ARTIFICIAL INTELLIGENCE AND THE TAX PRACTITIONER

Patrick Buckley[1]; Elaine Doyle[2]; Brendan McCarthy[3] and Ruth Gilligan[4]

Abstract

The advent of artificial intelligence (AI) and machine learning (ML) has sparked concern that many jobs are at risk of automation. This paper contributes to this debate in the context of the tax practitioner. We describe a methodological approach that redefines the appropriate loci of analysis as a combination of the level of task and the career stage rather than focussing on the tax role at a macro level. We use these revised loci to perform a meta-analysis of existing studies in order to examine the role of the tax practitioner. The change in focus of analysis reveals a number of insights which have been heretofore obscured.

Keywords: Artificial Intelligence, The Future of Tax, Tax Professionals and Emerging Technology.

1. INTRODUCTION

A significant trend in the evolution of Information Technology (IT) over the last two decades has been the increasing importance of technologies that enable the collection and analysis of large volumes of data. In parallel with the digitization of existing data sources, the introduction of new platforms, such as mobile phones and the Internet of Things (IoT), have led to an exponential increase in the volume of, and velocity at which, data that can be collected by information systems. A range of supporting techniques, usually referred to as “big data” enables the storage and analysis of these vast data streams. The development of a host of mathematical and algorithmic tools, some novel and some recently enabled by technical progress, has led some commentators to believe that Artificial Intelligence (AI) is beginning to reach the capabilities conceived of by its early proponents.

Against this background, a recent stream of academic research has emerged which seeks to predict the impact that information systems powered by these interrelated and rapidly developing technologies will have on the labor market (Brynjolfsson & McAfee, 2011). As evidenced by the historical origins of the word “Luddite”, concerns about automation and “jobless futures” are not new. Current concerns about “computerization” and the potential threat to occupations from current and near future technological advances were raised by Frey and Osborne (2017), who suggested that 47% of all jobs in the United States were at risk of automation by 2030. This research sparked a debate about the likely impact of technological development on the future of the job market.

Many of the studies in this area forecast that tax work is highly susceptible to being automated. For example, the two categories in Frey and Osborne’s (2017) study which specifically mention

[1] Dr. Patrick Buckley, Department of Management and Marketing, Kemmy Business School, University of Limerick, Ireland. Email: Patrick.buckley@ul.ie
[2] Prof. Elaine Doyle, Department of Accounting and Finance, Kemmy Business School, University of Limerick, Ireland. Email: Elaine.doyle@ul.ie
[3] Brendan McCarthy, Department of Accounting and Finance, Kemmy Business School, University of Limerick, Limerick, Ireland. Email: Brendan.mccarthy@ul.ie
[4] Ruth Gilligan, PwC Dublin, Ireland. Email: Ruth.x.gilligan@pwc.com

tax—"tax examiners and collectors, and revenue agents" and "tax preparers"—are assigned 93% and 99% probabilities of being computerized respectively. Many other occupations that would have similarities to tax practitioners—for example, "bookkeeping, accounting and auditing clerks"—are assigned equally high probabilities. This pattern can be observed across numerous studies with similar objectives. While we acknowledge that the role of the tax practitioner goes far beyond that carried out by tax preparers, these are nevertheless worrying statistics for the tax profession and merit academic attention.

This paper aims to contribute to this debate in a number of ways. First, answering calls in the literature for more nuanced analysis, we provide a methodology that can be used to analyze roles using a combination of the level of task and professional career stage rather than by occupation as a whole. We use a meta-analysis of existing studies to consider this in the context of the tax practitioner. This analysis reveals a number of insights that are obscured by an analysis which only operates at the occupational level. AI automation is forecast to automate many of the tasks traditionally associated with the tax practitioner. However, this automation is likely to be felt unevenly across tax roles. In particular, tasks traditionally associated with entry and low-level positions are most at risk from automation, while tasks traditionally assigned to more experienced employees are less vulnerable. From this perspective, AI automation is best conceived of as something that disrupts traditional career pathways rather than something that eliminates the tax practitioner role. Nonetheless, the likelihood of significant dislocation requires stakeholder engagement from across the tax profession in order to develop new models that can adapt to the changing environment.

The remainder of this paper is structured as follows. The study begins by reviewing the extant literature on the impact of technology on employment and the evolution of AI before reviewing current forecasts as to the impact of AI on the job market. We then examine the work carried out by tax practitioners and how this may be impacted by technological advances. This inquiry generates a number of open research questions which inform the analysis. In the methodology section, we describe a research design that aims to address some of the weaknesses inherent in existing studies. Moving on, the results section provides a case study that demonstrates our approach in operation in the context of the role of the tax practitioner. The paper concludes by presenting a number of findings and providing some suggestions for further research.

2. LITERATURE REVIEW

The General Impact of Artificial Intelligence

The evolution and future development of AI

The development of machines that can mimic or surpass human intelligence has been anticipated since before the invention of digital computers. For example, Isaac Asimov's formulation of the "Three Laws of Robotics" first appeared in print in 1942 (Asimov, 1950). The academic origin of AI is usually traced back to the Dartmouth Summer Research Project on Artificial Intelligence conference organized in 1956 by John McCarthy (Nilsson, 2009). Anticipation of progress in the field has continually seesawed. Periods of euphoric overexpectations—e.g., predictions in 1965 that computers would be able to undertake any work that a man was capable of (Crevier, 1993) —have been followed by periods of pessimistic retrenchment (Nilsson, 2009).

There is currently sustained interest in, and optimism about, AI research. One notable feature of today's AI is that programmers have developed algorithms that can self-enhance, becoming smarter as well as more efficient and effective (Alm et al., 2020). New techniques, such as genetic algorithms, have been developed while techniques with a longer pedigree, such as neural networks, have been reinvigorated by the use of innovative approaches such as deep learning. These advances have been allied with increasingly powerful hardware and data sets of a scale unimaginable even a few years ago. Taken together, these have allowed for advances in the development of AI-powered systems, such as voice assistants and self-driving cars (Badue et al., 2020; Hoy, 2018). While less eye-catching, AI has arguably had an even more significant impact in areas such as finance, medical decision support systems, recommender systems, face recognition, and machine translation (Marr & Ward, 2019). *The Economist*, a pillar of the establishment, proclaimed data to be the new oil and AI to be the dominant technology of the future (Parkins, 2017).

Despite this interest and general optimism, there is still a vast degree of uncertainty about the future development and impact of AI and its developmental trajectory (Autor et al., 2020). Many experts believe that there are no fundamental barriers to the development of artificial general intelligence (AGI) (Bostrom, 2016). Some of these analysts predict a "Cambrian explosion" of intelligence, where AI systems are leveraged to build more advanced AI systems which will, in turn, be tasked with developing even more advanced AI (Muehlhauser & Salamon, 2012). Forecasts of this nature often see an AI system with a level of intelligence comparable to that possessed by humans as being a temporary milestone along the road to systems that leverage the efficiencies associated with IT to quickly and dramatically exceed an individual human's intellectual capacity (Bostrom, 2016). Other experts are more cautious (Autor et al., 2020). While acknowledging the progress to date and the empirical evidence that evolution has already produced at least one species with human-level intelligence, they believe that the path to AI may be far more difficult than its cheerleaders suppose (Penrose, 2002). Some believe that intelligence is fundamentally non-algorithmic in nature. From this perspective, deterministic Turing machines will never be able to replicate intelligence (Penrose, 2002). Another, more philosophical, issue is whether the notion of conceiving intelligence as an attribute associated with a singular entity is fundamentally flawed (Clark, 2005). Instead, both consciousness and intelligence may be properties embedded in a larger cultural feedback loop. From this perspective, intelligence in any meaningful sense cannot be engineered in the absence of a social context (Dennett, 2017).

Despite the universally acknowledged difficulty of making predictions in such a space, some have attempted to make forecasts as to the likely date of specific achievements being reached in the development of AI. A commonly selected milestone for such forecasts is that of an AI system that demonstrates human-level general intelligence (Baum et al., 2011). Presenting an aggregated summary of several surveys of AI expert communities, Bostrom (2016) provides the following median estimates: a 10% probability of AGI by 2022, a 50% probability by 2040, and a 90% probability by 2075.

Uncertainty also dominates prognostications about the impact of AI on society. Broadly speaking, two futures are envisaged. The first forecasts the impact of AI to be positive (Kurzweil, 2005). Cognitively superior AI will supercharge the development of technologies such as genetic engineering and nano-technology that will extend and enhance human life. These technologies will help to develop solutions to challenges such as resource depletion and climate change. Economically, AI systems and robots will perform the physical and cognitive tasks required to produce goods and services. This will free humans from the necessity of offering labor in order to acquire the necessities of life. In a nutshell, the development of AI labor may mean that individuals need not work at all. Instead, they will have far more choice in how they spend their time, be that in consuming entertainment, or participating in creative endeavors or more traditional, economically focussed activities.

Pessimists proffer a far wider range of potential futures where the development of AI has negative impacts. Many of these dystopias arise from what Bostrom (2016) calls the principal-agent problem. Briefly, the suggestion is that an inferior intelligence will be unable to control either the capabilities or motivations of a superior one (Bostrom, 2016). In the same way that, for example, a dog or cat is unable to even conceive of human motivations, humans will be utterly unable to understand or control AIs that advance beyond a certain level of complexity. In this situation, some fear a future where humans become an endangered or extinct species (Joy, 2000). Others fear a more subtle but, ultimately, just as corrosive future, where human agency is diminished and eventually destroyed by the practical and philosophical superiority of AI systems (Harari, 2016).

Even in a scenario where technical limitations prevent AI from disappearing from human understanding beyond a cognitive horizon, pessimists raise serious concerns about the spread of AI (Arntz et al., 2016). On the face of it, predictions that AI systems and robots will perform the majority or all of the labor required to meet human needs seem benign. However, even such an eventuality raises numerous questions. The decline in the use of skills such as navigation and map reading due to satellite navigation is taken as evidence that systems that start as question-answering “oracles” have a tendency to evolve into authoritative “sovereigns”, which can lead to learned helplessness in their would-be masters (Bostrom, 2016). In an economy where production is managed by AI systems, social and economic power will reside with those who control the AI systems (Autor et al., 2020). If current trends continue, that would suggest that societal power will become vested in a small group of elite actors, while the majority of humanity has little or no real agency (Harari, 2016).

The impact of technology on employment

Concern about technology replacing human labor and the consequent impact on the economy and society has a long history. Nearly two centuries ago, Ricardo (1821) theorized that technology causes unemployment when equilibrium wages fall below the level needed for subsistence and results in workers not taking the relevant jobs. In the 1930s, Keynes (1936/2010) forecast that new technologies would lead to decreasing demand for human labor. Leontief (1983) wrote that the role of humans as the most important factor of production is bound to diminish in the same way that the role of horses in agricultural production was initially diminished and then eliminated by the introduction of tractors. Such prognostications often carry the weight of their proponent’s emotional propensity. Some predict a world where individuals can engage their artistic and creative faculties unfettered by the need to work to meet their physical needs (Kurzweil, 2005). Others forecast a dystopia where the majority of humanity submit to dependent bondage to the state or to corporate entities (Bostrom, 2016; Harari, 2016).

It is clear from history that the evolution of technology has had a significant impact on the situation (e.g., the move from rural to urban living), organization (e.g., focus on the individual/family moving to the guilds and further to the corporations), and type (e.g., agriculture to manufacturing to services) of labor market (Leontief, 1983). Furthermore, the observation that technological advancement can make occupations obsolete fails to take account of the larger context in which such advances occur. As economists have long understood, an invention that replaces workers with machines will have repercussions beyond the immediate market (Autor et al., 2020). Put briefly, technological progress has two effects on the job market (Aghion & Howitt, 1994). As technology substitutes for labor, there is a destructive effect. Workers are displaced by new machines and technologies. However, the process of introducing these new technologies leads to increased opportunities and higher productivity in other sectors of the economy. This leads to the capitalization effect, where companies enter industries where productivity is relatively high, leading to an expansion of employment in those industries (Aghion & Howitt, 1994). The overall effect leads to a change in the structure of the jobs market rather than a simple reduction in work available (Autor et al., 2020). As long as human labor retains the ability to adapt to changing conditions by acquiring new skills by means of education, the overall impact of technological change on the job market should be positive (Autor et al., 2020; Goldin & Katz, 1998).

AI and the future of employment

The uncertainty and variance that characterizes long-term, macro-level predictions about AI is mirrored in temporally local forecasts. One area that has been the subject of significant interest in recent times is the impact of AI systems on employment patterns and the structure of the labor market. Technological change has always impacted on the labor market. As described previously, the general consensus is that technological change tends to alter the structure and allocation of work within the labor market without necessarily changing the overall amount of work available (Autor et al., 2020).

This general consensus has been disturbed by the increasing ubiquity of IT and the rise of AI. In brief, the suggestion is that the human monopoly on tasks requiring significant cognitive processing is being broken (Loebbecke & Picot, 2015). Rifkin (1995) suggests that a new epoch in global economic activity, where fewer and fewer workers are needed to produce goods and services for the global population, is emerging. In a similar vein, Ford (2009) suggests that, as companies continue to automate their manufacturing processes, labor will comprise an ever smaller component of companies' cost structures. Other researchers analyze empirical data and point to significant losses of middle class jobs, and the digitization and automation of routine cognitive tasks, as harbingers of more significant dislocations (Autor & Dorn, 2013; Autor et al., 2020; Levy & Murnane, 2013). Some see no end to this trend. For example, Kurzeil (2005) suggests that AI systems will match and then quickly surpass human cognitive abilities in a relatively short period of time, rendering human workers obsolete in all economic activities. Others predict that computers will perform all tasks "for which logical rules or a statistical model lay out a path to a solution, including complicated tasks that have been simplified by imposing structure" (Levy & Murnane, 2013, p. 30).

A small but growing number of academic studies are attempting to quantify these risks. Current research aimed at evaluating the impact of AI automation on occupations was initiated by Frey and Osborne (2017). Their research suggested that 47% of all jobs in the United States may be at risk of automation by 2030. Since then, a number of other studies of the same phenomenon have arrived at different, although not necessarily contradictory, conclusions.

Any forecasts about the future are necessarily imprecise and uncertain. However, both theoretical and empirical evidence suggests that a significant dislocation of the labor market is occurring. Given that this dislocation is happening simultaneously with other trends, such as aging populations, rising protectionism, and climate change, there is an urgent need for research into this phenomenon to both inform and guide policymakers when they are making decisions. The COVID-19 pandemic has significantly exacerbated this situation, with all sectors of society turning to technology to facilitate working from home, communicating remotely with work colleagues, team members and clients, moving from physical to online delivery of goods and services, and so on.

Broadly speaking, the emerging consensus from the latest research is that AI will have a significant destructive effect on at least some occupations (Arntz et al., 2016; Frey & Osborne, 2017; Rifkin, 1995). However, there are still extremely significant lacunas in our knowledge, which stymie any proper planning aimed at managing these changes. In particular, while the general trend of predictions is clear, there is significant variance across the forecasts generated by different approaches. A second gap is that, while it is clear that occupations will change, it is less clear what form the change will take and whether particular occupations will be eliminated or merely altered. Several authors suggest that the shortcomings are caused by using occupations (at the macro level) as the loci of study (Frey & Osborne, 2017; Goos et al., 2009). A potentially more revealing analytical lens would be the tasks that occupations are composed of.

The Tax Profession

Deconstructing professions

There are a wide variety of perspectives on how to best to study, analyze, and categorize the diversity of professions extant in the modern world. Anteby et al. (2016) offer a three-part framework for conceptualizing professions, which suggests that professions can be understood through three lenses of "becoming", "doing" and "relating". These lenses are analytical tools that home in on different aspects of the professional experience. The "becoming" lens is concerned with professions as journeys of socialization, whereby communities induct members and maintain shared cultural values, norms, and worldviews (Van Maanen & Schein, 1979). The "relating" lens focusses attention on a profession's relationships, and how professions collaborate with other groups to perform interdependent work or compete to expand their social and economic influence.

For this study, the most appropriate perspective is provided by the third lens, which is referred to as the "doing" lens. A profession is often understood, at least partially, in terms of the work activities that its members undertake, or, as Abbott (2005) calls it, the "task area" of the profession (p. 322). In addition to providing a definitional structure, Abbott (2005) highlights competition for control and oversight of tasks as factors that can help us to understand professions and identify jurisdictional claims and boundaries between professions. The division of tasks within and between professions has significant consequences for a profession's relative standing and the growth or decline of its social and economic influence.

If a profession is defined, at least in part, in terms of the tasks that its members perform, this raises several important questions. First, how does the set of tasks perceived as being within the scope of competency of a profession change over time? Second, how does jurisdiction over tasks change over time between professions and how does that change the relationship between professions? The evolution of task competency is also important in that it can prompt the development of new occupations through mechanisms such as the hiving off of perceived menial tasks, the formation of proto-professions due to technological change, or the mobilization of non-professional actors to legitimize existing "non-work" activities (Hodson & Sullivan, 2012).

As the set of tasks that a profession claims jurisdiction over changes, the profession itself will evolve. For example, as IT replaces the in-person performance of many of the tasks traditionally associated with librarians, Nelson and Irwin (2014) describe how librarians redefined their profession from being "masters of search" to "masters of interpretation" to "connectors of people and information". This evolution in response to change in the wider ecological context is neither unexpected nor necessarily negative. It is, nonetheless, a phenomenon that individual professions must attend to in a constantly changing world.

The role of the tax practitioner

At a basic level, the role of the tax practitioner is to assist taxpayers to comply with tax legislation while also providing them with advice about how to structure transactions in order to optimize (usually to minimize) their tax liabilities (Hahn & Ormeño Pérez, 2020; Sorola et al., 2020). Tax advice is routinely dispensed by a broad range of business professionals, including accountants, auditors, lawyers, barristers, payroll agents, former and current members of the relevant government revenue authority, tax experts working within industry, and those officially designated as tax consultants as result of their membership of tax-dedicated professional bodies (Doyle et al., 2009; Hahn & Ormeño Pérez, 2020). The term "tax practitioner" attempts to cover this diverse range of individuals. Some work as sole practitioners or in accounting, legal, or tax specialist partnerships, and will undertake various kinds of tax work. Tax experts working in industry are more typically employees of a company or a group of companies and will identify with, and serve only, that company's interests as heads or members of an in-house/internal tax department. While there is a lack of consensus in the literature as to the precise definition of a tax practitioner, a study conducted by the Organisation for Economic Co-operation and Development (OECD) in 2008 describes the tax practitioner as the actor that sits between taxpayers and tax authorities in the tripartite relationship that exists within the tax field (OECD, 2008). This conceptualization distinguishes tax practitioners from tax authority employees (or revenue practitioners). For the purposes of this paper, we include the entire spectrum of actors acting as intermediaries between revenue authorities and taxpayers but exclude revenue practitioners (those working in tax administration) from our definition of tax practitioner.

On a basic level, tax practitioners working in practice typically provide two distinct services to their clients or employing organization (see, for example, Doyle et al., 2014; Frecknall-Hughes & Kirchler, 2015; Hahn & Ormeño Pérez, 2020). The first type of service comprises the provision of assistance to complete tax returns and to comply with the other administrative requirements of relevant revenue authorities, and assistance with the calculation of tax liabilities and meeting payment deadlines. These are generally called tax compliance services. The second category is the provision of what are habitually referred to as tax planning services, which are often intended to mitigate the client or employing organization's tax liabilities. Accounting practices of all sizes generally have dedicated tax departments that handle tax compliance and tax planning services for their clients. Tax experts working in industry also engage in tax compliance and tax planning work, but they will identify with, and serve only, their employing company's interests, as their employer is their only client (Frecknall-Hughes & Kirchler, 2015; Frecknall-Hughes et al., 2017). In order to work effectively as a tax practitioner, strong technical skills—including a thorough understanding of technical tax issues, tax legislation and case law—and the ability to both research source material and perform complex tax computations, are required (PricewaterhouseCoopers [PwC], 2017c).

Tax administration and technology

The increasing use of digital technologies in the tax field is being driven not only by the technological advances outlined above but by the pace of regulatory change and the digitalization of tax authorities. Often driven by budget deficits, cuts in staff numbers, and the inefficiencies of existing tax collection methodologies, many tax administrations have invested heavily in data integration and analytics in order to gain a more accurate view of business and personal transactions (Barton, 2020). Tax authorities worldwide are relying more and more on digital methods to collect and analyze taxpayer data, transforming how they collect tax (Alm et al., 2020; Barton, 2020; Dobell, 2017; Nibbe, 2020). In turn, they are requiring taxpayers to provide huge amounts of information and to perform real-time digital filing, which they are using to facilitate real-time or near real-time tax collection and audit selection (EY Global, 2020a; Nibbe, 2020). Using various statistical and data mining technologies to identify outliers, and unusual relationships and patterns, tax authorities can identify a wide range of non-compliant behaviors in a proactive, targeted, and cost-effective manner (Alm et al., 2020; Dobell, 2017). Tax authorities are also sharing information about specific taxpayers and tax structures with their counterparts worldwide more frequently. This sharing has been made feasible now that data is increasingly digitalized.

Some examples of specific technological innovations being considered by, or being used by, revenue authorities include: the use of blockchain in the area of e-voting in order to encourage the public to participate in the process of agenda setting (Myeong & Jung, 2019); prepopulating tax returns with third-party data (Alm et al., 2020); the use of chatbots to develop new digital channels of communication between the public and the government in Greece (Androutsopoulou et al., 2019); the adoption of advanced IT which works as a substitute for human resources by the tax bureau in China (Li et al., 2020); and the use of digital technologies to facilitate co-production between the government and the public in China (Huang & Yu, 2019). This evolution in how tax authorities are operating has meant that tax practitioners must keep pace with these technological developments in order to continue to meet their clients' needs in this changing environment. As a result of the increasing digitalization of revenue authorities and more general advances in technology, the nature of day-to-day tax work is beginning to change. Some examples of how tax practitioners are leveraging technology are outlined below.

Technology and tax practice

IT is enabling the use of accurate, detailed data from a wider range of sources to drive more in-depth analysis that would previously have been difficult, time-consuming, or even impossible to accomplish (PwC, 2019). The automation of source data pulls—using Extract, Transform and Load (ETL) solutions—can help to streamline the requirements of new complex calculations and the need to supply more granular data in order to respond to tax authorities' increasing demands for transparency (PwC, 2017b, 2019). Visualization tools are being used to enhance the quality and dynamic display of data for dashboard and presentation purposes (PwC, 2019). AI can also automate structured or unstructured tasks, mimicking the actions of humans but with greater speed and accuracy, thereby improving efficiency and effectiveness (EY Global, 2020b; PwC, 2019). AI can work 24 hours a day, seven days a week. The EY 2020 Global Tax Technology and Transformation Survey found that a typical tax team spends 40%

to 70% of its time gathering and manipulating data, when this can be done in a fraction of the time by AI (EY Global, 2020b).

Data analytics and modeling solutions are also being used to assist with tax planning work. This involves feeding a range of data inputs, including legislation, case law, company data, and corporate strategy, into an AI model so that it can quickly assess the impact of legislative changes on an organization and proactively make tax recommendations (Dobell, 2017; EY Global, 2020b; PwC, 2017b). These transformative capabilities apply throughout the tax lifecycle, from planning to compliance reporting and controversy (PwC, 2019).

Research contribution

This study aims to make a number of contributions. First, we provide a methodological approach that can be used to refocus existing empirical data in order to explore the issue of automation at the level of the task combined with career progression. Drawing on theory from the literature exploring the sociology of work, we use Hodson and Sullivan's (2012) concept of a "doing" lens in order to analyze a profession as the specific tasks that are performed by practitioners—a potentially more revealing analytical frame. To demonstrate the utility of this approach, we provide an analytical case study which applies our methodology to a specific case study, namely the role of the tax practitioner. The case study serves to validate our methodology. It also provides several suggestive insights about the effect of AI on the tax practitioner labor market which will be of interest to practitioners, policymakers, and researchers if they are established as being generalizable by broader studies.

3. METHODOLOGY

We examine the impact of AI on the role of the tax practitioner using a two-stage process. The stages can be broadly described as the task analysis phase and the digitization susceptibility phase. The purpose of the first phase was to provide a more nuanced understanding of a particular role by dividing it up into specific tasks. The idea is that, at this more granulated level of resolution, it will be possible to make more accurate estimates as to the likelihood of a particular activity being automated. To give a simple example, call routing is a traditional task associated with a receptionist. This specific task is clearly an activity that can be, and is, routinely automated. However, a receptionist may have numerous other tasks, such as meeting and greeting guests. The susceptibility of a particular occupation to digitization is best considered in terms of the tasks that make up the broader role.

Traditionally, the role of tax practitioner is seen as being a steady, secure, white collar job. However, Frey and Osborne (2017) estimate the role of tax preparer (typically carrying out tax compliance work, which is one of two categories of work done by a tax practitioner) to be one of the most susceptible to automation, assigning it a probability of 99%. One of the leading firms in the industry, PwC, issued a report that assessed the likelihood of people using AI systems rather than humans for tax preparation to be 54% (PwC, 2017a). The combination of the traditional security, prestige, and salary associated with the role, allied to its perceived susceptibility to automation, means that it is an ideal context for consideration in this study.

Task Analysis Phase

The purpose of the task analysis phase of the research is to identify specific tasks associated with a role. In order to achieve coverage, an approach using triangulation between three qualitative research methods was used. The first research method employed was a traditional review of the academic literature in order to identify task-based descriptions of the role of tax practitioner. The second method used was an analysis of websites identifying job vacancies for tax practitioners. These advertisements usually contain detailed descriptions of the roles involved, broken down into specific tasks, and so were valuable sources of data for this study. The third data source used was a number of semi-structured interviews with tax practitioners at different stages of their careers who were asked to identify the tasks they perform on a daily basis. An aggregated master list of tasks, in which some tasks were combined where appropriate, was created using the information obtained from these sources. While the approach was applied to the role of tax practitioner in this study, these data sources are freely available for most occupations, making it generalizable.

Automation Susceptibility Phase

After identifying the component tasks of the role, the next stage was to develop a probability estimate of the likelihood of that particular task being automated in the near future. As mentioned previously, there is considerable debate in the literature about the validity of the estimation approach used by virtually every study. In order to sidestep this debate, the approach taken in this case study was to average estimates from a range of studies. In order to maintain comparability, a number of criteria were used to select studies. First, the studies had to originate from a reputable source, defined as a peer-reviewed journal, a recognized national or international body, or a recognized corporate actor. Only macro-level analyses which set out to provide estimates across the entire labor market were included. Studies which focused on specific industries or professions were excluded. For comparability of analysis, only studies which generated probability estimates were included. A web and database search was conducted in order to identify a corpus of relevant studies, which were then pruned using the criteria identified above. A brief description of the five studies retained for use in the automation susceptibility analysis is outlined in Table 1.

Using the data contained in the reports below, a probability estimate was calculated for each task that was identified as being a component of the role of tax practitioner. For each individual task, each report was interrogated in order to find the occupation or job that best matched the task being analyzed. If no suitable match could be found, no data from the relevant report was included for that task. If a number of occupations or jobs were identified, all of them were included in the analysis.

Table 1: List of Studies Used to Generate an Estimate of the Automation Susceptibility of Individual Tasks.

Frey and Osborne (2017)	This study used a Gaussian process classifier to estimate the probability of automation for 702 occupations. The Gaussian process classifier estimated the probability of automation using O*NET data, which is collected from labor market analysis in the United States and is regularly updated using surveys of each occupation as they evolve over time.
White et al. (2019)	This report, published by the Office of National Statistics in the United Kingdom, analyzes the jobs of 20 million people in England. Data from the Program for International Assessment of Adult Competencies (PIAAC) was used to determine the tasks carried out by individuals when performing their role in the workplace. The PIAAC data was then used to assign a probability to specific occupations.
Arntz et al. (2016)	The OECD conducted a study in response to Frey and Osborne's (2017) report. It focuses on the susceptibility of individual tasks being automated. The study uses the National Statistics Office's PIAAC survey of adult skills to map the task composition of specific occupations and then generates a probability estimate based on that.
Fuei (2017)	This study examines the risk of automation among jobs in Singapore. While limited to a national context, the study does analyze the entire labor market, using the International Standard Classification of Occupations (ISCO) standard. Where multiple ISCO codes are mapped to an SSOC code, they use the average of the probabilities matched to a job.
Manyika et al. (2017)	McKinsey Global Institute published this report, which analyzed where AI can replace humans. The authors use a similar methodology to that employed by Frey and Osborne (2017). However, they disaggregate jobs into tasks and integrate expert opinion with the probability estimates.

4. FINDINGS

The Task Analysis Phase

As described earlier, triangulation between three data collection methods was used to create an aggregated list of specific tasks associated with the role of tax practitioner. First, a search of the academic literature found a number of papers that identified subtasks associated with the role. Frecknall-Hughes and Kirchler (2015) and others (Doyle et al., 2014; Hahn & Ormeño Pérez, 2020; Sorola et al., 2020) suggest that a macro-level examination of the role divides it into two distinct categories: tax compliance and tax planning. Within these specific roles, a number of subtasks can be identified, such as the preparation of tax returns, the provision of advice to clients in respect of how to manage their tax affairs, and policy advocacy. Thuronyi and Vanistendael (1996) discuss the six key tasks carried out by tax practitioners: tax planning, the provision of advice ancillary to financial services, the preparation of tax returns, the preparation and audit of commercial accounts, the representation of taxpayers before tax administration, and the representation of taxpayers before the courts.

Second, online resources which identified the subtasks associated with the tax practitioner role were consulted. O*NET (www.onetonline.org) is an online database of occupational information which was created by the United States Department of Labor. The Irish Tax Institute is a professional body representing tax practitioners in the Republic of Ireland. Their website (https://taxinstitute.ie/) provides a detailed analysis of the tasks that members are expected to perform as part of their professional duties. Another class of online resources consulted was recruitment websites, such as Myplan (https://myplan.ie) and Monster (https://www.monster.com). These sites regularly advertise tax roles and often contain detailed job descriptions for them.

The third data source used was a series of semi-structured interviews with tax practitioners, during which they were probed about the tasks they perform in their current role. Three individuals were interviewed in the context of this study, all of whom worked for a multinational accountancy practice. One individual was a newly graduated trainee while the other two were more experienced individuals at director level. The list of tasks associated with the role of the tax practitioner that emerged from this phase of the research is set out in Table 2 below.

In addition to identifying the tasks associated with tax practice, we gathered data about the level of employee (in terms of hierarchy) who usually performs a particular task. In the vernacular of the profession, these are referred to as tax trainees, tax managers, and tax directors. The tasks traditionally performed by practitioners operating at each level were mapped using the data sources above.

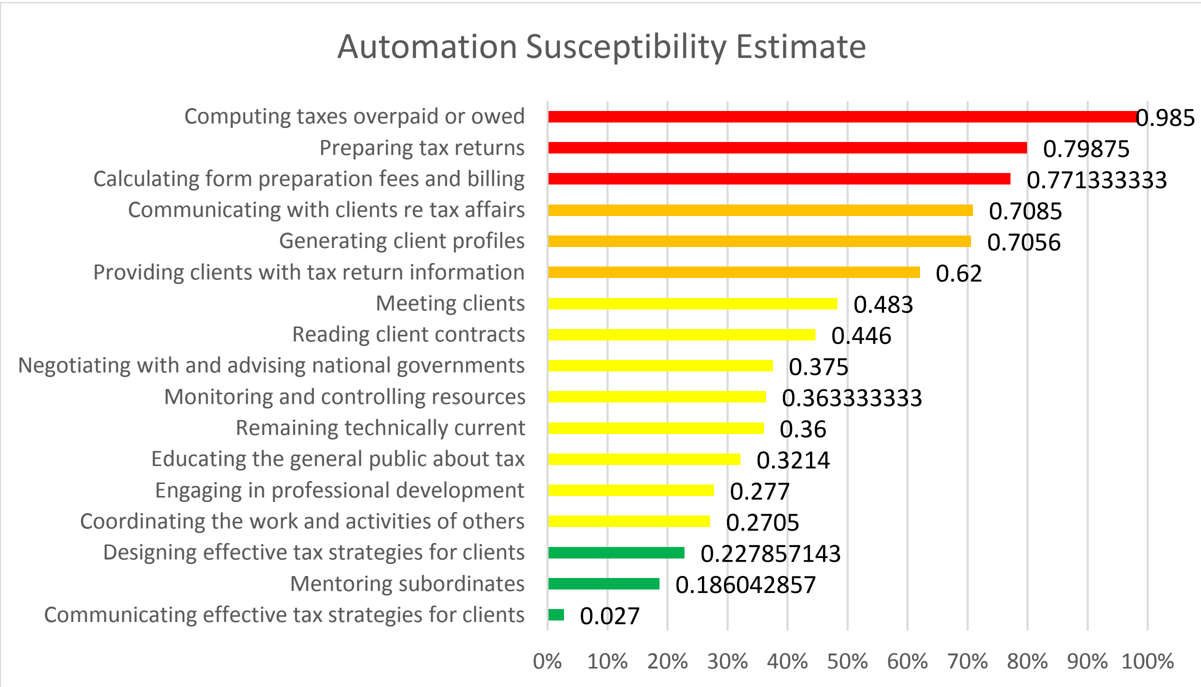
Table 2: Taxes Associated with the Role of Tax Practitioner.

Computing taxes overpaid or owed
Preparing tax returns
Calculating form preparation fees and billing
Communicating with clients re tax affairs
Generating client profiles
Providing clients with tax return information
Meeting clients
Reading client contracts
Negotiating with and advising national governments
Monitoring and controlling resources
Remaining technically current
Educating the general public about tax
Engaging in professional development
Coordinating the work and activities of others
Designing effective tax strategies for clients
Mentoring subordinates
Communicating effective tax strategies for clients

Automation Susceptibility Phase

Figure 1 displays a bar chart that summarizes the results of this analysis.

Figure 1: Task Automation Susceptibility Estimates for Tax Practitioners

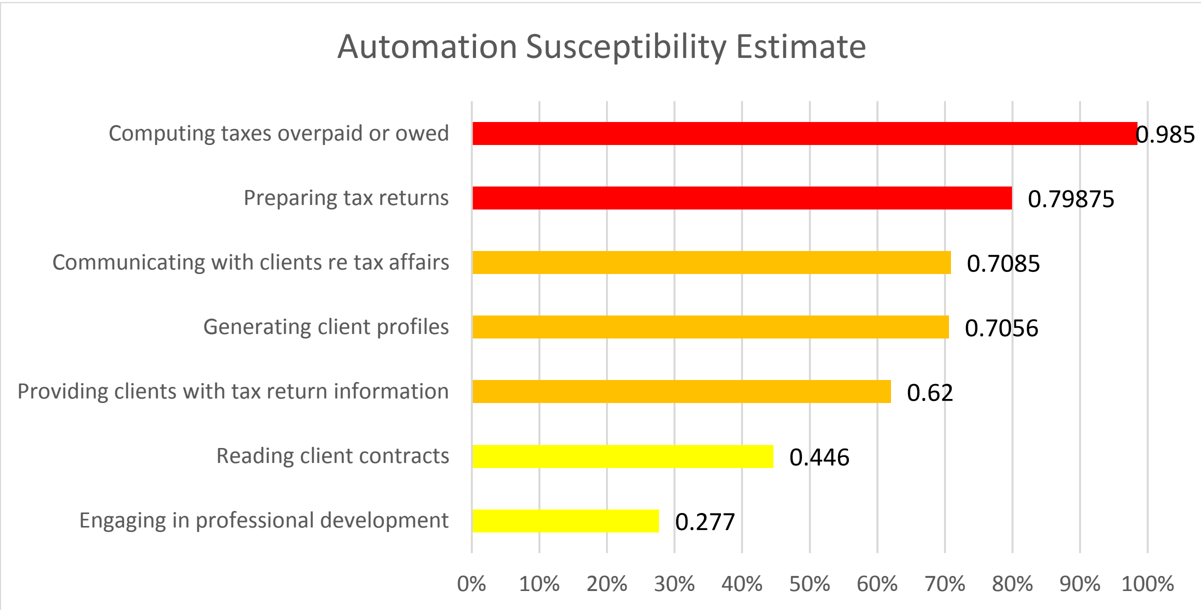


As might be expected, computing tax liabilities, preparing tax returns, and preparing fee notes for clients were the top three tasks most likely to the automated, with probabilities of 99%, 80%, and 77% respectively. The tasks that appear at the bottom end of Table 1 are designing effective tax strategies, communicating these effectively to clients, and managing staff, all of which involve less quantitative skill. Interestingly, of the 17 tax practitioner tasks examined, only six are estimated to have a susceptibility to automation of more than 50% and these mainly fall into the tax compliance category of tax practitioner work. Once the work involves reading contracts, educating clients and others, managing teams, and tax planning, there is a much lower likelihood of automation.

In the task analysis phase, as well as gathering data about the tasks considered part of the role of tax practitioner, we gathered data about the level of employee who usually performs a particular task. Figures 2, 3, and 4 illustrate tasks associated with tax trainees, tax managers, and tax directors respectively.

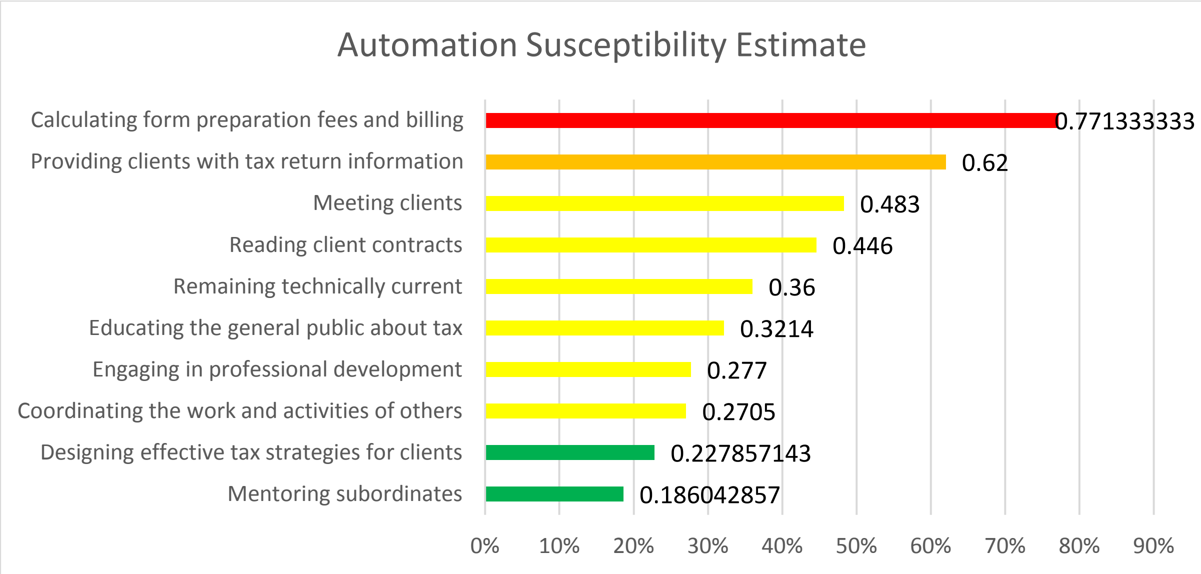
Once we begin to break down the tasks according to the level of seniority of the tax practitioner, we really begin to get a better picture of what the future tax practice role might look like. The tax compliance type tasks most likely to be automated are typically the ones carried out by tax trainees during their initial training years. Indeed, of the seven tasks usually carried out by tax trainees, five have a greater than 62% likelihood of automation, with the others being reading contracts (45% chance of automation) and engaging in professional development (just 28% likelihood of automation).

Figure 2: Task Automation Susceptibility Estimates for Tax Trainees



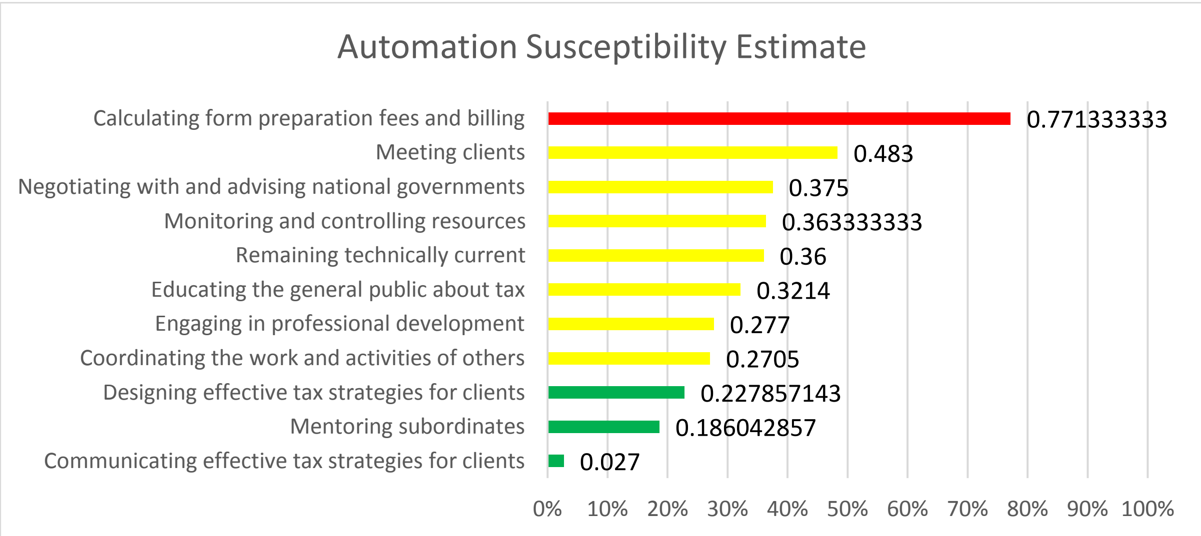
Turning to tax managers, we begin to see the aspects of the role that are less likely to be automated becoming more important. While tax managers are still involved in tax compliance work, the tasks of keeping up to date with tax developments, coordinating the work of others, and designing effective tax strategies are more important at this career stage, all of which are much less susceptible to automation. Only two of the ten tasks associated with this level of tax practitioner have a greater than 50% likelihood of becoming automated.

Figure 3: Task Automation Susceptibility Estimates for Tax Managers



At tax director level, almost all tasks are categorized as having a less than 50% susceptibility to being automated, with most having a less than 38% susceptibility. At that career stage, tax practitioners spend most of their time carrying out tax planning work for clients, managing people and resources, and engaging in tax education and policy advising work. All of these tasks are much less likely to be carried out by a machine in the future.

Figure 4: Task Automation Susceptibility Estimates for Tax Directors



5. DISCUSSION AND CONCLUSIONS

Rapid, disruptive technological change is arguably the dominant feature of modern life. Societies, countries, and economies are in a continual state of flux driven by the creative-destructive energies that are released by rapid technological innovation. In the past, technologies such as electricity, the internal combustion engine, and telecommunications have been the sources of this change. Today, many commentators suggest that AI and ML are the nascent technologies that will drive social and economic change for the next generation.

This prospect is viewed with uncertainty by all and with trepidation by many. While some suggest that AI will lead to a golden age of prosperity, many others forecast that it will have a wide range of negative impacts, ranging from the dystopian to the apocalyptic. What unites commentators is a general acceptance that our current forecasts are too uncertain to serve as reliable guides for planning and policy formulation.

One particular area of significant concern is the likely impact of AI-enabled automation on the labor market, particularly traditionally secure, high status professions associated with middle-class employment. The same uncertainty that bedevils forecasts in other AI-related spheres affects forecasts within this domain. Some suggest that there is nothing new in heaven or earth and that labor market dislocation due to technological innovation is neither particularly new nor particularly concerning. Others posit that AI systems will supplant human employees in much the same manner as the internal combustion engine did the horse (Leontief, 1983).

Our purpose in this paper is to attempt to move this debate forward in the context of tax practice work. By applying a methodological approach that uses a combination of tasks and career stage as a lens rather than macro-level occupation, we develop a much more nuanced understanding of how automation is likely to affect the role of tax practitioner as a whole. The revised level of resolution at the task and career progression level rather than at the occupational level brings several issues to the fore.

There is general acceptance in the literature that AI automation will have a significant impact on tax practice. Our case study supports this, with several of the tasks traditionally associated with tax practice seen as being highly susceptible to automation (mainly the tasks associated with tax compliance). However, our case study clearly demonstrates that blunt analysis at the level of a particular occupation hides important granularities. Our analysis forecasts that some tasks are very likely to be automated while others remain unlikely to be automated, at least for the foreseeable future. Our analysis suggests that rather than the tax practitioner role disappearing, it can be better characterized as needing to evolve.

Our analysis suggests that the effects of automation will be felt differently at different stages of a traditional pathway through the tax practice career. It is the tasks that are mostly performed and associated with early career practitioners that are seen as being most vulnerable to AI automation. This feature raises several important questions that all stakeholders associated with the profession must address.

First, how will tax practice be repopulated if traditional pathways to career advancement are dislocated? Our results do not suggest that tax practitioners will become extinct. However, it is certainly plausible that far fewer individuals will be needed at the level associated with tax trainee. If so, a key question moving forward is how tax practitioners will replenish their more senior ranks if the bottom rungs of the career progression ladder are populated by significantly fewer trainees.

Related to this is the issue of skill and knowledge development. It is generally the case in organizations that more cognitively demanding tasks are performed by more experienced individuals. The tasks most vulnerable to AI automation are often seen as being repetitive and undemanding. At first glance, the automation of such tasks may seem to be a positive development for employers and employees alike. However, this perspective takes no account of the development of knowledge and skill that is engendered by performing these tasks. For example, being able to design effective tax strategies for clients may require the kind of practical knowledge that is only developed through years of experience of computing tax liabilities. In an extreme case, firms may face severe skills shortages a few years after engaging in significant automation. Higher order skills may atrophy and disappear because a lack of entry-level positions is rupturing the supply pipeline of employees capable of performing such tasks.

Several remedies for this potential challenge can be prescribed. Educational institutions will be expected to adopt their offerings to close the skills gap. However, this will be a challenge, particularly in respect of the development of soft, applied skills that are difficult for non-practitioners to acquire outside of a realistic professional context. A more radical possibility is that employers will allocate tasks to employees despite their relative inefficiency in order to foster the knowledge required for the development of higher order skills.

It is possible to discern other potential impacts of AI automation beyond the employee-employer relationship and the supply of labor to the economy. Entry-level positions have traditionally been gateways to well remunerated, high status roles. The relatively large number of such entry-level positions has generally served to encourage social mobility. Organizations need large numbers of employees at these levels and are content to hire numerous trainees because they do not earn high salaries. In other words, there are lots of opportunities available for those who wish to embark on a career. However, in a situation where AI automates these tasks, organizations will need far fewer entry-level employees. It is easy to imagine a situation arising where "who you know" becomes important in obtaining one of the far fewer, albeit higher status positions. Such a development would have a detrimental effect on meritocratic social mobility.

A final consideration is that this altered career path may also impact upon the desirability of pursuing a career in the tax profession. A reduction in the number of entry-level positions would mean that the career pyramid would become far narrower. Individuals would need to achieve promotion within their organization at a speed that dwarfs even today's fast pace or risk being left behind permanently. The profession may evolve towards a state where a small number of individuals (say 5%) perform high-value tasks and are remunerated accordingly, while the other 95% are relegated to performing low-value tasks that cannot be automated but are, nonetheless, poorly paid. In other words, a rational, risk-weighing decision maker (the very type of intellect the tax profession seeks to attract) may deliberately avoid a career where the chances of obtaining "good" money are very low because they require a combination of difficult skills that take time to acquire, coupled with relatively few opportunities. In the long run, the reduction of opportunities may have a significant deleterious effect on tax practice as a whole.

The use of technological innovations, such as robotics and AI, will not diminish the need for tax practitioners to have technical tax expertise. However, tax professionals will need to upskill in order to adapt to an environment where humans and machines work increasingly together, and enhance their technology and data analysis skills. Tax practitioners also need to adapt to the way in which tax authorities are digitally administering the tax system. Those who can leverage technology and data analytics in order to manipulate large volumes of data efficiently will free up valuable time for tax planning and the evaluation of key tax and finance performance indicators for their clients or employing organization. Tax practitioners will need to ensure that they are involved in cross-functional technology implementation and process management controls so that tax practitioners can optimally leverage data collected from financial reporting systems. Tax practitioners will also need to add value in other ways—for example, by understanding the nuances of the business and interacting more closely with other organizational functions, or leveraging new insights into data that the technologies provide—in order to address their clients' (or employing organization's) wider objectives. Building relationships, influencing decisions across business functions, and communication skills will become essential competencies.

Forecasting the future is a notoriously uncertain endeavor. Prognostications regarding the impact of AI on tax practice must be treated with skepticism. This study provides a more nuanced analysis of where particular stress points may emerge in the profession. When this analysis is added to the weight of numerous other studies which forecast significant disruption within tax practice, the sum effect is to sound a clear call for significant reflection amongst all stakeholders associated with the profession as to how to future is to be met.

BIBLIOGRAPHY

Abbott, A. (2005). Sociology of work and occupations. In N. J. Smelser & R. Swedberg (Eds.), *The handbook of economic sociology* (2nd ed., pp. 307-330). Princeton, NJ: Princeton University Press.

Aghion, P., & Howitt, P. (1994). Growth and unemployment. *The Review of Economic Studies*, *61*(3), 477-494. https://doi.org/10.2307/2297900

Alm, J., Beebe, J., Kirsch, M. S., Marian, O., & Soled, J. A. (2020). New technologies and the evolution of tax compliance. *Virginia Tax Review, 39*(3), 287-356.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly, 36*(2), 358-367. https://doi.org/10.1016/j.giq.2018.10.001

Anteby, M., Chan, C. K., & DiBenigno, J. (2016). Three lenses on occupations and professions in organizations: Becoming, doing, and relating. *Academy of Management Annals*, *10*(1), 183-244. https://doi.org/10.5465/19416520.2016.1120962

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (OECD Social, Employment and Migration Working Papers, No. 189). https://doi.org/10.1787/5jlz9h56dvq7-en

Asimov, I. (1950). *I, robot*. Garden City, N.Y.: Doubleday & Company, Inc.

Autor, D. H, & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, *103*(5), 1553-1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D., Mindell, D., & Reynolds, E. (2020). *The work of the future: Building better jobs in an age of intelligent machines*. Cambridge, MA: Massachusetts Institute of Technology.

Badue, C., Guidolini, R., Carneiro, R. V., Azevedo, P., Cardoso, V. B., Forechi, A., Jesus, L., Berriel, R., Paixão, T. M., Mutz, F., de Paula Veronese, L., Oliveira-Santos, T., De Souza, A. F. (2020). Self-driving cars: A survey. *Expert Systems with Applications*, *165*, Article 113816. https://doi.org/10.1016/j.eswa.2020.113816

Barton, K. (2020, December 17). *Why tax was - and will remain - at the epicenter of COVID-19 recovery*. EY.com. https://www.ey.com/en_gl/tax/why-tax-was-and-will-remain-at-the-epicenter-of-covid-19-recovery

Baum, S. D., Goertzel, B., & Goertzel, T. G. (2011). How long until human-level AI? Results from an expert assessment. *Technological Forecasting and Social Change*, *78*(1), 185-195. https://doi.org/10.1016/j.techfore.2010.09.006

Bostrom, N. (2016). *Superintelligence: Paths, dangers, strategies* (reprint). Oxford, England: Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Lexington, MA: Digital Frontier Press.

Clark, A. (2005). Intrinsic content, active memory and the extended mind. *Analysis*, *65*(1), 1-11. https://doi.org/10.1093/analys/65.1.1

Crevier, D. (1993). *AI: The tumultuous history of the search for artificial intelligence*. New York, NY: Basic Books.

Dennett, D. C. (2017). *From bacteria to Bach and back: The evolution of minds*. New York, NY: W. W. Norton & Company.

Dobell, J. (2017, May 30). The future of tax technology is now. *International Tax Review*. https://www.internationaltaxreview.com/article/b1f7n77lbf6703/the-future-of-tax-technology-is-now

Doyle, E. M., Frecknall-Hughes, J. F., & Glaister, K. W. (2009). Linking ethics and risk management in taxation: Evidence from an exploratory study in Ireland and the UK. *Journal of Business Ethics*, *86(*2), 177-198. Retrieved from https://doi.org/10.1007/s10551-008-9842-9

Doyle, E., Frecknall-Hughes, J., & Summers, B. (2014). Ethics in tax practice: A study of the effect of practitioner firm size. *Journal of Business Ethics*, *122*(4), 623-641. https://doi.org/10.1007/s10551-013-1780-5

EY Global. (2020a). *How to build an intelligent tax function*. https://www.ey.com/en_gl/tax/how-to-build-an-intelligent-tax-function

EY Global. (2020b). *How artificial intelligence will empower the tax function*. https://www.ey.com/en_gl/tax/how-artificial-intelligence-will-empower-the-tax-function

Ford, M. R. (2009). *The lights in the tunnel: Automation, accelerating technology and the economy of the future*. n.p.: Acculant Publishing.

Frecknall-Hughes, J., & Kirchler, E. (2015). Towards a general theory of tax practice. *Social & Legal Studies*, *24*(2), 289-312. https://doi.org/10.1177/0964663915571787

Frecknall-Hughes, J., Moizer, P., Doyle, E., & Summers, B. (2017). An examination of ethical influences on the work of tax practitioners. *Journal of Business Ethics*, *146*(4), 729-745. https://doi.org/10.1007/s10551-016-3037-6

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019

Fuei, L. K. (2017). Automation, computerization and future employment in Singapore. *Journal of Southeast Asian Economies*, *34*(2), 388-399. https://doi.org/10.1355/ae34-2h

Goldin, C., & Katz, L. F. (1998). The origins of technology-skill complementarity. *The Quarterly Journal of Economics*, *113*(3), 693-732.

Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *American Economic Review*, *99*(2), 58-63. https://doi.org/10.1257/aer.99.2.58

Hahn, T.-A., & Ormeño Pérez, R. (2020). Tax professionals in the academic spotlight: A review of recent literature. *Journal of Tax Administration*, *6*(1), 96-161.

Harari, Y. N. (2016). *Homo Deus: A brief history of tomorrow*. London, England: Harville Secker.

Hodson, R., & Sullivan, T. A. (2012). *The social organization of work*. Belmont, CA: Wadsworth Publishing Company.

Hoy, M. B. (2018). Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Medical Reference Services Quarterly*, *37*(1), 81-88. https://doi.org/10.1080/02763869.2018.1404391

Huang, B., & Yu, J. (2019). Leading digital technologies for coproduction: The case of "visit once" administrative service reform in Zhejiang Province, China. *Journal of Chinese Political Science*, *24*(3), 513-532.

Joy, B. (2000). Why the future doesn't need us. *Wired magazine*, *8*(4), 238-262.

Keynes, J. M. (2010). *The general theory of employment, interest and money.* Kila, MT: Kessinger Publishing. (Original work published 1926).

Kurzweil, R. (2005). *The singularity is near: When humans transcend biology*. London, England: Viking Penguin.

Leontief, W. (1983). Technological advance, economic growth, and the distribution of income. *Population and Development Review*, *9*(3), 403-410. https://doi.org/10.2307/1973315

Levy, F., & Murnane, R. J. (2013). *Dancing with robots: Human skills for computerized work*. Washington, D.C.: Third Way.

Li, J., Wang, X., & Wu, Y. (2020). Can government improve tax compliance by adopting advanced information technology? Evidence from the Golden Tax Project III in China. *Economic Modelling*, *93*, 384-397. https://doi.org/10.1016/j.econmod.2020.08.009

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems*, *24*(3), 149-157. https://doi.org/10.1016/j.jsis.2015.08.002

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., Sanghvi, S. (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. n.p.: McKinsey & Company.

Marr, B., & Ward, M. (2019). *Artificial intelligence in practice: How 50 successful companies used artificial intelligence and machine learning to solve problems*. Chichester, England: John Wiley & Sons Ltd.

Muehlhauser, L., & Salamon, A. (2012). Intelligence explosion: Evidence and import. In A. H. Eden, J. H. Moor, J. H. Søraker, & E. Steinhart (Eds.), *Singularity hypotheses: A scientific and philosophical assessment* (pp. 15-42). Heidelberg, Germany: Springer-Verlag Berlin Heidelberg.

Myeong, S., & Jung, Y. (2019). Administrative reforms in the fourth industrial revolution: The case of blockchain use. *Sustainability*, *11*(14), 3971. https://doi.org/10.3390/su11143971

Nelson, A. J., & Irwin, J. (2014). "Defining what we do—All over again": Occupational identity, technological change, and the librarian/internet-search relationship. *Academy of Management Journal*, *57*(3), 892-928. https://doi.org/10.5465/amj.2012.0201

Nibbe, J. (2020, January 29). Should tax be keeping pace with transformation, or help shape it? *EY.com*. https://www.ey.com/en_uk/digital/should-tax-be-keeping-pace-with-transformation-or-shaping-it

Nilsson, N. J. (2009). *The quest for artificial intelligence: A history of ideas and achievements*. New York, NY: Cambridge University Press.

Organisation for Economic Co-operation and Development. (2008). *Study into the role of tax intermediaries*. Paris, France: OECD Publishing.

Parkins, D. (2017, 6th May). The world's most valuable resource is no longer oil, but data. *The Economist*. https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data

Penrose, R. (2002). *The Emperor's new mind: Concerning computers, minds, and the laws of physics*. Oxford, England: Oxford University Press.

PricewaterhouseCoopers (2017a). *Bot. Me: A revolutionary partnership: How AI is pushing man and machine closer together*. n.p.: PwC.

PricewaterhouseCoopers. (2017b). Tax function of the future: Upskilling the tax professional. *PwC*. https://www.pwc.com/us/en/services/tax/library/tax-function-upskilling-tax-professional.html

PricewaterhouseCoopers. (2017c). *The tax professional of the future. Staying relevant in changing times*. np: PwC.

PricewaterhouseCoopers. (2019). *How tax is leveraging AI—Including machine learning —in 2019*. np: PwC.

Ricardo, D. (1821). *On the principles of political economy and taxation*. London, England: John Murray.

Rifkin, J. (1995). *The end of work: The decline of the global labor force and the dawn of the post-market era*. New York, NY: G. P. Putnam's Sons.

Sorola, M., Karavidas, D., & Laheen, M. (2020). Addressing gender issues through the management of tax talent. *Journal of Tax Administration*, *6*(1), 51-73.

Thuronyi, V., & Vanistendael, F. J. G. M. (1996). Regulation of tax professionals. In V. Thuronyi (Ed.), *Tax law design and drafting* (Vol. 1, pp.135-163). Washington D.C.: International Monetary Fund.

Van Maanen, J., & Schein, E. H. (1979). *Toward a theory of organizational socialization. Research in Organizational Behavior, 1*, 209-264.

White, S., Lacey, A., & Ardanaz-Badia, A. (2019). The probability of automation in England: 2011 and 2017. n.p.: Office for National Statistics.