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Opportunities and risks in the use of AI in career development practice

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The Covid-19 pandemic required many aspects of life to move online. This accelerated a broader trend for increasing use of ICT and AI, with implications for both the world of work and career development. This article explores the potential benefits and challenges of including AI in career practice. It provides an overview of the technology, including current uses, to illustrate ways in which it could enhance existing services, and the attendant practical and ethical challenges posed. Finally, recommendations are provided for policy and practice that will support career development professionals in managing these risks and maximising benefits to service users.

Introduction

The Covid-19 pandemic accelerated the increasing prevalence of digital technologies in the daily lives of people in the Global North. The sophistication of these technologies has also increased, with Artificial Intelligence (AI) being incorporated into a wide variety of digital services. AI is the term used for technology that allows computers to perform tasks autonomously that would otherwise require human intelligence (European Commission, 2020; Scottish Government, 2021). The impact of automation on work and society is potentially far reaching, although, Hooley (2017) has cautioned against alarmist dystopian visions of an automated future, arguing that career guidance has a role in helping manage this transformation. Similarly, there is a growing body of research focused on how to deploy new technologies in a way that maximises the benefits to individuals and reflects the social values of the context in which they are used (Blodgee & O'Connor, 2017; Rahwan, 2018; Willson, 2017). In this article, the focus is specifically on the use of AI by career development services.

Careers Information, Advice and Guidance (CIAG) has historically been a domain that has shown proficiency in incorporating the benefits offered by new technologies and engaging critically with the risks (Hooley et al., 2010; Moore & Czerwinska, 2019; Watts, 2002). However, research on how AI technologies are currently being incorporated into practice is limited. This article aims to explore the emerging possibilities for the use of AI in CIAG practice, and anticipate the attendant risks, empowering CIAG professionals to bring AI into their practice in a way that realises the benefits, while mitigating the risks.

Background

Work by Hooley et. al.'s (2010) typology identifies three purposes that technology serves in CIAG services to clients: a conduit for communication between CIAG practitioners and their clients, to present information, or as means for allowing clients to independently engage in automated interactions with career related information. AI is considered an example of the latter category in that it customises information based on users' interactions with the system (Hooley & Staunton, 2020). However, this obscures a fundamental difference between 'traditional' technologies and AI. The former are designed as a tool to aid or automate tasks where the processes, inputs and desired outcomes are pre-defined during system design based on concrete rules., whereas AI is intended to handle interactions that it has not been provided with explicit rules to manage. Automated interaction with traditional IT systems means the user is presented with information that has been filtered based on criteria that have been designed by a human and applied to a limited range of information explicitly provided by the user. Automated interactions with AI systems are more akin to human communication, in that the form and structure used to provide information can be much more varied, and the responses to them are not pre-determined.

The use of AI technology in online interactions has become ubiquitous (Willson, 2017), a trend accelerated by the Covid-19 pandemic (Laberge et al., 2020). Internet users may encounter AI when receiving personalised recommendations whilst using online shopping and entertainment platforms (Fry, 2018). It is also used to facilitate humans' interactions with technology, e.g. voice controlled digital assistants (Følstad & Brandtzæg, 2017). As the technology aims to mimic human interactions, it can be difficult for users to identify when they are engaged with an AI system, or understand how it is designed to execute complex tasks that humans perform intuitively (Gran et al., 2020). Furthermore, the 'uncanny valley' effect of anthropomorphising machines can make users feel uncomfortable using certain types of AI (Ciechanowski et al., 2019).

Broadly speaking, AI operates based on pattern identification. An algorithm analyses data relevant to the intended task to identify elements that are indicative of a particular output. This 'training' is then used by the AI to predict appropriate outputs for previously unseen inputs. Whereas traditional ICT systems would require these relationships to be explicitly provided by a developer, AI is capable of handling complex and novel information without explicit pre-programmed instructions, by detecting complex patterns in enormous datasets. For example, AI shopping recommendations are generated by an algorithm with a large dataset containing information about users' online purchases. The algorithm identifies patterns in user profiles, browsing and purchasing habits that can be used to make recommendations to a future shopper with similar characteristics. This process of determining an output based on similarities between the current situation and previously seen examples is the foundation of AI systems irrespective of whether they are used to generate text, recommend a video clip, or make a medical diagnosis.

System designers can influence which factors are used or prioritised, but ultimately the outputs generated depend on how the system design and training data interact, which can yield unexpected results. The ability to explain/interpret how an output was reached has been identified as a pre-requisite for trustworthy AI systems (OECD, 2021b). This means that the outputs of an AI enabled system may simulate human intelligence, however, the inferences made by AI are not grounded by an understanding of reality that can be compared to human cognition. Human understanding includes implicit personal and societal 'intentions, values and social goals' as intrinsic factors that technology does not have access to (Vallor, 2021). Nonetheless, AI technology can act autonomously to execute complex tasks that historically would have required direct human involvement.

Learning from AI applications in analogous settings

CIAG services can be conceptualised in a variety of ways: for example, as career counselling; career information; career learning; or as matching to suitable occupations. In recent years, AI has been deployed in fields that present similar social challenges. Given the current lack of research specific to CIAG, experience from these analogous settings can shed some light on career-related applications. These fields are therapeutic counselling, library and information services, education, and employee selection.

Counselling services

Automated therapeutic counselling services could offer rapid treatment without waiting lists, and without the potential shame or embarrassment of having to discuss a very personal issue with a human. The promise of wider access to treatment is appealing, and attempts have been made to realise this. One example is Woebot[1], a popular smart phone app that supports users with mental health conditions. It employs a range of approaches including mood management, psycho-education, and cognitive behavioural therapy (Fitzpatrick et al., 2017; Prochaska et al., 2021). However, quantitative studies of the effects on users

1 https://woebothealth.com/

of this app report mixed results for the impacts on users' mood (Fitzpatrick et al., 2017; Prochaska et al., 2021; Suharwardy et al., 2020), and qualitative studies have identified user concerns regarding the privacy, efficacy and transparency of chatbots for mental health support (Kretzschmar et al., 2019). This suggests that users' understanding of the technology may be an important factor in ensuring clients benefit from these applications in career counselling.

Information services

Library services are a close 'analogue' to careers services, in that they curate large amounts of information and assist users in their selection. They have also been identified as a domain where AI chatbots have the potential to mitigate known problems, like library users' anxiety and limited availability of professional staff for assistance (Saldeen, 2020). Users would not have to acquire the specialist vocabulary or technical skills required to use traditional methods for database searching, thus lowering the barriers for self-serving their information needs. Research in an academic library highlights the importance of involving library staff in the development of the technology to ensure it can meet the diverse needs of the intended users, and identify when to refer to a human (Mckie & Narayan, 2019).

This applies to AI systems that aim to provide curated access to Labour Market Information (LMI). CIAG practitioners' insights are essential for anticipating the complex and wide-ranging queries a client may initially present with (Bimrose, 2021). However, the purpose of careers related information seeking means that the stakes for automated curation of LMI are higher than with academic literature searches. Search results for users self-serving LMI can have potentially substantial impact on their lives. When a client uses LMI to explore and evaluate the feasibility of their career options, the information that is omitted from search results has an implicit effect in that it removes these from consideration. Using AI to provide personalised LMI introduces a risk that the criteria used by the algorithm for personalisation is inappropriate or too simplistic. For example, using a client's age and gender to identify careers commonly preferred by others who share that age and gender, will serve to replicate existing demographic inequalities in career outcomes.

AI is already being deployed to gather LMI. For example, the OECD have used AI to map 17,000 discrete skills listed in job adverts to a taxonomy of 61 categories, creating a rich source of LMI, that reflects current trends and requires fewer resources to update than traditional approaches (Lassébie et al., 2021). AI tools for increasing the efficiency with which LMI can be accessed by clients are also being developed, for example, the CiCi chatbot, which allows users to access personalised careers information in a conversational format (Hughes, 2021). Both examples involved CIAG experts directly in the design of the technology, which mirrors the emerging trend for co-design as a key requirement for effective and ethical AI (Floridi et al., 2018). They also serve to demonstrate how AI can support efficient dissemination of LMI, whilst reducing expert resources required for its curation.

Education

There has been extensive use of automated systems in educational settings, including applications for vocational education and training (Hai-Jew, 2009). Notwithstanding great hopes for the sophistication of intelligent tutoring systems, in practice those adopted for use have tended to be quite simple (Baker, 2016). Although narrow in scope, research on student outcomes after using AI virtual tutoring systems indicates that they are effective tools that employ a variety of pedagogical approaches effectively to instil understanding of a specific topic (Olney et al., 2012; Paladines & Ramírez, 2020). However, Heffernan (2003) highlights that while AI tutoring systems reduced demands on teacher time, young people have to dedicate more time to covering material delivered this way than they would with standard classroom teaching. AI tutors have the potential to extend the availability of career education, where staff availability is the limiting factor. Although, as this style of intervention requires more from clients than a traditional approach, it is unlikely to be an effective intervention for clients with low levels of motivation, or who would be unable to commit to its use.

Employee selection

Commercial 'off-the-shelf' AI-based recruitment solutions have been adopted by employers (Chamorro-Premuzic et al., 2019; Gee, 2017; van Esch & Black, 2019). These are most commonly used in the early stages of the selection process to automatically screen application forms or candidates' video interviews (Black & van Esch, 2020; van den Broek et al., 2019). Unilever were early adopters of this technology; reporting increased diversity of recruits and significant cost savings (Gee, 2017). However, the proprietary nature of the software, and the potential competitive advantage offered by new selection methods, means that while they gain media attention (Booth, 2019; Gee, 2017), they are notably absent in published academic research. This severely limits the transparency of both how data is processed, and how outcomes are determined. Nonetheless, the technology is being marketed, including to higher education career services as a tool for developing interview skills among students[2].

The application of AI to the problem of employee selection is analogous to a traditional matching conception of careers work. It is particularly informative because it provides a domain in which to explore some of the ethical challenges that AI presents to career development services, as explored below.

Ethical challenges as illustrated by AI-assisted recruitment

Recruitment has proved to be a contentious domain for AI, (Forum for Ethical AI, 2019; OECD, 2021a) given the impact that recruitment decisions can have for individuals and society. Proponents of AI in recruitment, including software vendors, cite cost savings and the elimination of human error and unconscious bias from the process as key benefits (Hirevue, 2021; Schmidt, 2018). However, historic examples of AI decision-making algorithms have been found to exhibit bias, even in cases where protected characteristics have been intentionally removed from the data, (Birhane, 2021). This is caused by use of attributes that are correlated with the protected characteristics. For example, an experimental attempt to use AI to automate CV evaluation resulted in an algorithm that rejected CVs that included phrases indicative of gender, such as references to women's sport or women's colleges, despite candidates' protected characteristics being consciously excluded from the data (Dastin, 2018). The size of the datasets involved means it is often difficult for humans to foresee these unintentional correlations, and the increasing complexity of the system architecture means that retrospectively identifying the factors that influenced AI decisions requires specialist technical knowledge. This issue is compounded by the fact that humans have been found to trust the output of AI, even when it contradicts their own well-founded knowledge (Suresh et al., 2020). In the context of CIAG, this could mean unknowingly providing users with information and advice that replicates existing imbalances in the labour market. It also highlights the need for on-going monitoring of outcomes to ensure that AI supported interventions are commensurate with the values and ethics of CIAG practice.

Attempts to mitigate this by manipulating the data face both technical and ethical issues. The complexity of the system architecture means that even where attempts are made to 'de-bias' the dataset, prejudiced outcomes can persist due to interactions with the algorithms, or difficulties in identifying which aspects of the data are creating bias in the dataset (Bender et al., 2021). While ensuring effective monitoring of live systems to detect unintended outcomes could potentially mitigate this, complex ethical issues remain. Manipulating the outputs of systems that have a direct impact on individuals and society, means that these systems are no longer just reflecting the world, but changing it in potentially significant ways. Concerns have been raised around the impacts of algorithmic decision-making in perpetuating and exaggerating existing hegemonies, especially given that AI is already being used for tasks in fields like social security, criminal justice, and recruitment (O'Neil, 2017; Tambe et al., 2019). Therefore, determining what the target profile for outputs should be for an AI system to be classified as 'de-biased' or 'fair', and who governs this, is a complex legal, social, and ethical issue; not a technical one.

2 https://www.theaccessgroup.com/en-gb/digital-learning/software/career-development/developing-student-employability/

This is further complicated when the technology is intended for use across national and cultural borders, where consensus may be difficult to achieve. The ability for all stakeholders to understand the design, and to monitor the outputs of AI is a pre-requisite for achieving this, hence the importance placed on explainability and interpretability of AI systems (Linardatos et al., 2020). Thus, the basic threshold for determining if technology that incorporates AI is trustworthy is the explainability and interpretability of the decisions made.

The prominence of third-party vendors in AI recruitment complicates this, as answers to these questions may be considered commercially sensitive by the software developer. This also illustrates issues of accountability when deploying AI. Where the domain or company specific knowledge is provided by the software purchaser and implemented by use of their data, but the outputs are produced by a propriety algorithm owned by the vendor (van den Broek et al., 2019), who is accountable for ensuring compliance with legal and ethical obligations? This is further complicated by the fact that there is the potential for the software purchasers' data to be used to improve the algorithm performance for subsequent customers of the vendor (Wagner, 2020), introducing issues of data privacy. The potential for personal data to be unknowingly included in training data is an acknowledged risk in certain types of AI systems (Bommasani et al., 2021). If personal data is unintentionally disclosed who would be accountable? CIAG practitioners who use, or recommend, AI technologies should ensure that they understand and inform users how their personal data will be collected and used by third-parties. This is particularly true where services are being provided by commercial organisation, who may be motivated primarily by profit when collecting and processing users' information (Zuboff, 2019).

Policy guidance on the use of AI published to date calls for accountability across all stakeholders involved in the development and deployment of AI (European Commission, 2020; OECD, 2021b; Scottish Government, 2021). However, specific legislation for AI is still being developed (Centre for Data Ethics and Innovation, 2021; Floridi, 2021), and, as such, does not yet provide detail on how accountability should be allocated when the software used by a service provider is proprietary to a third-party vendor. Nonetheless, given that adequate protection of personal information is a requirement of the Career Development Institute Code of Ethics (CDI, 2019), CIAG professionals should ensure that service users' data will be handled securely by any ICT resource they incorporate into their practice, including more opaque uses of this data for training AI algorithms.

In addition to concerns around the security of personal data, AI-assisted recruitment highlights the difficulty in ensuring that users of AI systems perceive themselves to have been treated fairly (Baldwin, 2006). Introducing AI in this context means that all application forms, CVs, and interviews can be assessed with a consistency that would not be possible for humans (Chamorro-Premuzic et al., 2019). From the candidate's perspective, the flexibility of access and standardised approach offered by AI-assisted recruitment is a clear benefit (Suen et al., 2019; van Esch et al., 2019). However, this should be caveated by highlighting the limited research focused on candidate experiences, especially those with disability, neurodiversity or who are using their non-native language. Recent research found candidates' experiences of AI recruitment to be negatively impacted by lack of understanding of the technology, and their preoccupation with aligning to an unknown pre-determined criteria during interviews (Jaser et al., 2021). This highlights the importance of CIAG services ensuring their clients are adequately informed about how the AI systems operate and can opt out without adverse impacts.

Managing risks and realising benefits

A European Commission publication on responsible use of AI and algorithmic governance cites recruitment as an example of a high-risk domain for use of AI. The justification for highlighting recruitment is due to its 'significance for individuals…and addressing employment equality' (European Commission, 2020, p. 18). By these criteria, some CIAG activities would also be considered high-risk for the deployment of AI, given its role in improving individuals' lives and supporting equality (Blustein et al., 2019). The role of public policy in regulating AI is an emerging topic that has attracted national and international attention (Centre for Data Ethics and Innovation, 2021; European Commission, 2020; Exec. Order No. 13859, 2019; OECD, 2021b; Scottish Government, 2021). Common themes across these documents are provisions to support the realisation of the potential benefits AI can bring to society, tempered by an acknowledgement of the risks of both deliberate misuse and unintended consequences. Commentary on the emerging policies highlight the difficulty of regulating emerging, highly-specialised, impactful technology that crosses international borders (Floridi, 2021). Using AI within CIAG requires an understanding of the potential impacts for clients, practitioners, and society during system design and deployment in order to successfully achieve an appropriate balance between the risks and benefits.

This requires ensuring CIAG experts and practitioners are involved throughout the process, as exemplified in the CiCi and LMI examples discussed above (Hughes, 2021; Lassébie et al., 2021). The governance standards that AI is held to should not be limited to only policies developed specifically for the technology, but should include the relevant professional standards for the domain it is operating in. Due to the autonomous nature of the technology, AI used in CIAG should be required to demonstrate active compliance with the same code of ethics that a human professional engaging in a comparable activity would. The majority of software vendors developing these systems will not have the knowledge and experience required to evaluate this compliance, and therefore, should actively seek guidance from CIAG professionals during development to ensure ethical considerations are a fundamental component of system design, not something that is considered during sales and marketing, or, at worst, in response to issues that arise post deployment. CIAG services can benefit from the increased scope of the interventions that AI can deliver in a cost-effective way. However, this requires an approach to AI introduction that focuses on increasing value for clients, not reducing staff costs.

Conclusions

The use of AI technology offers practitioners the opportunity to dramatically extend the capacity for delivering curated information. It diminishes limits on when and where clients can access advice and reduces the pre-requisite knowledge they need to self-serve career information. However, the wide-ranging nature of CIAG work means that the introduction of AI should include a careful consideration of the potential benefits and risks that automation could have on both individuals and society. This means exercising reflexivity when commissioning or recommending AI technology to ensure the task is suitable for automation. Where AI is suitable, explainability of the system design, and ongoing monitoring are essential to identify and mitigate unforeseen consequences. Furthermore, the fact that clients can access these tools independently, means that even where a system can be comfortably deployed for a particular use, the technology must be designed with a built-in ability to recognise and refer appropriately when it is not a suitable intervention for a particular client.

When identifying an appropriate AI product, CIAG professionals should use their knowledge and expertise of their own domain to inform the questions they ask about the technology. Although some understanding of the real-world benefits and risks inherent to this kind of technology is necessary to know the questions that should be asked, these should be framed in terms of CIAG, not technology. The key questions should not be limited to efficiency, performance, and cost, but instead must encompass the ability of the technology to effectively and ethically operate on behalf a CIAG service. This should be supported by inter-disciplinary research that identifies best practice in the design and deployment of AI technologies for the maximum benefit of CIAG clients.

The ability to act autonomously when providing automated interactions with clients means that AI is not a tool; it is an agent (Kim, 2020; van Rijmenam et al., 2019). Therefore, the successful introduction of AI into CIAG in practice should not be undertaken as a traditional software development or procurement project, but is more akin to service design.

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