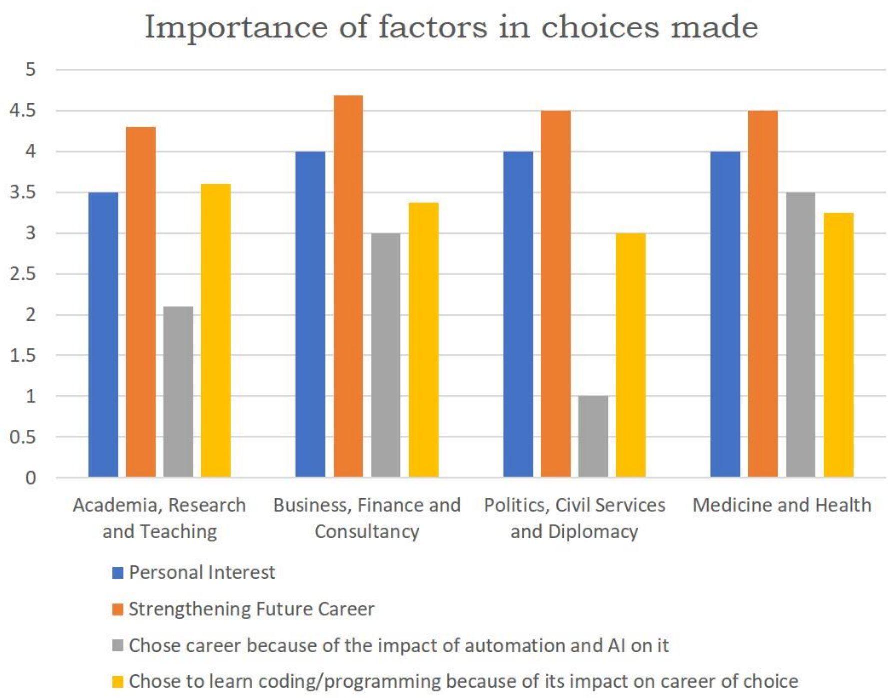

Figure 2.

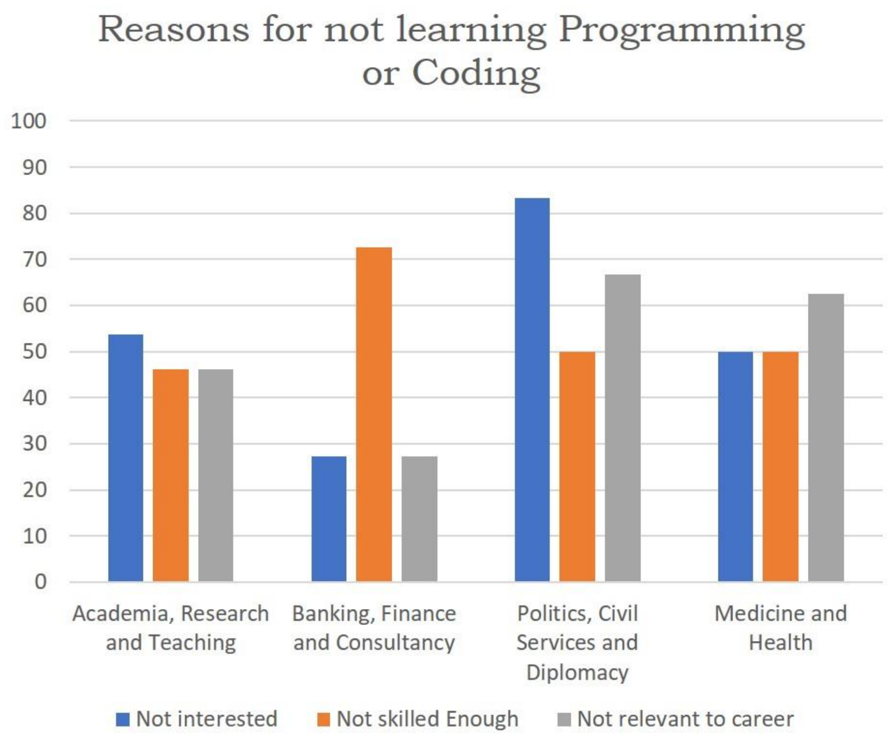

Figure 3.

Those intending to work in the medicine and health sector have assigned the maximum mean value (following the same scale) of 3.5 to how much importance the future role of automation and AI had on their choice of career. This could be interpreted in accordance with the idea that healthcare roles such as doctors, psychologists, therapists, nurses, etc are less likely to be impacted by automation and AI, particularly in the near future, since they require characteristics of empathy and feeling to satisfy patients. Therefore, those intending to work in those sectors feel that automation and AI will only have some positive impact on their future careers. Similarly, they seem to assign less importance than all other sectors (excluding, understandably, politics and diplomacy) in the said impact being a factor in their choice to pursue programming, something those in academia, teaching and banking and finance give greater importance to.

The mean perception of impact of automation and AI on their own career was calculated by sector, with the scale ranging from -5 being “extremely negative” to +5 being “extremely positive”. (see Figure 4) A median split on interaction of gender and income on the perception and nature of the impact of automation and AI on their careers was performed – the result had a significance level of 3%, and the result showed that in the upper 50% of the income distribution, there seems to be little difference in the perceptions by gender, but in the lower 50%, females seem to think the impact of automation and AI on their career will be somewhat positive, while males seem to think the impact will be limitedly negative (the corresponding values are about 2.2 and -0.98 on the “-5 to 5” scale.) (See Figure 5)

	Mean	**Standard Deviation**
Academia, Research and Teaching	0.982 (Limited positive impact)	2.45
Banking, Finance and Consultancy	0.92 (Limited positive impact)	2.95
Law	1.6 (Some positive impact)	2.04
Engineering	2.49 (Moderate to significant positive impact)	2.1
Medicine and Health	1.58 (Some positive impact)	2.6
Politics, Civil Services and Diplomacy	1.625 (Some positive impact)	1.6

Figure 4.

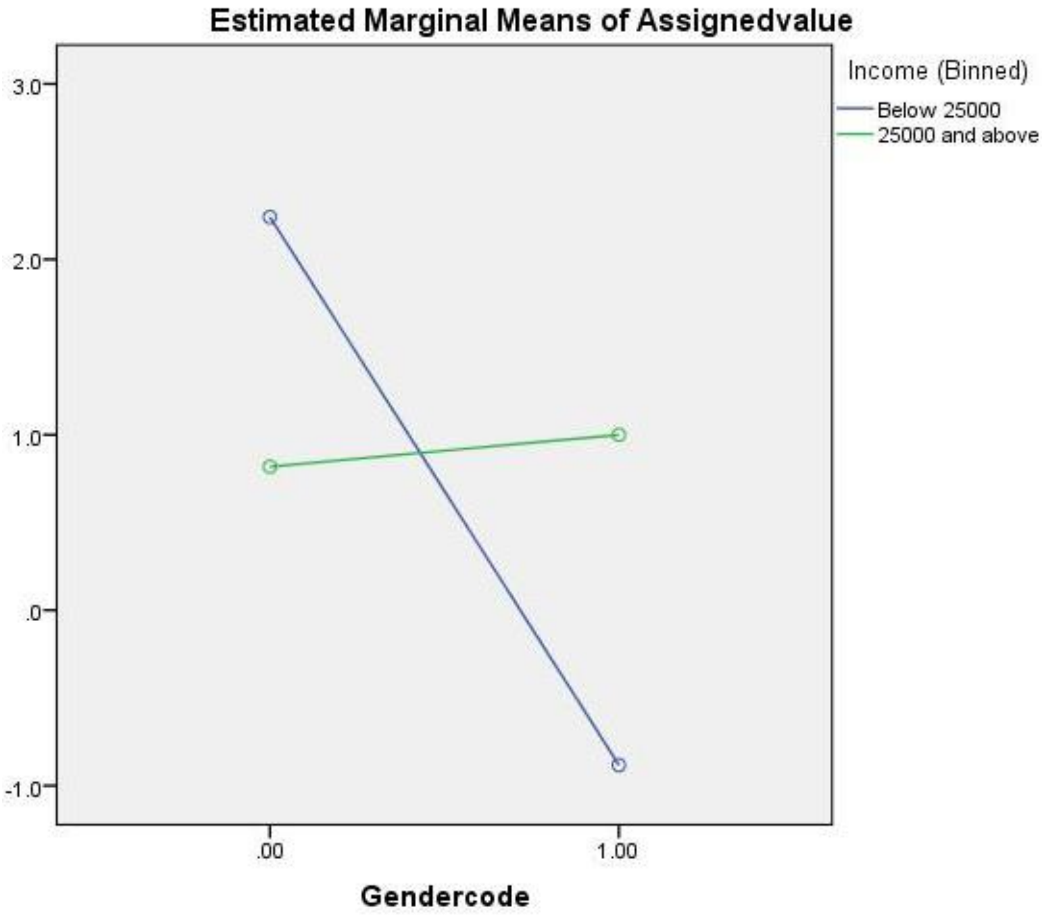

Figure 5. (Note that the y axis denotes the same scale as Figure 4 and on the x axis 0 and 1 stand for female and male respectively)

Figure 4 gives the means and standard deviations of each sector. Notably, no sector's mean value is negative. This, while a broad generalisation, could be explained somewhat by the fact that in reality as of today, jobs most immediately threatened by automation and AI tend to be jobs that are not usually occupied by those who shall be graduating from university, and thus in general, such students on average have a positive outlook – perhaps expecting advances in ease and accuracy to supplement their own intended jobs as opposed to replacement or competition from automation and AI.

Qualitative interviews

Degree of automatability

The majority of respondents thought their job could only be supplemented, not automated, while a minority will see their whole job being replaced. The former group justified their projection with the fact that their job involves skills no machine could ever do. Most of these were “human skills” mentioned in the literature review such as empathy and building rapport and trust. Rapport is crucial to make the customer buy, as noted by a retail manager: “[shop assistance] is about the lasting impression the customers have”. He did not think it viable that shop assistance could be automated entirely, and drew on experience with self-scan machines, which he and the other respondent said had neither destroyed jobs nor lead to wastage in their stores. Trust was pointed out as a factor for gaining investment banking clients as well as for taxi-driving: ”Business people won’t trust driverless pods to drive them around.” Apart from the above non automatable skills, one interpreter added the skill to review translations which she thought could never be done by a machine.

A minority of respondents found that their jobs may be replaced entirely. In lack of human contact, tube drivers’ human skills are not relevant, and all acknowledged that their job may be replaced; however they rely on alternative jobs guaranteed by their union (see theme 3). Although human skills are required for teaching, the teacher thought that a lot of the pertinent tasks were automatable. Giving individual answers to student questions could be done by an Artificial Intelligence (AI) teacher displaying capacities beyond those it had been programmed for: “the students were learning things that they wouldn’t have learned from an actual physical teacher”, something which had been demonstrated at a conference. In turn she thought that “[E]ven the jobs that we assume are safe, that we assume require soft skills and human communication (...) are not safe”.

Temporal dimension of automation: estimations of how soon automation will be a reality

In asking respondents about potential worries regarding the degree of automation in their own lives and across society generally, feelings of uncertainty mentioned were to a large extent influenced by how soon they thought it would be widely implemented. Although Train of London (TfL) services aim to implement fully automated tube trains by the 2020s (*The Independent*, 2014), both tube drivers we interviewed reported thinking this was an ‘ambitious’ project, and that it would take longer to introduce driverless trains on all lines without any human presence to supervise. Moreover, some tube and taxi drivers reported that if driverless transportation was likely to affect future generations, their own age and upcoming retirement meant that their job stability would not be affected. In terms of artificial intelligence, one student in computer engineering reported that the current levels of this technology were not yet developed enough to fully replace human jobs, but that this was a real possibility, especially with the introduction of quantum computing. This eventuality was seen as an impending threat by the teacher mentioned above who had attended a conference displaying an AI teacher. The fact that this technology already existed was a source of worry for herself and other colleagues who feared that their implementation might replace ‘physical teachers’ in the near future, a similar concern to that found by the Pew Research Center’s pessimistic responses about any jobs ever remaining that wouldn’t be automated (Rainie and Anderson, 2017:22).

Role of institutions

During the interview we conducted, workers across sectors revealed their personal perceptions regarding the role of different institutions in the age of automation, which we hypothesised might be a vital factor affecting people’s degrees of uncertainty about their jobs. With regards to the government’s plan to invest in driverless cars, a taxi driver in Milton Keynes said: “they’re going to spend […] £56 million on these driverless pods, I think half of that’s going to be paid by the government. We’ve got people living on the streets, do you really think we should be affording that? It’s not gonna work.” Furthermore, concerns about the likely impact of government policies were observed in tube drivers. In addition, respondents tended to think that authorities were more likely to invest in automation if its profitability was significant. One Bakerloo Line tube driver commented: “Bakerloo [line] is not very profitable […], the line that makes the most money will get changed earlier”. A similar opinion was also conveyed by a university teacher we interviewed, who believes that if automation seems profitable, it will happen. Moreover, organizations like labour unions may impact people’s perceptions regarding the uncertainty of their job. Both tube drivers we interviewed perceived the union’s power as strong, and showed less concern about job-loss, largely due to their belief that the union would protect their interest. In contrast, the teacher who perceived the teachers’ union as having weak power seemed more worried about automation, as she did not think it would be able to secure teaching jobs if those were to be automated. Her opinion that the institution representing her sector did not really care about her job security was reflected in a taxi driver’s claim that the council was not doing anything to protect their position: “They’re affecting our livelihood. And that’s why I haven’t earned any money.”

Conclusion

From our mixed-methods analysis, it seems that most of the respondents, especially taxi drivers and the interpreter, did not see the potential immediacy of changes as suggested by the literature review (see Table 1).

Probability of automation	Profession
0.89%	Taxi Drivers and Chauffeurs
0.035%	Lawyers
0.23%	Financial Analysts
0.38%	Interpreters and Translators

Table 1. Source: Frey and Osborne 2013

In contrast, the undergraduate students surveyed generally seemed to attach greater importance to the advances of automation and AI and were more likely to adjust their career decisions and skillsets accordingly. Intuitively, such observations make sense due to the facts that (1) the undergraduate students are at a more flexible stage of their career where they can pivot their activities around developments as they become more apparent but that (2) because they do not yet have full time jobs, they are more uncertain about securing a job in the future as opposed to those interviewed, most of whom already have a job.

We recognise that our research is not detailed enough to pinpoint to any strong causality, given the time and resources available. However, we believe it has shed light on a number of trends in the uncertainty around automation, both in terms of knowledge and in terms of expected effects on different sorts of careers as perceived by students and workers themselves. With a larger pool of students and professionals, it might be possible to chart definitive trends in the expected impact of automation and AI more robustly than we were able to. In the process, policy implications could also become apparent, through which policy makers will be able to address misconceptions of the public and perhaps better prepare and equip them for the eventualities of automation that are all too inevitable over time.

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Appendix

Respondents by Gender

	Frequency	Percent
Female	66	62.3
Male	39	36.8
Other	1	.9
Total	106	100.0

Respondents by Annual Household Income

	Frequency	Percent
Below £10,000	21	19.8
£10,000 to £25,000	25	23.6
£25,001 to £50,000	13	12.3
£50,001 to £100,000	12	11.3
£100,001 to £250,000	9	8.5
£250,001 to £500,000	2	1.9
£500,001 to £1,000,000	2	1.9
Above £1,000,000	1	.9
Don't know	13	12.3
Prefer not to say	8	7.5
Total	106	100.0

Respondents by region of origin

	Frequency	Percent
East Asia	18	17.0
Middle East	5	4.7
South Asia	27	25.5
Southeast Asia	32	30.2
USA	1	.9
West Europe	23	21.7
Total	106	100.0

Respondents by intended sector of career

	Frequency	Percent
Academia, Research and Teaching	23	21.7
Banking, Finance and Consultancy	30	28.3
Creative Industry	4	3.8
Engineering	7	6.6
Interpersonal relations	1	.9
Journalism	2	1.9
Law	5	4.7
Medicine and Health	12	11.3
Other	14	13.2
Politics, Civil Services and Diplomacy	8	7.5
Total	106	100.0