Department of Political Economy

Algorithm sleuths vs. human hawkeyes: Resume fraud detection

Gonçalo Nobre Martins Almeida

Master in Human Resources Development Policies

Thesis supervisor
Prof. Doctor Maria Teresa Féria de Almeida, invited assistant professor, ISCTE - Instituto Universitário de Lisboa

September, 2024

CIÊNCIAS SOCIAIS
E HUMANAS

Department of Political Economy

Algorithm sleuths vs. human hawkeyes: Resume fraud detection

Gonçalo Nobre Martins Almeida

Master in Human Resources Development Policies

Thesis supervisor
Prof. Doctor Maria Teresa Féria de Almeida, invited assistant professor, ISCTE - Instituto Universitário de Lisboa

September, 2024

Acknowledgements

This academic work marks a huge step in my academic life full of challenges, tribulations, joys, and opportunities for growth. As this chapter closes, another opens, and I will never forget all the lessons I had the honor of learning from colleagues and teachers, as well as all the connections I created and will carry for life.

Firstly, I would like to give special thanks to my supervisor, Professor Doctor Maria Teresa Féria de Almeida, who from the beginning of the process has always shown herself available to answer my questions, offer me guidance and listen to my ideas. Her unparalleled help and insightful critique were the cornerstone for the development of this study.

I also have a deep gratitude to my parents, who gave me every opportunity to enroll in my master's degree and who supported my goals and stood by me through all the challenges and celebrated my achievements. Thank you, from the bottom of my heart, for all your sacrifices.

I would also like to thank all my friends who supported me and showed interest throughout the process. I would like to give a special thanks to Guilherme, who listened to all my complaints, projects, and ideas (there are no words to express how much you have helped me) and to Francisco who, in addition to being a great friend who still follows my growth to this day, helped me a lot in the process of collecting participants. Without their support this thesis would not have been possible.

I would also like to thank my girlfriend Margarida, who with her unconditional support, her advice, and her words of motivation and love helped me work on this great project of my life.

Finally, I would like to thank all the people who helped in sharing the study and all the participants who took part in it and who contributed to making this research possible. I am eternally grateful.

(This page was purposely left blank)

Resumo

A Inteligência Artificial é cada vez mais utilizada nas organizações, sobretudo em tarefas de rotina, como a triagem de currículos. Esta fase do processo de seleção é de extrema relevância, pois determina se os candidatos avançam para fases seguintes, como as entrevistas. No entanto, é também uma fase vulnerável, em que candidatos podem apresentar um currículo que não reflete exatamente a sua realidade. Com base nestas premissas, esta tese teve como objetivo realizar uma análise comparativa da capacidade de agentes humanos e de um agente sintético na deteção de fraudes em currículos. Inicialmente, realizou-se um estudo qualitativo com sete entrevistas a recrutadores humanos, para identificar os tipos de fraude mais comuns. Seguidamente, foi conduzido um estudo experimental quantitativo, através de um questionário online, para comparar o desempenho de recrutadores humanos (77 participantes) e de sistemas baseados em IA (i.e., ChatGPT) na identificação de currículos artificiais e fraudulentos. Resultados demonstraram que nem humanos nem a IA conseguem detetar fraudes nos currículos. No caso da IA, os resultados contrariam a literatura, uma vez que não demonstrou melhores resultados que os humanos na triagem de currículos. Este estudo contribui para a literatura ao fornecer uma compreensão mais abrangente das limitações e capacidades de humanos e IA na deteção de fraudes. Tem ainda um papel cautelar na medida em que poderá informar organizações que pretendem integrar este tipo de tecnologias na triagem de currículos sobre algumas especificidades de uso de IA neste campo.

Palavras-chave: Recrutadores humanos, Inteligência Artificial, ChatGPT, Fraude de currículos

Código JEL: M12, O15

Abstract

Artificial Intelligence is increasingly used in organizations, especially in routine tasks, such as resume screening. This phase of the selection process is extremely important, as it determines whether candidates advance to the next phases, such as interviews. However, it is also a vulnerable phase, in which candidates may present a resume that does not exactly reflect their reality. Based on these premises, this thesis aimed to conduct a comparative analysis of the ability of humans and a synthetic agent to detect resume fraud. Initially, a qualitative study was carried out with seven interviews with human recruiters, to identify the most common types of fraud. Then, a quantitative experimental study was conducted, through an online questionnaire, to compare the performance of human recruiters (77 participants) and AI-based systems (i.e., ChatGPT) in identifying artificial and fraudulent resumes. Findings demonstrated that neither humans nor AI can detect resume fraud. In the case of AI, the results contradict the literature, since it did not demonstrate better results than humans in screening resumes. This study contributes to the literature by providing a more comprehensive understanding of the limitations and capabilities of humans and AI in detecting fraud. It also has a precautionary role in that it can inform organizations that intend to integrate this type of technology in resume screening about some specificities of using AI in this field.

Keywords: Human Recruiters, Artificial Intelligence, ChatGPT, Resume fraud

JEL code: M12, O15

General Index

Index of Tables

Index of figures

CHAPTER 1
Introduction

The selection process, particularly the resume screening phase, is a critical component of Human Resources Management (HRM). It allows the selection of the best and most suitable applicants - those possessing the right qualifications and skills, aligned with the organization’s culture and objectives - to progress to an interview and ultimately fill a position (Kuhn, 2014).

A significant issue in this phase, more common than we may think, is resume fraud (Zvi & Shtudiner, 2021). Resume fraud can be defined as an "intentional misrepresentation of information on a resume in an effort to present oneself more favorably than is accurate. Resume fraud is designed to deceive recruiters, to create personal advantages in hiring processes, to attain employment interviews, and eventually to secure job offers” (Henle et al., 2019, p. 88). Two motives for lying on a resume can be identified: to gain a competitive edge in the job market and advance in one's career, and to secure a higher salary (Wexler, 2006). Examples of resume fraud can be falsifying previous work experience and responsibilities, lying about qualifications (Bible, 2012), misrepresenting salary from a previous job, fabricating organizations, and educational institutions, and omitting employment gaps (O’Rourke, 1995). Such behaviors can be inflated due to lack of psychical or interpersonal communication during the screening process (Guillory & Hancock, 2012), as resume screening is a text-based process that does not involve a direct interaction with another person.

The use of Artificial Intelligence (AI) in organizational contexts has been increasing in recent years, either replacing or complementing human efforts in certain tasks due to AI’s ability to reduce many biases inherent in human decision-making, allowing for more rigorous performance (Rodgers et al., 2023). Moreover, as mentioned, the nature of tasks like resume screening makes them well-suited for execution by AI systems, as demonstrated by current applications (Cowgill, 2018; Ore & Sposato, 2021), and as we have already witnessed in other fields (Agrawal et al., 2017; Davenport & Ronanki, 2018). While there is existing research on the impact and effectiveness of AI-based algorithms in HRM (Makarius et al., 2020; Vrontis et al., 2021), to our knowledge, no studies have yet compared the abilities of humans and AI in detecting resume fraud.

Therefore, this study was designed to assess the ability of both AI and humans to detect resume fraud. To achieve this overarching goal, three specific objectives were established: 1) to identify the most common types of fraud; 2) to determine which types of fraud are more easily detected by humans and synthetic agents; 3) to compare the detection capabilities of humans and AI, including their levels of recommendation for fraudulent resumes.

To address the study's objectives, we began conducting a qualitative study that allowed us to answer the first of our objectives. This qualitative phase provided the essential framework and insights necessary for designing the subsequent quantitative study, which was of experimental nature. This experimental study aimed to tackle objectives two and three, building on the results from the initial qualitative analysis.

Thus, this thesis is organized into eight chapters. The second chapter provides a literature review addressing topics such as the conceptualization of resume fraud in the selection phase, the rise of AI in organizational contexts, and the advantages and challenges of using AI in HRM, particularly in resume screening.

Then, we present the method and results section for each study (quantitative and qualitative), chapters three to six.

The seventh chapter will include the discussion and conclusion of the study regarding the performance of human recruiters and AI in the screening process, in particular, to their ability to detect resume frauds.

Finally, the eighth chapter will address limitations of the study and provide recommendations for future research.

CHAPTER 2

Literature Review

2.1 HRM and the importance of selection

Human Resource Management (HRM) is a set of practices used to manage employees and encompasses traditional activities such as administration and workforce management (Chang & Huang, 2005; Greenwood, 2002). HRM is composed of multiple practices, including recruitment, selection, training, development, onboarding, performance management, compensation, and benefits, among many others (Armstrong & Taylor, 2009). In today's business environment, the strategic aspect of HRM, known as Strategic Human Resource Management (SHRM), is essential. It emphasizes the alignment of human resources practices with the organization's strategy, goals, culture, and structure, with a greater focus on achieving results and improving overall productivity (Harrison & Bazzy, 2017; Hendry & Pettigrew, 1986; Paauwe & Boon, 2018).

While all HRM practices have their due importance, selection is particularly critical as it ensures the recruitment of individuals who possess the right skills and mindset, and fit the company's culture, since people are at the core of any organization (Shahhosseini & Sebt, 2011). Selection is aimed at assessing the suitability of candidates for a specific role/job based on their past professional experiences, academic background, skills, and mindset, with resumes playing a pivotal role in this process (Armstrong & Taylor, 2009).

If this process is done poorly—such as hiring someone lacking the necessary skills, misaligned with the organization's goals, or who has lied on their resume—it can result in a significant loss of resources. This includes time spent on the selection process and integrating the new worker into the organization's culture and job, financial resources spent on selection, and further monetary loss if the individual's lack of skills or qualifications diminishes the overall organization performance. In the worst case, additional costs may arise from having to terminate the employment (Kuhn, 2014).

The selection phase begins with the screening of candidates' resumes, which are the primary application tool used universally by individuals seeking employment. and assessed by recruiters to identify qualified and suitable candidates for subsequent interviews, ultimately aiming to fulfill an open position (Varma et al., 2006). Resumes are evaluated based on candidates' work experience, academic qualifications, skills, and other relevant factors (Cole et al., 2004).

As the first point of contact with the organization, the selection phase is critically important, giving candidates the opportunity to present themselves properly and effectively. However, some individuals resort to deceitful tactics and fraudulent information in their resumes to create a more favorable first impression (Kuhn et al., 2013; Wood et al., 2007). While the public availability and scrutiny of resumes on the internet might reduce the likelihood of candidates lying about past jobs and academic qualifications, this issue remains prevalent and requires further study (Guillory & Hancock, 2012).

2.2 Resume Fraud

As mentioned, resume fraud is defined as an “intentional misrepresentation of information on a resume in an effort to present oneself more favorably than is accurate. Resume fraud is designed to deceive recruiters, to create personal advantages (over others), in hiring processes, to attain employment interviews, and eventually to secure job offers. It includes only intentional deceptions while excluding unintentional mistakes and oversights (e.g., listing the wrong supervisor for past jobs, forgetting employment dates for jobs held in the distant past, failing to mention immaterial information like irrelevant short-term jobs)” (Henle et al., 2019, p. 88).

Candidates may believe that by not engaging in resume fraud, they are putting themselves at a disadvantage, as others might use deceptive tactics to secure a position (Kaplan & Fisher, 2009). Research also suggests that resume manipulations may lead decision-makers to favor candidates who engage in such practices (Varma et al., 2006). Both high and low-ranking candidates may commit resume fraud, regardless of their position (Kidwell, 2004). The likelihood of committing resume fraud is yet dependent of the candidate's personality traits (e.g., values and moral identity) and their perceived risk of detection and punishment (Kim, 2011). Personality traits such as Machiavellianism, narcissism, and moral identity have been linked to resume fraud, suggesting that individuals with these traits are more inclined to engage in deception (Henle et al., 2019; Zvi & Shtudiner, 2021).

The literature seemed to identify three main types of fraud used when candidates wanted to modify their resumes to convey a better image: inventing, embellishing, and omitting. This typology was first identified and worked on by Wood et al. (2007), Bible (2012), and Henle et al. (2019). *Fabrication* (Henle et al., 2017), *falsification* (Bible, 2012) or *commission* (Wood et al. 2007), involves outright lies, such as inventing qualifications or work experience (e.g., do not hold a master's degree), lying about the higher education institution frequented (the institution might not exist), lying about references (usually are friends and close people), or lying about the course (the institution might exist but not with the specific course). *Embellishment* (Henle et al., 2017) or *Inflation* (Bible, 2012), consists of exaggerating facts, such as inflating skills, past responsibilities (was project manager for a large team / was assistant project manager), years of experience (e.g., is 22 years old with 5 years of experience) or exaggerating the number of languages they can speak. Resumes that contain significant a significant degree of embellishments are often referred to as "too good to be true resume" and while not strictly fraudulent, warrant closer examination. *Omission* (Bible, 2012; Henle et al., 2019; Wood et al., 2007), involves leaving out crucial information, such as gaps in employment, which candidates may try to conceal with vague explanations like "full-time volunteering." Henle et al. (2019) demonstrates, through their research, that individuals are more inclined to omit or exaggerate information than to engage in outright deception. It is crucial to note, however, that the latter is still prevalent (Henle et al., 2019).

Some argue that embellishment can be a useful tool in job applications and all the candidates should practice it — since it is difficult to ensure everyone adheres to a no-embellishment rule (Marcoux, 2006). However, Marcoux (2006) overlooks the consequences of resume fraud to the company, to the employer and to the employee, such as poor hiring decisions that can lead to significant costs (e.g., time and money), damage to the employer's and firm reputation, and unfairness toward honest and qualified candidates (Kim, 2011). Resume fraud can also erode the relationship between employee and employer, creating mistrust (Bishop, 2006; Kidwell, 2004).

Although resume fraud is a widespread problem, some recruiters consider certain types of misrepresentation more acceptable, particularly when the information is unrelated to the job at hand. For example, falsely claiming a degree in human resources when applying for an IT (Information technology) position might be viewed as irrelevant. However, as the relevance of the job increases, misrepresentations are more likely to be seen as lies. In any case, selecting candidates who lie on their resumes can negatively affect the organization's performance and reputation, as such individuals may continue to deceive in their day-to-day work (Wood et al., 2007).

Interestingly, research shows that HR professionals are less sensitive to resume fraud when compared to management students, possibly because HR professionals are more accustomed to encountering misrepresentations and may have become more tolerant (Wood et al., 2007). However, it remains essential to detect and address all forms of fraud during resume screening, as there can be both professional and legal consequences for individuals found to have lied (Lowery & Blinebry, 2014).

Detecting and responding to resume fraud is challenging (Mishra & Venkatesan, 2021). Recruiters are responsible for selecting the best candidates for their organization and dismissing a potentially candidate without certainty carries the risk of losing a talented individual (Babcock, 2003). Therefore, organizations need effective mechanisms to detect fraud. One innovative solution is the use of AI in HRM, particularly in resume screening. The use of AI, along with other technologies, is increasingly being adopted by organizations to complement or replace humans in HR tasks (Budhwar et al., 2022).

2.3 The Role of Technologies in HRM

Many tasks that were once exclusively handled by humans are now being performed by technologies, while HR professionals are getting assisted by those technologies or playing a secondary role in traditional functions (Dengler & Matthes, 2018).

Over the past few decades, technological advancements have significantly impacted HRM, bringing about innovations in every process. The shift toward a digital employer branding through social networks (Mihalcea, 2017) and the conducting of remote interviews has facilitated easier access for both organizations and candidates (Saarijärvi & Bratt, 2021). The adoption of e-learning platforms (that allowed employees to develop skills remotely) as well as the rise of remote or hybrid work environments (accelerated by the COVID-19 pandemic) are examples of how technology continues to reshape the workplace dynamics. The creation of Enterprise Resource Planning (ERP) systems such as SAP and Oracle integrate various business functions, including HR, to streamline tasks like recruitment, selection, and performance management (Johnson et al., 2016). The large automation of the payroll process and the use of computers and data bases to storage files and information (Personnel record keeping) can be considered examples of how technology can be used to increase business efficiency. Additionally, Applicant Tracking Systems help employers manage large volumes of job applicants by sorting, filtering, and tracking candidates who match job descriptions (Zhou et al., 2021).

These technology advancements and the AI also extend beyond HRM into broader fields. In healthcare, AI has sped up drug discovery (Yu et al., 2018), in education, it sometimes replaces or assists teachers (Xu et al., 2021), in agriculture, AI can also play a pivotal role through crop monitoring (Liu, 2020), in humanitarian and environmental efforts, predicting natural disasters and reducing greenhouse gas emissions, through the optimization of industrial processes to reduce waste and energy (Benbya et al., 2020; Cheong et al., 2022; Saberikamarposhti et al., 2024).

The concept of AI is rooted in Turing's early work from 1950. If a man was put in a conversation with both another human being and a machine and could not identify who is which, then it is said that the machine is intelligent (Turing, 1950). Over the years, multiple definitions of AI have appeared in the literature, and to this day there is no consensual definition (High-level expert group on artificial intelligence [AI HLEG], 2019). The literature offers different definitions of AI (e.g., McCarthy, 2007; Visvikis et al., 2019; Wang, 2019). Nevertheless, we opted for the following definition because it is provided by a High-Level Expert Group on AI set up by the European Commission and is relatively recent. According to this same Group of experts we can define AI as a " (…) software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions." (High-level expert group on artificial intelligence [AI HLEG], 2019, p. 6).

2.4 Technologies and AI in HRM: advantages and challenges

Recent studies elaborate on the advantages of using AIs on organizational processes, including HRM. Humans are more susceptible to prejudices and making mistakes than AI, which is objective. AI can process vast amounts of data and perform tasks more efficiently and faster than humans. Its work is consistent, they never get tired, and can operate 24/7, yielding the same (or better) results and productivity (Hunkenschroer & Luetge, 2022; Miller, 2019). Despite the initial economic investment required to purchase and train AI, humans can be more expensive in the long term (Hanson III & Marshall, 2001; Lacroux & Lacroux, 2022). The applications of AI in HRM are diverse, encompassing its involvement in performance management and evaluations by providing real-time feedback and predicting future performance levels based on data. Additionally, AI can play a pivotal role in employee retention and engagement, analyzing employee sentiments through surveys, social media, and other channels, which can also be used to identify areas in which the organization can enhance its practices and even predict employees who are at risk of leaving the organization (Armstrong & Taylor, 2020). Nevertheless, the focus of this work is to examine the phase of selection, specifically AI's role in resume analysis. Some literature considers AI to be more effective and efficient, even in the resume screening process (Albassam, 2023).

However, despite all these advantages, research states that it is necessary to be cautious with the implementation and use of this technology, as there are numerous factors that can result in a poor implementation of AI, both in terms of performance, ethics, and morals (Nelson, 2019). Many organizations and literature claim that AI can "debias" resume screening (e.g., by removing "race" and "gender" from the algorithm). However, bias in AI cannot be ignored, as it is not easily removed from AI tools, their algorithms, and their training (Drage & Mackereth, 2022). This is evident from examples such as Tay, an AI chatbot released by Microsoft via Twitter. Tay was intended to mimic the speech patterns of an American millennial girl but was quickly taken offline after tweeting ninety-three thousand racist and sexist messages due to its training from interactions with Twitter users (Bridge et al., 2021). This demonstrates that AI is also susceptible to prejudice and discrimination.

Some ways to mitigate bias include cooperation between humans and AI. Humans possess emotional intelligence, creativity, intuition, and cultural sensitivity, making them effective partners. We believe an augmentation perspective offers the greatest benefits, promoting cooperation rather than substitution (De Cremer & Kasparov, 2021). Ensuring continuous involvement of experts during AI training is crucial, as this stage is known for fostering bias (Soleimani et al., 2022). The training phase is critical because it allows AI to adapt its original code, either exacerbating biases in the data or maintaining an ethical process and code (Lee, 2018). The use of diverse data in AI training is also essential to minimize bias (Ferrara, 2023). To ensure ethical use of AI and minimize bias, programming and training should strive for neutrality (Ferrara, 2023; Ntoutsi et al., 2020). Fighting bias is important because AI can perpetuate prejudice against minorities and undermine organizations by creating a homogeneous, less creative, and less productive workforce (Shen et al., 2009; Zou & Schiebinger, 2018).

Other issues must also be considered, such as technological problems in software or hardware that may cause "glitches" (unexpected malfunctions), jeopardizing the selection process and HRM (Van Esch et al., 2019), the economic investment required to integrate this technology into organizations - both the cost of purchasing AI and training workers - is often impossible for small and medium-sized firms. Even larger firms may consider it a risky investment (Barbosa & Faria, 2022). Other current concerns when using AI are data security and privacy, being necessary to protect workers' data from unauthorized access (Budhwar et al., 2023). Another limitation of AIs is their inability to replicate human intuition or "capture the subtle connections between people that drive human behavior" (Armstrong, 2020, p. 155). Accountability is also a theme under debate, regarding who should be held responsible for biased decisions made by AI (Budhwar et al., 2023). While there is an extensive discussion on this topic, some literature suggests that firms, should be held accountable for the ethical, social, and economic implications of the AIs, as they are the ones deploying this technology (Martin, 2019).

While acknowledging that AI is not free of bias and errors (Tambe et al., 2019), we can analyze and improve its algorithms and training methods to mitigate bias, errors, and subjectivity introduced during creation or training. This addresses issues that may have been introduced by the programmers or emerged during the training process (Hunkenschroer & Luetge, 2022). A Controlled AI development can benefit organizations and society by reducing these issues and fostering a technology that serves the common good (Autor, 2022).

Considering all this, do humans trust AI as a "partner" and as a worker? It may seem so, but the answer is not simple. The trust we have in AI is closely related to the concept of

Algorithm Aversion, defined as a "biased assessment of an algorithm which manifests in negative behaviors and attitudes towards the algorithm compared to a human agent" (Jussupow et al., 2020, p. 4). The extent to which Algorithm Aversion affects our trust in the AI and our disregard of the AI intervention is depends on multiple factors. Algorithm Aversion is negatively associated with decision's magnitude and the individual education while positively associated with algorithms' complexity and the individual age (Mahmud et al., 2022). Trust in AI also depends on other factors, such as the nature of the task - people are more likely to trust AI for tasks that do not require social or emotional intelligence or ethical decision-making (Langer et al., 2023). Additionally, trust is also influenced by the perceived intelligence of the AI - higher perceived intelligence leads to greater reliance and trust - and the form of the system (e.g., robot, chatbot, or digital avatar) (Makarius et al., 2020). The human experience with AI, also factors the trust they have on this technology. When humans observe AI making mistakes, they tend to lose confidence in its abilities. Even if they recognize that humans make more than twice as many errors, they still often prefer a human agent over AI (Dietvorst et al., 2015).

Despite research demonstrating the superiority of AI over humans in specific tasks, some individuals continue to reject its use. In a context where an unwise decision can lead to critical consequences, it is essential to explore ways to eliminate Algorithm Aversion (Dietvorst et al., 2015; Mahmud et al., 2022). Trust in AI is also crucial for fostering productive employees who work effectively with this technology (Glikson & Woolley, 2020). While no specific solutions exist to eliminate Algorithm Aversion, we can still mitigate it by promoting collaboration between AI and Humans on the job, an augmented perspective (Burton et al., 2020; Jussupow et al., 2020). Additionally, continuous, and positive interactions with AI, i.e., the positive experience with this technology can also increase its acceptability by the user (Filiz et al., 2021). Besides trust, Barbosa & Faria (2022), state that successful implementation of AI also requires training for workers, and they should be given time to get used to it. It is important to make the purpose of the AI and the process by which it works transparent to the stakeholders as well (Makarius et al., 2020).

Despite the need for caution and the possible challenges in using AI correctly, it is a technology that has a lot of potential, that is constantly developing and that already has and will have an impact on the future, and that its use (in the right way) will be of great interest to human beings (Eapen et al., 2023; Hassani et al., 2020).

Accordingly, there are many ways that AI can be applied to the selection phase: filtering resumes by keywords considered necessary by the organization, giving AI access to a large database to filter employees who do not meet the criteria they want when screening, and using AI in the video interview process (for example, HireVue) used by firms like PwC, Vodafone, and Oracle (Albassam, 2023; Trziszka, 2023). The subject of AI in fraud detection is not widely covered and is usually only applied to the financial and accounting sectors. In these areas, it is possible to observe some success on the part of AI in mitigating frauds like data mining, forensic accounting, and auditing. This leads not only to an increase in the organization's performance levels but also to an improvement in its reputation (Choi & Lee, 2018; Dhieb et al., 2020; Mohanty et al., 2023). However, as far as we know, there is still no information or studies on the use of this technology for fraud detection in the resume screening process.

The responsibility of reviewing resumes has long been undertaken by human beings. However, the contemporary use of AI in this process is currently a subject of examination (Black & van Esch, 2020). This discussion is supported by the numerous advantages of AI and by all the possible errors, bias, and subjectivity inherently human. The main root cause of most human mistakes is their subjectivity. Subjectivity in evaluation, as different HR professionals have different criteria for evaluating resumes, which leads to inconsistency. One person gives more value to soft skills and willingness to learn, while another gives more value to hard skills and past experiences. Moral subjectivity, regarding the prejudices held by different people (Chen, 2022), can lead to not only inconsistency in selection but also to moral lapses, resulting in the loss of potential and valuable assets to the organization (Shen et al., 2009). Furthermore, other human errors in resume analysis, such as affinity bias (the preference for people who share similar tastes and backgrounds) and confirmation bias (giving more weight to evidence that is congruent with their values or ideologies), can contribute to flawed assessments, resulting in the faulty selection of individuals who may not align with the organization's values or the requirements of the respective role they are applying for (Russell et al., 2019)

AI should also have the capacity to not only verify what is written in resumes but also perceive meaningful and hidden messages (Prokopenko, 2014). This capability is useful when a candidate overindulges in some skills (for example, overstating the number of languages they know), which could raise suspicion. In this scenario, AI should have the ability to perceive such anomalies.

Therefore, the literature argues that this new type of technology eliminates much of the human inconsistency while providing other advantages: faster task performance; automation of the most boring and routine tasks, leaving human beings room for more creative and interesting tasks (Hassani et al., 2020; Vrontis et al., 2021); and long-term cost savings from a strategic perspective (Al Meslamani, 2023; Aydın & Turan, 2023).

Despite the challenges, research suggests that conscious and prudent use of AI in HRM and consequently in the selection process can bring significant benefits to stakeholders. One of AI's most valuable features is its continuous access and processing of vast amounts of data from the internet and databases (Ghosh et al., 2018). In this way, we think that a large access to information can easily contribute to helping enhance its resume fraud detection. Therefore, we believe that AI should prove itself more capable of detecting resume fraud over a human recruiter.

H1: An AI system can detect resume fraud better than a human recruiter

CHAPTER 3

Method – Qualitative Study

3.1 Procedure

Semi-structured interviews were conducted via Zoom to gather information about resume fraud. Participants were initially recruited by a convenience sampling, a nonprobability sampling used for the advantage of an easier access to participants to take part in the study in the given time, such as those within our social circles (Etikan et al., 2016). Additionally, some participants were recruited through snowball sampling, where former participants referred others who matched the characteristics of the target population (Babbie, 2014). This approach was chosen due to the exploratory nature of the study and to enhance access to the relevant population. The interviews took place between January 2024 and March 2024 and had an average duration of 33 minutes (ranging from; min 25; max 41)

The goal was to enrich existing classifications of resume fraud by identifying the most common types and understanding how they are typically presented (either individually or in combination). It was also important to complement the existing literature with recent insights from experts in the field regarding the most frequent types of fraud.

3.2 Sample

Seven semi-structured interviews were conducted via Zoom with Portuguese Human resources professionals who either currently work or have recently worked in resume screening during the selection phase (within the past year). The sample size was determined based on theoretical saturation, i.e., interviews continued until no new categories emerged. Of the interviewees, four were women and three were men. Their ages ranged from 23 to 57, and their experience in resume screening varied from one to sixteen years. Two participants held master's degrees, while the remaining five had bachelor's degrees.

3.3 Data analysis strategy

The goal was to conduct a descriptive and classificatory analysis of the types of fraud commonly found in resumes, examining whether they are used individually or in combination, to expand the existing literature and facilitate the resume tampering and creation happening in our quantitative study.

We transcribed and conducted a qualitative content analysis of the interviews. Our aim was to describe the phenomenon of resume fraud by analyzing the content of the interviews, specifically focusing on the written and oral elements they contained (Erlingsson & Brysiewicz, 2017). Through Meaning Unit analysis, we created two tables (Table 4.1 and Table 4.2) that summarize the frequency of responses from all interviewees regarding "What is valued in resumes," "Types of fraud," and "How frauds are presented." Our coding units included words, sentences, and paragraphs.

The content analysis of the interviews was carried out using both deductive and inductive approaches using à priori categories (e.g., work experience, academic background) and à posteriori categories (e.g., resume length, correct spelling). The former categories were drawn from the literature and prompts generated by ChatGPT (also being confirmed in the interviews), while the latter emerged solely from the interviews (Fereday & Muir-Cochrane, 2006). Throughout the content analysis process, we ensured the following: Almost all of the à priori subcategory, and types of resume fraud, were based on an already validated study. For example, misrepresentations of job history are addressed by O'Rourke (1995), and embellished achievements or awards are discussed by Zvi & Shtudiner (2021) (coherence); Each code or subcategory is presented in a table, along with its frequency and an illustrative quote (transparency); The same person performed two separate interpretations of the interviews, with a time interval between them (Reliability) (Bauer, 2000).

3.4 Measures

We opted for a semi-structured interview and script, as it is considered flexible enough to adapt according to the flow of the interview - allowing for changes in the order of questions or the addition of new ones relevant to the study (Adams, 2015; Barriball & While 1994). The interview script was then developed with the aim of identifying what is valued in resumes, the types of fraud and how they are most frequently used, considering the available literature on resume fraud and the specific needs of our research. The script consisted of 15 questions (see annex A), divided into different sections: five questions focused on sample characterization, including the participant introduction, education levels, and years of experience with resume screening; one question regarding the resume analysis, where we asked participants what they most value in a resume; nine questions that explored the participants' experiences with resume fraud, asking whether they or someone they knew had encountered fraudulent resumes, how these frauds were typically presented and which types were the most difficult to identify.

CHAPTER 4

Results - Qualitative

To answer the first objective, we thought it would be useful not only to identify the types of fraud most commonly used, but also what is most valued by recruiters. We therefore begin by presenting the results regarding what is most valued by recruiters and then the results of the types of fraud identified.

Through content analysis we observed that participants tend to prioritize certain elements in a resume, including language skills, a detailed and straightforward description of the individual previous functions, resume length, demographic characteristics, work experience, and academic background. Among these, work experience and academic background were the most frequently mentioned, as shown in Table 4.1.

Between all the frauds identified by the participants, the most conspicuous ones were Misrepresentation of Job History, Misrepresentation of Academic Background, and Exaggeration of Soft or Hard Skills, as illustrated in Table 4.2. Other types of fraud, such as Embellished Achievements/Awards, Lying about Possessing Documents Required for Work in a Country, and Misrepresentation or Omission of Country of residence, were mentioned less frequently. Additionally, the data suggested that resume frauds tend to occur as standalone issues rather than in combination, meaning each fraudulent resume typically contains only a single instance of fraud.

Regarding these findings, we can conclude that the areas most valued by participants in a resume—work experience and academic background—are also where frauds are most likely to occur. This reinforces the need to study this subject, as it is of the utmost importance to select the best and truthful candidates to an organization (Babcock, 2003).

Based on the qualitative results we selected the three most commonly mentioned fraud categories, which simultaneously correspond to the dimensions that are most valued by recruiters, which are also well-documented in existing literature: Misrepresentation of Job History (inventing organizations), Misrepresentation of Academic Background (fabricating courses and higher education institutions), and Exaggeration of Soft or Hard Skills (overstating language proficiency). These categories were also highlighted in pre-tests of ChatGPT, when it asked to evaluate resumes without any dimension defined by us. It is important to note that these categories were used to construct the fraudulent resumes.

According to the interviewees' testimony, some frauds are characterized by their difficulty or impossibility to be identified solely in the resume screening process, namely Embellishment of achievements/awards and Skills embellishment. However, due to the notorious presence of skills embellishment, we decided to make use of this fraud in the creation of the artificial resumes. All others were not considered for the quantitative study. Furthermore, the à posteriori category identified in the interviews, “Misrepresentation or Omission about the country of residence”, was not included in the resume creation process due to the limited number of participants who mentioned it. Similarly, other categories from the literature, such as “Embellished achievements/awards” and “Lying about owing documents to allow work in the country”, were not used also because they were rarely discussed during the interviews.

Table 4.1

Interview Results - Valued Characteristic in Resumes

Main Categories	Sub-categories	Definition	Exemplificative quote	Frequencies
What is valued in Resumes?	Work Experience (Chen, 2023)	Past roles and experiences in their career history	"(…) the second thing I look at especially is how long the person has had their experiences and how many experiences they've had since they started working" (P7, 2024).	P1, P3, P4, P5, P6, P7
	Academic Background (Ingold & Langer, 2021)	Educational history and qualifications attained.	"'I value the academic background (...) that is asked for in the advertisement, and this has to respond exactly to what the advertisement asks for, in other words, if the advert contains a degree, or a master's degree (...)" (P2, 2024).	P1, P2, P3, P5, P6, P7
	Language proficiency (à posteriori)	Fluency in languages (both written and spoken)	"(…) It was English. It could not fail. English had to be very good. It was one of the first things I identified (...) because if you cannot speak English, you cannot write in English, there is no point in going any further in the process." (P3, 2024).	P1, P3, P6
	Proficiency in a specific tool or machine (Brown & Campion, 1994)	Competence in operating specific equipment	"(…) if I was recruiting someone who had to know a lot about how to operate a particular machine in a factory, how a particular chemical process works, if the person didn't identify in the CV that there was in fact experience of operating that type of machinery, it wouldn't be worth interviewing that person either" (P3, 2024).	P3
	Detailed and straightforward function description (O' Rourke, 1995)	Comprehensive explanation of a task or role	"(…) they do not have to say anything too long, but they should talk about what they actually did. (…) (...) I am not personally interested in the number, but in the content of what you have worked on (…)" (P6, 2024).	P3, P4, P5, P6, P7
	Contacts of the candidate (Cowgill, 2018)	Information for reaching out to the candidate	"(…) at the top of every CV, I think we should have, apart from the name, of course, we should also have information such as the candidate's address, it doesn't have to be anything super detailed, but at least the city and country where they live, all their contact details, such as phone number, email, also the LinkedIn link is something quite important these days" (P4, 2024).	P4
	Resume Size (à posteriori)	Length of a Resume (generally encompasses, for example, job history, academic background)	"(…) not too long either (…) the recruiter doesn't have all that time to read 5, 6 pages of each, each candidate." (P6, 2024).	P4, P5, P6
	Correct spelling (à posteriori)	Writing the resume without spelling errors	"A CV with spelling mistakes bothers me a lot, okay?" (P5, 2024)	P5
	Extracurricular activities and/or hobbies (Guillory & Hancock, 2012)	Personal interests and activities outside of professional or academic realms	"Then, what I am trying to understand is what the candidate has done throughout his or her life, (...) be it from the point of view of hobbies, from the point of view of voluntary work or not, or from the point of view of other types of experiences that may be part of his or her life. (…)" (P5, 2024).	P5
	Demographic Characteristics (for example, Age, Sex, Nationality) (Costa, 2021)	Individual atributes	"I have a client, he's asking for a CV with call center experience between the ages of 18 and 35 (...) 'look, they can't have a Brazilian accent, they can't be a woman, they can't be this, they can't be that'." (P7, 2024).	P2, P4, P5, P7

Table 4.2

Interview Results – Types of Fraud

Main Categories	Sub-Categories	Definition	Exemplificative quote	Frequencies
Types of fraud	Misrepresentations of Job history (*Bible*, 2012; *Henle et al.*, 2019; *O'Rourke*, 1995)	False or inaccurate information about past employments	"(…) has a lot to do with an employee's actual experience, because it is very easy for us to go to LinkedIn, isn't it? And look at a profile and try to figure out what looks good (…) but then I cannot keep track of what I write (…)" (P5. 2024).	P1, P2, P3, P4, P5, P7
	Misrepresentation about academic background (*Bible*, 2012; *Guillory & Hancock*, 2012; *Wood* et al., 2007)	False or inaccurate information regarding educational history	"It is quite common (...) because... I'll give you an example: I can put on my CV that I have a degree, and if I don't present it or if the recruiter doesn't ask for the qualification certificate, I'll pass very lightly, if I sell myself well at the interview, and I'll join the company without that qualification (…)" (P2, 2024).	P2, P3, P5, P7
	Lying about owing documents to allow work in the country (*Bible*, 2012)	Providing false information to be allowed to work in a country	"(…) to draw certain job opportunities to certain countries where you need a visa, for example, and then people didn't actually have a visa." (P3, 2024).	P3
	Misrepresentation or Omission about the country of residence (à Posteriori)	Omitting or providing false information about one's country of residence	"I've been receiving a lot of CVs in which the country of residence is Portugal and then, for example, we go to LinkedIn, or we check the phone number, and it turns out that this person isn't actually in Portugal, but in Brazil." (P4, 2024).	P4, P7
	Embellished achievements/awards (*Zvi* & *Shtudiner, 2021)*	Overstated accomplishments	"I've also seen other types of fraud, such as mentioning jobs or achievements (...), and then, during the interview, it turns out that this person hasn't actually done anything they've mentioned in their CV, or else they don't know how to explain what they've put on their CV at all." (P4, 2024).	P4
	Exaggerating a particular soft or hard skill (*Bible*, 2012; *Wexler*, 2006)	Overstating proficiency in a specific soft or hard skill	"(…) people say they're quite fluent in English, and we often have to ask people to tell us how, for example, what they do in their spare time in English, and then those people can't really answer." (P1, 2024).	P1, P3, P6
How are the frauds presented?	Standalone	Frauds presented separately (e.g., one for each resume)	"(…) Normally only one is used and only one is detected (…)" (P2, 2024).	P2, P3, P4, P7
	Combined	Frauds presented together (e.g., more than one are often found in each resume)	"(…) linguistics was a very common occurrence (...) And, for example, this could be done, this could be done at the same time (...) people saying that they have, for example, 4 years' experience in a certain area (...) And when I went to check, in some cases the person actually said that they had more years of experience than they actually had (…)" (P1, 2024).	P1

CHAPTER 5

Method – Quantitative Study

5.1 Study design

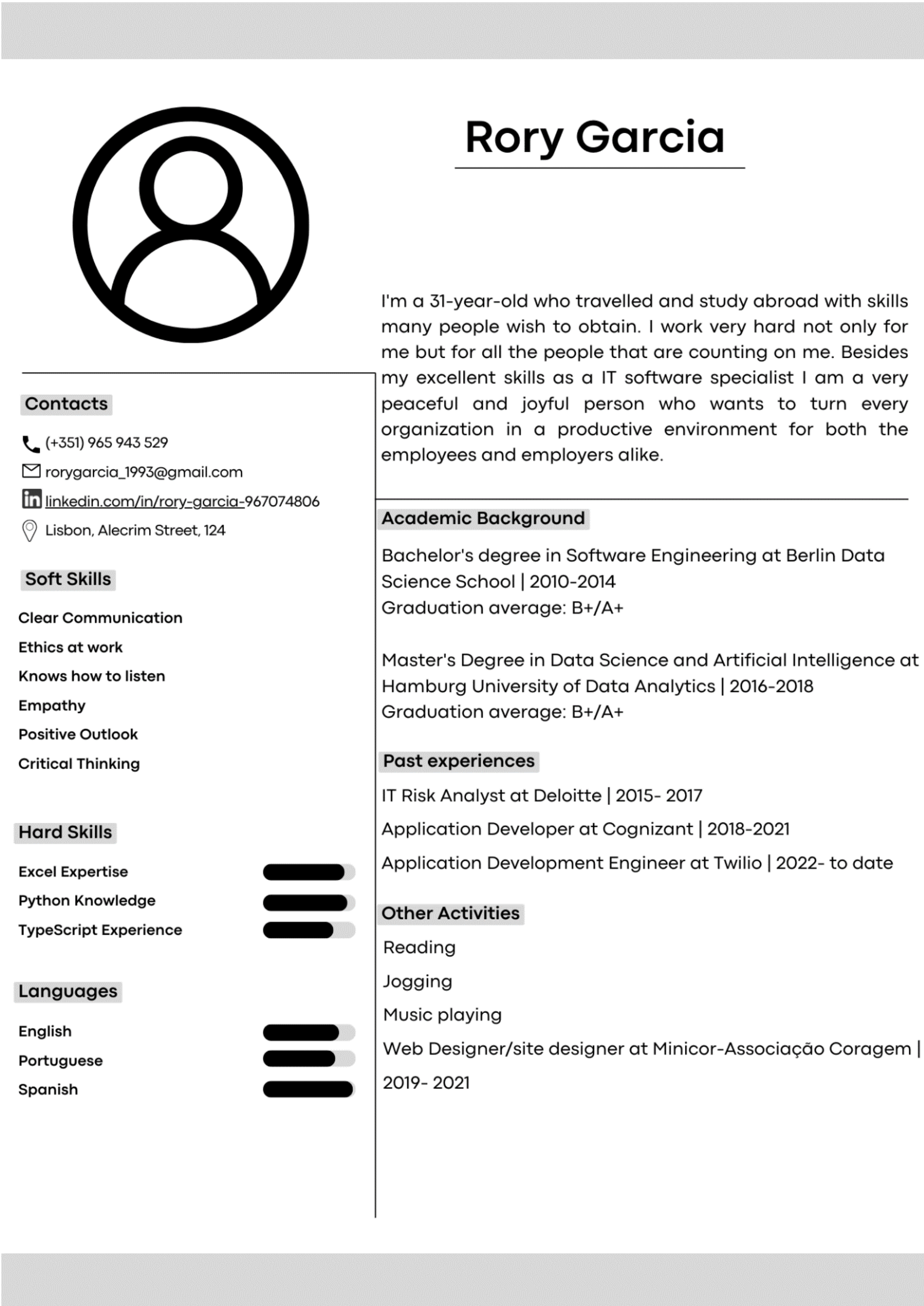
To fulfil objectives 2 and 3 of our thesis (i.e., to determine which types of fraud are more easily detected by humans and AI; and to compare the detection capabilities of the two types of agents, including their recommendation levels for fraudulent resumes), an experimental study was designed in which resumes for a vacancy were presented to Humans and AI. We designed a hypothetical job vacancy in IT, providing a function description to facilitate comparison of resumes with the job's required skills and experience.

As mentioned in the qualitative section, we created six resumes based on the interview data, literature and ChatGPT's pre-tests: four fraudulent resumes, one truthful vacancy-oriented resume (control resume), and one truthful but vacancy-misaligned resume (mirrored resume). The mirrored CV was presented to the participants in order to test their attention when answering the survey and to see if they were able to respond to it. The control resume was used when comparing its evaluation with the fraudulent resumes to observe if there was any difference in the evaluation by the two types of agents of a truthful resume and a fraudulent one. In Figure 5.1 we can see an example of a fraudulent resume we created, regarding the higher-education institution (invented). The other fraudulent resumes will be presented in the annexes (see Annex B for details). Before launching the resumes, we tested ChatGPT to ensure it possessed all relevant information, so any failure to detect fraud could not be justified by a lack of accessible information. During pre-tests, the Chat could detect frauds when the information was presented individually/out of a resume (a fabricated course, higher-education institution, and organization). We also opted for submitting the resumes to the ChatGPT multiple times, as pre-tests indicated some variation in its responses.

The survey was made available via Qualtrics for the humans, where they analyzed the resumes pre-defined characteristics (from the interviews, Chat's pre-tests, and literature) and

Figure 5.1

Experimental Condition “Fraudulent resume with invented higher education institution fraud” – CV Fraud 3



Rory Garcia

I'm a 31-year-old who travelled and study abroad with skills many people wish to obtain. I work very hard not only for me but for all the people that are counting on me. Besides my excellent skills as a IT software specialist I am a very peaceful and joyful person who wants to turn every organization in a productive environment for both the employees and employers alike.

Contacts

(+351) 965 943 529
rorygarcia_1993@gmail.com
linkedin.com/in/rory-garcia-967074806
Lisbon, Alecrim Street, 124

Soft Skills

Clear Communication
Ethics at work
Knows how to listen
Empathy
Positive Outlook
Critical Thinking

Hard Skills

Excel Expertise
Python Knowledge
TypeScript Experience

Languages

English
Portuguese
Spanish

Academic Background

Bachelor's degree in Software Engineering at Berlin Data Science School | 2010-2014
Graduation average: B+/A+

Master's Degree in Data Science and Artificial Intelligence at Hamburg University of Data Analytics | 2016-2018
Graduation average: B+/A+

Past experiences

IT Risk Analyst at Deloitte | 2015- 2017
Application Developer at Cognizant | 2018-2021
Application Development Engineer at Twilio | 2022- to date

Other Activities

Reading
Jogging
Music playing
Web Designer/site designer at Minicor-Associação Coragem | 2019- 2021

tried to assess the presence of frauds. Each participant reviewed only three resumes to help reduce dropouts: the control resume, the mirrored resume, and one fraudulent resume. The fraudulent resume was randomized across the four we created, giving participants different frauds to identify. For the Chat, the process was similar, nevertheless, as the dropouts were not an issue, the AI evaluated all the resumes/conditions. We also made sure that the resumes and the scales were randomly presented to the participant to reduce the possibility of order effect bias when analyzing the resumes and answering the survey (Perreault, 1975). For the complete visualization of the survey, see annex C.

5.2 Procedure

The survey was shared via an anonymous link available in Qualtrics, through our social networks and some social platforms to extend to other relevant participants to maximize responses. The data collection took place between May 2024 and August 2024.

Initially, pre-tests were conducted in which human participants ended up responding to all conditions (all resumes designed by us). However, we did verify that response times were quite high, as well as a high number of dropouts. With this in mind, the survey was modified so that each participant responded to only three conditions. As already stated, each participant responded to only one randomized fraudulent resume (among the four we had).

ChatGPT ended being tested by submitting all six resumes multiple times (20 submissions per fraudulent resume, matching the number of human responses).

5.3 Sample

The initial sample consisted of 197 human responses, however, many were incomplete, and others were from participants that did not fit the study's target population. We opted for a target population consisting of human recruiters, with experience in resume screening. Although previous experience in resume screening was a mandatory requirement to participate, to ensure that participants were able to fulfill this role, we compared the overall impression and interview recommendation for the control CV and the mirrored one. After removing extreme cases, a paired-sample t-test showed that the means for both the overall impression and interview recommendation are higher for the control resume than for the mirrored one ($M_{cont\_Ov.Imp}$.=4.32; $SD_{cont\_Ov.Imp}$=1.36; $M_{inad\_Ov.Imp}$=3.91 ; $SD_{inad\_Ov.Imp}$=1.58 t(76)=2.244 , p=.028; $M_{cont\_Int.}$=53.63 ; $SD_{cont\_ Int}$ =25.67 ; $M_{inad\_ Int}$ = 42.43; $SD_{inad\_ Int}$ =27.59 t(75)=3.293 , p=.002). We validated 77 answers. Of these 77 responses.

The sample was composed of 49 women (63.6%), 23 men (29.9%), one non-binary participant (1.3%), and four participants who preferred not to disclose their gender (5.2%). The age of participants ranged from 20 to 74 (M= 31.95, SD=11.27), though more than half were concentrated in the 20-to-27-year age group. There was no dominant nationality, as we aimed for and succeeded in collecting a diverse sample from across the globe. The three most represented nationalities were Portuguese (11 participants; 14.29%), English (10 participants; 12.99%) and American (four participants, 5.19%). Some participants opted for not to disclose their nationality.

Regarding academic background, nearly all participants held a degree, with a significant portion having a master's degree (37 participants; 48.1%) and others holding a bachelor's degree (28 participants; 36.4%). Finally, in terms of experience in resume screening, more than half of the participants reported having two years or less of experience in this field (min 3 months; max 30 years; M=4.65, SD=6.16).

5.4Data analysis strategy

For the quantitative phase of our study, we did a descriptive analysis and a mean comparison from the participants answers of the survey scales. As the number of participants per group was small, we conducted non-parametric tests through the software IBM SPSS. Namely, the Wilcoxon test was used to compare paired groups (i.e., fraud identification by the two types of agents individually; control resume vs. fraudulent resumes). We also opted to use the Mann-Whitney test to compare independent samples (i.e., resume evaluation of: AI vs Human)

5.5 Measures

Before the questions on resume fraud detection, human participants were asked about their experience in resume screening. This step ensured that only individuals within our target study population would continue in the survey. The following questions were answered for each resume.

Resume's valued characteristics. The resume's valued characteristics were evaluated with a single item ("Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)?", e.g., academic qualifications, professional experience, resume clarity). The measured categories were, as already stated, identified in interviews, literature, and Chat's pre-tests.

Resume's fraud assessment. To assess the identification of frauds in resumes, we adapted Henle et al.'s (2017) scale. Similar to above, the resume's fraud assessment was evaluated with a single item ("To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?", e.g., Invented degrees they do not have, Invented higher education institutions and Included things that were exaggerated). Due to survey length concerns and the potential for participant dropout, only the most relevant items from the original scale (those with the highest factor loadings) were included. We also added two more items to this scale as they were mentioned in the interviews and Chat's pre-tests "Invented higher education institutions" and "Claimed overlapping work experiences" (despite the resume regarding this fraud having been discarded during the study design). It is important to note that our adaptation also differs from the original, as Henle et al.' (2017) scale was a self-report measure (where individuals reported their own fraudulent behavior), while our study used a third-person evaluation (where participants identified fraud in others' resumes).

Resume's Overall Evaluation. The overall evaluation of each resume was measured with a single item "Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)".

Probability to pass to an interview. The likelihood of the participants selecting a resume for an interview was also measured with a single item "What is the probability of selecting the candidate to an interview, from 0 to 100%?)".

At the end of the survey, we included several questions to collect demographic information about the participants. These questions covered variables such as age, gender, and experience in resume screening. Age and experience were measured using open-ended questions, allowing participants to provide numeric responses. In the other hand, education level was assessed with a multiple-choice question that allowed only one selection. Nationality and gender were also measured using multiple-choice questions, with an option for participants to provide a custom response to capture more diverse answers.

CHAPTER 6

Results – Quantitative Study

To respond to the second objective of our study (to determine which types of fraud are more easily detected by humans and synthetic agents) we will start by presenting the results for both the human and Chat conditions individually in both Table 6.1 and 6.2, respectively. Then, we will present the comparisons between these two groups illustrated in Table 6.3 to test the Hypothesis 1 established by us (An AI system can detect resume fraud better than a human recruiter). The items in bold in the following tables represent the frauds that each resume contains.

Regarding CV Fraud 1, the results show that in the human condition, there were no differences between the values for the control condition and the Fraud condition, neither when comparing with the degree fraud (z= -1.038, p=.299). Therefore, humans could not identify any fraudulent information.

The same can be observed in CV Fraud 2, showing a low disparity between values for both conditions regarding the detection of the fraud (z= -.403, p= .687). It is also shown that the presence of a substantial number of languages is evaluated very positively by the candidates rather than something to be wary of (z= -3.457, p= <.001). We can also verify significative differences between the values of other activities (z= -2.522, p= .012) and the resume clarity (z= -2.268, p= .023) of both the CVs.

In CV Fraud 3 we found that the participants detected a difference between the two CVs regarding the work experience ownership (z= -2.201, p= .028) and Work overlapping (z= -2.234, p= .025). Nevertheless, the participants did not detect the fraud presented (invented higher education institution) or any difference in this matter regarding the two CVs (z= -.240, p= .811).

CV Fraud 4 presents the same tendency observed where the participants cannot identify differences regarding the fraud between CVs (z= -.158, p= .874), but state differences between the values for Unfavorable information suppression (z= -.166, p= .868). There is also a difference between the two CVs in the values of resume clarity (z= -2.074, p= .038) and overall impression (z= -.158, p= .874). In these last two CV Frauds we can also verify a more positive

Table 6.1

Results from the resumes evaluation by humans[1]

Human condition CV Characteristics	Mean CV Control	Mean CV Fraud	p-value Wilcoxon test	CV frauds	Mean CV Control	Mean CV Fraud	p-value Wilcoxon test
CV Fraud 1 - Degree							
Academic qual	5.23	5.00	.313	Wk exp not have	3.64	3.68	.893
Prof experience	4.64	4.59	.887	Overlapping work	3.05	3.55	.057
Soft skills	4.50	4.86	.261	**Degrees not have**	3.27	3.59	.299
Hard skills	4.45	5.00	.085	Inv. high ed inst.	3.14	3.55	.293
Languages	4.91	4.82	.788	Exaggerated	3.55	3.59	.968
Other activities	4.45	4.59	.631	Supp. unfav. Inf.	3.45	3.91	.290
Clarity resume	4.41	4.77	.354				
Overall Impression	4.36	4.64	.365				
Interview	58.00	59.00	.952				
CV Fraud 2 - Language							
Academic qual	4.85	4.95	.859	Wk exp not have	3.80	3.70	.949
Prof experience	4.55	5.00	.240	Overlapping work	3.70	3.10	.249
Soft skills	4.40	4.90	.196	Degrees not have	2.85	3.50	.194
Hard skills	4.45	4.70	.499	Inv. high ed inst.	3.30	3.00	.410
Languages	4.60	6.25	.001	**Exaggerated**	3.35	3.15	.687
Other activities	3.80	4.80	.012	Supp. unfav. Inf.	3.25	3.40	.604
Clarity resume	4.20	4.90	.023				
Overall Impression	4.25	4.55	.385				
Interview	49.17	56.50	.215				
CV Fraud 3 – HighEdInst							
Academic qual	5.25	5.65	.208	Wk exp not have	4.10	3.20	.028
Prof experience	4.60	5.10	.146	Overlapping work	4.00	3.05	.025
Soft skills	4.65	5.00	.299	Degrees not have	3.20	3.30	.914
Hard skills	4.70	5.15	.407	**Inv. high ed inst.**	2.85	3.05	.811
Languages	4.65	5.40	.033	Exaggerated	3.85	3.25	.192
Other activities	4.50	4.85	.268	Supp. unfav. Inf.	3.45	3.40	.776
Clarity resume	4.80	4.90	.596				
Overall Impression	4.35	4.80	.218				
Interview	55.33	63.56	.244				
CV Fraud 4 - Organization							
Academic qual	5.55	5.55	1.000	**Wk exp not have**	3.18	3.14	.874
Prof experience	4.82	5.45	.148	Overlapping work	3.09	3.14	.754
Soft skills	4.86	5.18	.711	Degrees not have	2.73	2.86	.580
Hard skills	4.36	5.05	.111	Inv. high ed inst.	2.55	2.50	.897
Languages	5.23	5.86	.020	Exaggerated	3.05	3.18	.541
Other activities	4.23	4.68	.064	Supp. unfav. Inf.	3.09	3.05	.868
Clarity resume	4.14	4.86	.046				
Overall Impression	4.27	4.86	.038				
Interview	52.25	64.20	.080				

[1] Abbreviations: Wk exp not have - Claimed work experience that they do not actually have; Overlapping Work - Claimed overlapping work experiences; Degrees not have - Invented degrees they do not have; Inv. high ed inst - Invented higher education institutions; Exaggerated - Included things that were exaggerated; Supp. Unfav. Inf - Suppressed information that may not look favorable.

Human N (CV Fraud 1, N= 22; CV Fraud 2, N= 20; CV Fraud 3, N= 20; CV Fraud 4, N= 22) approach to the language, nonetheless, not as notable as CV Fraud 2 (z= -2.129, p= .033), (z= -2.325, p= .020).

Table 6.2

Results from the resumes evaluation by AI (ChatGPT)

AI condition CV Characteristics	Mean CV Control	Mean CV Fraud	p-value Wilcoxon test	CV Frauds	Mean CV Control	Mean CV Fraud	p-value Wilcoxon test
CV Fraud 1 – Degree							
Academic qual	5.40	6.00	.007	Wk exp not have	1.10	1.15	.317
Prof experience	5.10	5.25	.366	Overlapping work	1.10	1.15	.317
Soft skills	5.60	5.55	.705	**Degrees not have**	1.00	1.00	1.00
Hard skills	5.30	5.40	.317	Inv. high ed inst.	1.00	1.00	1.00
Languages	5.65	5.60	1.00	Exaggerated	1.90	2.00	.157
Other activities	4.50	4.55	.705	Supp. unfav. Inf.	1.80	1.90	.157
Clarity resume	5.55	5.90	.020				
Overall Impression	5.20	5.50	.058				
Interview	68.75	70.50	.253				
CV Fraud 2 - Language							
Academic qual	5.40	6.20	.001	Wk exp not have	1.10	1.15	.317
Prof experience	5.10	6.10	.000	Overlapping work	1.10	1.15	.317
Soft skills	5.60	6.00	.033	Degrees not have	1.00	1.00	1.00
Hard skills	5.30	5.85	.005	Inv. high ed inst.	1.00	1.00	1.00
Languages	5.65	6.70	.000	**Exaggerated**	1.90	1.95	.564
Other activities	4.50	5.15	.001	Supp. unfav. Inf.	1.80	1.80	1.00
Clarity resume	5.55	6.15	.001				
Overall Impression	5.20	6.10	.000				
Interview	68.75	79.25	.000				
CV Fraud 3 – HighEdInst							
Academic qual	5.40	5.95	.018	Wk exp not have	1.10	1.10	1.00
Prof experience	5.10	5.55	.013	Overlapping work	1.10	1.10	1.00
Soft skills	5.60	5.70	.527	Degrees not have	1.00	1.00	1.00
Hard skills	5.30	5.25	.705	**Inv. high ed inst.**	1.00	1.00	1.00
Languages	5.65	6.00	.071	Exaggerated	1.90	1.95	.317
Other activities	4.50	4.85	.008	Supp. unfav. Inf.	1.80	1.85	.317
Clarity resume	5.55	5.80	.025				
Overall Impression	5.20	5.70	.004				
Interview	68.75	73.50	.031				
CV Fraud 4 - Organization							
Academic qual	5.40	6.05	.001	**Wk exp not have**	1.10	1.15	.317
Prof experience	5.10	5.90	.000	Overlapping work	1.10	1.10	1.00
Soft skills	5.60	5.70	.480	Degrees not have	1.00	1.00	1.00
Hard skills	5.30	5.65	.052	Inv. high ed inst.	1.00	1.00	1.00
Languages	5.65	6.10	.013	Exaggerated	1.90	1.95	.317
Other activities	4.50	5.00	.004	Supp. unfav. Inf.	1.80	1.85	.317
Clarity resume	5.55	5.95	.052				
Overall Impression	5.20	5.75	.002				
Interview	68.75	76.25	.002				

Regarding the AI evaluation of the resumes presented in Table 6.2, we can identify different tendencies when comparing with the human data. In CV Fraud 1 we can see a more positive evaluation of the fraudulent CV regarding his academic qualifications (z=-2.676; p= .007) and

Table 6.3

Results from the resumes evaluation – Human vs AI

Human vs. AI condition CV Characteristics	Mean Human	Mean AI	p-value Mann Whitney test	CV Frauds	Mean Human	Mean AI	p-value Mann Whitney test
CV Fraud 1 – Degree							
Academic qual	5.00	6.00	.006	Wk exp not have	3.68	1.15	<.001
Prof experience	4.59	5.25	.076	Overlapping work	3.55	1.15	<.001
Soft skills	4.86	5.55	.060	**Degrees do not have**	3.59	1.00	<.001
Hard skills	5.00	5.40	.257	Inv. high ed inst.	3.55	1.00	<.001
Languages	4.82	5.60	.013	Exaggerated	3.59	2.00	<.001
Other activities	4.59	4.55	.442	Suppressed unfav. Inf.	3.91	1.90	.001
Clarity present resume	4.77	5.90	.014				
Overall Impression	4.64	5.50	.008				
Interview	59.00	70.50	.165				
CV Fraud 2 - Language							
Academic qual	4.95	6.20	.080	Wk exp not have	3.70	1.15	<.001
Prof experience	5.00	6.10	.027	Overlapping work	3.10	1.15	.001
Soft skills	4.90	6.00	.007	Degrees do not have	3.50	1.00	<.001
Hard skills	4.70	5.85	.005	Inv.high ed inst.	3.00	1.00	<.001
Languages	6.25	6.70	.471	**Exaggerated**	3.15	1.95	.252
Other activities	4.80	5.15	.486	Suppressed unfav. Inf.	3.40	1.80	.012
Clarity present resume	4.90	6.15	.001				
Overall Impression	4.55	6.10	<.001				
Interview	56.50	79.25	.001				
CV Fraud 3 - HighEdInst							
Academic qual	5.65	5.95	.283	Wk exp not have	3.20	1.10	<.001
Prof experience	5.10	5.55	.114	Overlapping work	3.05	1.10	<.001
Soft skills	5.00	5.70	.022	Degrees do not have	3.30	1.00	<.001
Hard skills	5.15	5.25	.883	**Inv. high ed inst.**	3.05	1.00	<.001
Languages	5.40	6.00	.107	Exaggerated	3.25	1.95	.001
Other activities	4.85	4.85	.665	Suppressed unfav. Inf.	3.40	1.85	.001
Clarity present resume	4.90	5.80	.007				
Overall Impression	4.80	5.70	.005				
Interview	63.56	73.50	.317				
CV Fraud 4 - Organization							
Academic qual	5.55	6.05	.119	**Wk exp not have**	3.14	1.15	<.001
Prof experience	5.45	5.90	.234	Overlapping work	3.14	1.10	<.001
Soft skills	5.18	5.70	.216	Degrees do not have	2.86	1.00	<.001
Hard skills	5.05	5.65	.224	Inv. high ed inst.	2.50	1.00	.003
Languages	5.86	6.10	.440	Exaggerated	3.18	1.95	.003
Other activities	4.68	5.00	.226	Suppressed unfav. Inf.	3.05	1.85	<.001
Clarity present resume	4.86	5.95	.001				
Overall Impression	4.86	5.75	.008				
Interview	64.20	76.25	.024				

resume clarity (z= -2.333, p= .020). The participants also cannot identify any difference regarding the presence of the ownership of degrees fraud to both conditions (z=0; p= 1.00). CV fraud 2 has a particularity, all the values of the CVs characteristics are significative. The Chat evaluates the fraudulent CV more positively than the control CV, in all the aspects, in the overall impression and probability to pass to an interview. It still does not find any difference in the values regarding the fraud committed (z=-.577; p= .564).

The Chat also gives a more positive score in CV fraud 3 to the fraudulent CV regarding his academic qualifications (z=-2.368; p= .018), professional experience (z=-2.496; p= .013), other activities (z= -2.646, p= .008), resume clarity (z= -2.236, p= .025), overall impression (z= -2.887, p= .004) and probability to pass to an interview (z= -2.151, p= .031). In this case we cannot also see any difference between the evaluation of two conditions regarding the fraud used, invention of a higher education institution (z=0 p= 1.00).

In CV Fraud 4 we identify difference between the evaluations of the two CVs - regarding academic qualifications (z=-3.357; p= <.001), professional experience (z=-3.557; p= <.001), languages (z=-2.496; p= .013), other activities (z= -2.887, p= .004) overall impression (z=-3.051; p= .002), and probability to pass to an interview (z=-3.073; p= .002) - with a more positive evaluation of the fraudulent CV. In this situation we do not see any significant values regarding the identification of frauds between the two CVs, and neither the identification of the fraud presented (z=-1.000; p= .317).

Finally, we compare the evaluation of the four fraudulent resumes by the two sources, human and the Chat/AI, as it is illustrated in Table 6.3. Regarding the first CV, we can see a more positive evaluation of the AI, especially in the academic qualifications (U= -2.742, p= .006), language (U= -2.486, p= .013), resume clarity (z= -2.445, p= .014) and overall impression fields (U= -2.653, p= .008), with a significance in these evaluations. We can also verify that humans tend to be more suspicious about frauds, nevertheless, cannot identify the proper fraud presented (U= -4.836, p= <.001).

In the second CV we can observe the same tendency of more positive approach of the AI regarding the professional experience (U= -2.216, p= .027), the soft skills (U= -2.714, p= .007), the hard skills (U= -2.811, p= .005), resume clarity (U= -3.406, p= <.001) the overall impression (U= -4.265, p= <.001) and the probability to pass to an interview (U= -3.200, p= .001). Even though we can perceive a significance for almost all the values of the fraud's evaluation between the two sources, this significance is not found in the particular fraud used in the CV

($U= -1.146$, $p= .252$). Even if the humans have a more down to earth approach, they still cannot identify the fraud.

In the third CV we can find differences between the values of each source regarding soft skills ($U= -2.299$, $p= .022$), resume clarity ($U= -2.703$, $p= .007$) and overall impression ($U= -2.808$, $p= .005$). We can also spot differences between all the values of each source when analyzing the frauds evaluation. Once again, we emphasize the higher scores by humans regarding the possibility of fraud.

Ultimately, the fourth CV has a significant difference in the values of resume clarity ($U= -3.253$, $p= .001$), overall impression ($U= -2.646$, $p= .008$) and probability to pass to an interview ($U= -2.256$, $p= .024$). We can also see that even though there are differences between all the values in the fraud detection (with higher scores given by humans), both sources cannot identify the fraud used in this CV ($U= -3.972$, $p= <.001$). In general, the Chat would give higher scores to the CV and its characteristics, when humans would be more suspicious about its content and the possibility of frauds. Nonetheless, both showed an inability to identify any of the frauds presented in the CVs.

CHAPTER 7

Discussion and Conclusion

Firstly, we will analyze the results of our qualitative study, that also allowed us to answer to the first objective of our study (to identify the most common types of fraud) and the impacts they have to the present literature.

Our qualitative study enabled us to explore what individuals with experience in human resources value most in resumes. The interview findings reinforce the significance of categories already established in the literature, such as "Work Experience", "Academic Background" and "Contacts of the candidate". Additionally, we uncovered other categories that complement existing research, such as "Language proficiency" and "Resume size".

In terms of resume fraud, the interviews confirmed the prevalence of frauds discussed in the literature, such as "Misrepresentation of Job History" and "Misrepresentation of Academic Background." However, we also identified a fraud not previously noted in the literature: "Misrepresentation or Omission about the Country of Residence." This suggests the need for further investigation into other potential frauds absent from the existing body of research.

As mentioned, these results demonstrate that the areas most valued in resumes are also where candidates are most likely to commit fraud. Therefore, it becomes essential to study ways of detecting fraud in resumes (Costa, 2021).

Finally, our qualitative approach also allowed us to verify that resume frauds are mostly presented as a standalone issue. This impacts the literature insofar as, to date, as far as we know, no studies have yet explored how resume frauds are typically presented.

In order to fulfil the second objective of our study (to determine which types of fraud are more easily detected by humans and AI) we will analyze the performance of the two types of agents in more detail.

The results in Table 6.1 show that there are no significant values in the detection of fraud regarding the specific fraud manipulated in the specific resume (identified in bold), i.e., humans cannot identify the fraud in the resume. Humans tend to give higher scores in the resume characteristics, overall impression, and probability to pass to an interview to the fraudulent resumes over the non-fraudulent resume (although the difference is most of the time not so significant). In almost all the resumes we see remarkably similar evaluations regarding their characteristics (regardless of the fraud), nevertheless, something that should be particularly emphasized is that the resume that has an exaggerated number of languages also has a much higher score in this field (compared to the other resumes). In this way, we deepen our state that the humans not only fail to detect fraud but are also susceptible to being biased towards embellishment fraud. These results are coherent with the literature as HR professionals may have become less sensitive to resume frauds, because they are already used to encountering it (Wood et al., 2007), which emphasizes the importance and urgency of finding mechanisms and/or strategies to help in this process (Budhwar et al., 2022). This becomes even more relevant considering the critical role of selection in HRM and the negative impacts that selecting a person who lies on a resume can have to an organization. (Kuhn, 2014).

ChatGPT also illustrates its inability to detect any fraud as presented in the Table 6.2. The Chat also gives higher scores to the fraudulent resumes over the control resume in terms of the characteristics of the resume, its overall evaluation, and the likelihood of getting through to an interview. ChatGPT not only fails to identify embellishment (regarding the exaggerated number of languages in one of the resumes) but it is also susceptible to this. This can be proved by the higher scores in this field and in this resume when compared to the rest of the resumes. Thus, we can conclude that even though Chat has access to information (regarding the existence or non-existence of organizations, universities, and courses) and can identify frauds when presented individually in pre-tests, when presented in a resume, it demonstrates that it does not have the ability to detect fraud. Although it is a tool with enormous potential for use in the selection process, and in this case resume screening, it may still be too early to use it without any kind of complementarity with the human being. The results regarding AI are also not coherent with the available literature. Although no studies have been conducted on AI's ability to detect fraud in resume screening, as far as we know, research in other fields, such as finance and accounting, has shown very positive results in the application of AI for fraud detection. (Choi & Lee, 2018; Dhieb et al., 2020; Mohanty et al., 2023). This discussion becomes even more relevant as AI-based systems in the selection phase are classified as high-risk in Annex 3, number 4, point a), of the European Commission's 2021 proposals for regulating AI.

Comparing the results between the two types of agents allowed us to answer to the third objective of our study, as well as to test our hypothesis (H1: An AI system can detect resume fraud better than a human recruiter). Both demonstrate an inability to consistently detect fraud in resumes when analyzing the Table 6.3. However, despite humans appearing to perform slightly better in assessing resumes and identifying potential fraud, the close values in both characteristics and fraud detection fields indicate not an ability to detect fraud, but rather an indifference or lack of sensitivity toward fraudulent information. Even when analyzing individual human performance, they could not detect any fraud when it occurred. In fact, humans often identified fraud in areas where no manipulation existed. We also believe that humans' assessment of the presence of fraud in resume may be slightly superior to that of AI because humans have shown themselves to be more suspicious and critical of resumes. Regarding the similarity between humans and AI in overvaluing language skills (while being biased towards embellishment fraud), it might be relevant to reference Marcoux (2006). Since both humans and AI systems tend to rate embellished resumes more positively than truthful ones, they inadvertently create an environment that incentivizes dishonesty. This may encourage candidates to embellish their resumes to compete on an equal footing with those who already engage in such practices, reinforcing a cycle of inflated qualifications and false representation. Once again, this contradicts the literature, as AI does not demonstrate the ability to "read between the lines" or interpret implied messages, for example, the claim that someone speaks multiple languages might be something worth scrutinizing (Prokopenko, 2014). Furthermore, given that embellishment is the most common type of fraud, this increases the likelihood that many individuals will slip through the cracks and enter organizations, thereby exposing them to various risks, such as reduced performance, financial losses, and potential damage to their reputation (Kim, 2011). The results of this quantitative study allow us to conclude that the hypothesis we proposed is rejected, as ChatGPT has not demonstrated to be superior to human recruiters in detecting fraud in resumes. These may also foster algorithm aversion since the experience of detecting fraud using AI has failed. Experience, both positive and negative, has an influence on algorithm aversion (Filiz et al., 2021; Makarius et al., 2020).

Although there is an active argument about the replacement of humans by AIs in the selection phase, particularly in the screening process (Cai et al., 2024), we believe that this is may not an easy solution as neither AI nor humans seems apt to identify frauds. They may be in a likely future, nevertheless for the time being and even for that hypothetical future we believe that an augmentation perspective may be much more valuable to fight against potential bias originated from the two and two get a better performance overall (Langer et al., 2023).

This study can also be highly valuable for organizations, especially to those considering integrating AI in the selection process or that are planning to replace human recruiters with it, since, as far as we know, there were no studies regarding the use of this technology in the detection of fraud in the screening process, only in the finance and accounting fields (Choi & Lee, 2018; Dhieb et al., 2020; Mohanty et a., 2023). While AI systems are capable of handling large amounts of data and identifying patterns (Ghosh et al., 2018), it seems they are currently limited in their ability to detect nuanced and context-specific fraud, such as embellishments in language skills and fabrication of higher education institutions, courses, and organizations. Additionally, this study also helps the organizations being aware of how AI can unintentionally perpetuate issues like resume embellishment.

CHAPTER 8

Limitations and future research

We must understand that this work, like any other, must be analyzed in light of its limitations. Subsequently, we will also offer proposals for future research in this field.

There are ethical implications regarding the use of AI that we ended up leaving out of our study. We tried to eliminate variables such as gender (by using neutral names), ethnicity (not using photos on resumes), age (setting an age range of 30-35 years), geographical location (all resumes claim to live in the city of Lisbon). However, it is not something that can be eliminated, nor is it something so easily solved as we have also observed in the literature, and although it is not a topic we have discussed, it could be something that future studies could focus on. This is a present issue that must always be present in our discussions regarding the use of AI (Drage & Mackereth, 2022; Nelson, 2019).

Our qualitative study was designed to be carried out until the point of theoretical saturation, nevertheless, this does not imply that our conceptual model is definitive, but it has been developed to be conceptually robust within the study's qualitative scope (Corbin & Strauss, 1998; Low, 2019).

While our quantitative study focused on the selection of resumes for an IT position (with resumes oriented to IT experience, academic background and skills that might prove useful in the area), it might also be interesting for future studies to explore the application to other areas.

Although the intended human sample of our study was only recruiters, due to the difficulty in collecting responses, we still had to include human resources students (11.69% of the sample). Therefore, the results we obtained may differ slightly from a context in which the intended sample and final sample are the same. Despite the majority of the sample being recruiters (88.31%), it may be interesting for future research to study each of the populations.

Due to the nature and time required to carry out this work, we were unable to study other possible types of fraud that could be interesting to study in the near future, like Misrepresentation or Omission about the Country of residence, or other frauds not identified by us and the literature. It can also be considered worthwhile to focus on a specific type of fraud and explore and study it in greater depth, as we have conducted a general analysis on the detection of multiple types of fraud.

Despite resume frauds being mostly presented as a standalone issue, it may be interesting for future research to study them when used in combination (more than one fraud per resume).

Our analysis was carried out in relation to Chat's ability to detect resume fraud or not, however, the results we obtained cannot be extrapolated to all IAs. This study serves as an exploratory and introductory study into a much larger subject that has not yet been explored. It will also be up to other researchers to analyze the applicability of these results to other AIs.

References

Adams, W. C. (2015). Conducting semi-structured interviews. In K. E, Newcomer., H. P, Hatry., & J. S, Wholey (Eds). *Handbook of practical program evaluation (*4th Ed., pp. 492 - 505*)*. Jossey-Bass. DOI: DOI:10.1002/9781119171386

Agrawal, A., Gans, J. S., & Goldfarb, A. (2017). What to expect from artificial intelligence. *MIT Sloan Management Review*, *58*: 1-9. https://sloanreview.mit.edu/article/what-to-expect-from-artificial-intelligence/

Al Meslamani, A. Z. (2023). Beyond implementation: The long-term economic impact of AI in healthcare. *Journal of Medical Economics, 26,* 1566-1569. DOI: 10.1080/13696998.2023.2285186

Albassam, W. A. (2023). The power of artificial intelligence in recruitment: An analytical review of current AI-based recruitment strategies. *International Journal of Professional Business Review,* *8*(6), 1-25. DOI: https://doi.org/10.26668/businessreview/2023.v8i6.2089

Armstrong, M., & Taylor, S. (2009). *Armstrong's handbook of human resource management practice* (13th ed.). London: Kogan Page. https://e-uczelnia.uek.krakow.pl/pluginfile.php/604792/mod_folder/content/0/Armstrongs%20Handbook%20of%20Human%20Resource%20Management%20Practice_1.pdf?forcedownload=1

Armstrong, M., & Taylor, S. (2009). *Armstrong's handbook of human resource management practice* (15th ed.). New York: KOGAN PAGE LTD

Autor, D. (2022). The labor impact of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty. *NBER Working-Paper 30074*, 1-34. DOI:10.2139/ssrn.4122803

Aydın, E., & Turan, M. (2023). An AI-based shortlisting model for sustainability of human resource management. *Sustainability*, *15*(3), 1-15. DOI: https://doi.org/10.3390/su15032737

Babbie, E. R. (2014). The *practice of social research* (13th ed). Nelson Education.

Babcock, P. (2003). Spotting lies. *HR Magazine*, *48*(10), 46–52. URL: https://www.shrm.org/topics-tools/news/hr-magazine/spotting-lies

Barbosa, N., & Faria, A. (2022). Digital adoption and productivity: Understanding micro drivers of the aggregate effect. *GEE Paper 162*, Ministério da Economia, 1-37.

Barriball, K. L., & While, A. (1994). Collecting data using a semi-structured interview: A discussion paper. *Journal of Advanced Nursing-Institutional Subscription, 19*(2), 328-335. DOI: https://doi.org/10.1111/j.1365-2648.1994.tb01088.x

Bauer, M. W. (2000). Classical content analysis: A review. In Bauer, M. W and Gaskell, G (Eds) *Qualitative researching with text, image and sound: A practical handbook* (pp. 131–151). Sage.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: current state and future opportunities. *MIS Quarterly Executive, 19*(4). URL: https://aisel.aisnet.org/misqe/vol19/iss4/4/

Bible, J. D. (2012). Lies and damned lies: Some legal implications of resume fraud and advice for preventing it. *Employee Relations Law Journal, 38*, 22-47. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&AuthType=ip,uid&db=bsu&AN=82861568&lang=pt-pt&site=ehost-live&scope=site

Bishop, J. D. (2006). Moral intuitions versus game theory: A response to Marcoux on résumé embellishing. *Journal of Business Ethics, 67*, 181-189. DOI: 10.1007/s10551-005-2412-5

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: what is it and how should a manager use it? *Business Horizons, 63*(2), 215-226. DOI: https://doi.org/10.1016/j.bushor.2019.12.001

Bridge, O., Raper, R., Strong, N., & Nugent, S. E. (2021). Modelling a socialised chatbot using trust development in children: Lessons learnt from Tay. *Cognitive Computation and Systems, 3*(2), 100-108. DOI: 10.1049/ccs2.12019

Brown, B. K., & Campion, M. A. (1994). Biodata phenomenology: Recruiters' perceptions and use of biographical information in resume screening. *Journal of Applied Psychology, 79*(6), 897. DOI: https://doi.org/10.1037/0021-9010.79.6.897

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., DeNisi, A., Dey, P. K., Guest, D., Knoblich, A. J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., Rogelberg, S., Saunders, M. N., Tung, R. L., & Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal, 33*(3), 606-659. DOI: 10.1111/1748-8583.12524

Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: A review and research agenda. The International Journal of Human Resource Management, 33(6), 1065-1097.

Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making, 33*(2), 220-239. DOI: 10.1002/bdm.2155

Cai, F., Zhang, J., & Zhang, L. (2024). The impact of artificial intelligence replacing humans in making human resource management decisions on fairness: A case of resume screening. *Sustainability, 16*(9). DOI: https://doi.org/10.3390/su16093840

Chang, W. J. A, & Huang, T. C. (2005). Relationship between strategic human resource management and firm performance: A contingency perspective. *International Journal of Manpower, 26*(5), 434-449. DOI: 10.1108/01437720510615125

Chen, Z. (2023). Collaboration among recruiters and artificial intelligence: Removing human prejudices in employment. *Cognition, Technology & Work, 25*, 135-149. DOI: https://doi.org/10.1007/s10111-022-00716-0

Cheong, S.-M., Sankaran, K., & Bastani, H. (2022). Artificial intelligence for climate change adaptation. *WIREs Data Mining and Knowledge Discovery, 12(5).* https://doi.org/10.1002/widm.1459

Choi, D., & Lee, K. (2018). An artificial intelligence approach to financial fraud detection under IoT environment: A survey and implementation. *Security and Communication Networks, 2018*(1). DOI: https://doi.org/10.1155/2018/5483472.

Cole, M. S., Feild, H. S., & Giles, W. F. (2004). Interaction of recruiter and applicant gender in resume evaluation: A field study. *Sex Roles, 51*, 597-608.

Corbin, J., & Strauss, A. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory* (2nd ed.). London: Sage Publications

Costa, P. (2021). *Résumé Fraud? The Effects of Résumés' Embellishment on Perceptions of Business Graduates' Hireability* (Master's thesis). Universidade do Porto

Cowgill, B. (2020). Bias and productivity in humans and algorithms: Theory and evidence from resume screening. Working Paper, Columbia Business School.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116. URL: https://blockqai.com/wp-content/uploads/2021/01/analytics-hbr-ai-for-the-real-world.pdf

De Cremer, D., & Kasparov, G. (2021). AI should augment human intelligence, not replace it. *Harvard Business Review, 18,* 1-8. URL: https://www.daviddecremer.com/wp-content/uploads/HBR2021_AI-Should-Augment-Human-Intelligence-Not-Replace-It.pdf

Dengler, K., Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, *137,* 304-316. DOI: https://doi.org/10.1016/j.techfore.2018.09.024

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1). DOI: http://dx.doi.org/10.1037/xge0000033

Dhieb, N., Ghazzai, H., Besbes, H., & Massoud, Y. (2020). A secure AI-driven architeture for automated insurance systems: Fraud detection and risk measurement. *IEEE Access, 8*, 58546-58558. DOI: 10.1109/ACCESS.2020.2983300

Drage, E., & Mackereth, K. (2022). Does AI debias recruitment? Race, gender, and AI's "eradication of difference." *Philosophy & Technology, 35*, 1-25. DOI: https://doi.org/10.1007/s13347-022-00543-1

Eapen, T., Finkenstadt, D. J., Folk, J., & Venkataswamy, L. (2023). How generative AI can augment human creativity. *Harvard Business Review, 101*(4). URL: https://hbr.org/2023/07/how-generative-ai-can-augment-human-creativity

Erlingsson, C., & Brysiewicz, P. (2017). A hands-on guide to doing content analysis. *African Journal of Emergency Medicine*, *7*, 93-99. DOI: http://dx.doi.org/10.1016/j.afjem.2017.08.001

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1-4. DOI: 10.11648/j.ajtas.20160501.11

European Commission. (2021). Anexos da Proposta de Regulamento do Parlamento Europeu e do Conselho que Estabelece Regras Harmonizadas em Matéria de Inteligência Artificial (Regulamento Inteligência Artificial) e Altera Determinados Atos Legislativos da União. *COM (2021) 206 final* - ANNEXES 1 to 9. URL: https://eur-lex.europa.eu/resource.html?uri=cellar:e0649735-a372-11eb-9585-01aa75ed71a1.0004.02/DOC_2&format=PDF

Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International*

Journal of Qualitative Methods, 5(1), 80-92. https://doi.org/10.1177/160940690600500107

Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci, 6*(1), 1-15. DOI : https://doi.org/10.3390/sci6010003

Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2021). Reducing algorithm aversion through experience. *Journal of Behavioral and Experimental Finance, 31*. https://doi.org/10.1016/j.jbef.2021.100524

Ghosh, A., Chakraborty, D., & Law, A. (2018). Artificial intelligence in Internet of things. *CAAI Transactions on Intelligence Technology, 3*(4), 208-218. DOI: 10.1049/trit.2018.1008 www.ietdl.org

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of Empirical Research. *Academy of Management Annals, 14*, 627-660. DOI: https://doi.org/10.5465/annals.2018.0057

Greenwood, M. R. (2002). Ethics and hrm: A review and conceptual analysis. *Journal of Business Ethics, 36*, 261-278. DOI: https://doi.org/10.1023/A:1014090411946

Guillory, J., & Hancock, J. T. (2012). The effect of LinkedIn on deception in resumes. *Cyberpsychology, Behavior, and Social Networking, 15*, 135-140. DOI: 10.1089/cyber.2011.0389

Hanson III, C. W., & Marshall, B. E. (2001). Artificial intelligence applications in the intensive care unit. *Critical Care Medicine, 29*(2), 427-435. DOI: 10.1097/00003246-200102000-00038

Harrison, T., & Bazzy, J. D. (2017). Aligning organizational culture and strategic human resource management. *Journal of Management Development, 36*(10), 1260-1269. DOI: DOI 10.1108/JMD-12-2016-0335

Hassani, H., Silva, E. S., Unger, S., TajMazinani, M., & Mac Feely, S. (2020). Artificial intelligence (AI) or intelligence augmentation (IA): What is the future? *Ai, 1*(2), 143-155. DOI: http://dx.doi.org/10.3390/ai1020008.

Hendry, C., & Pettigrew, A. (1986). The practice of strategic human resource management. *Personnel Review, 15*(5), 3-8. DOI: http://dx.doi.org/10.1108/eb055547

Henle, C. A., Dineen, B. R., & Duffy, M. K. (2019). Assessing intentional resume deception: Development and nomological network of a resume fraud measure. *Journal of Business and Psychology, 34,* 87-106. DOI: https://doi.org/10.1007/s10869-017-9527-4

High-level expert group on artificial intelligence [AI HLEG]. (2019). A Definition of AI: Main Capabilities and Scientific Disciplines. Definition Developed for the Purpose of the AI HLEG's Deliverables. *European Commission,* 1-7. Retrieved from https://digital-strategy.ec.europa.eu/en/library/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics, 178,* 977-1007. DOI: https://doi.org/10.1007/s10551-022-05049-6

Ingold, P. V., & Langer, M. (2021). Resume= Resume? The effects of blockchain, social media, and classical resumes on resume fraud and applicant reactions to resumes. *Computers in Human Behavior, 114.* DOI: https://doi.org/10.1016/j.chb.2020.106573

Johnson, R. D., Lukaszewski, K. M., & Stone, D. L. (2016). The evolution of the field of human resource information systems: Co-evolution of technology and hr processes. *Communications of the Association for Information Systems, 38*(1), 533-553. DOI: 10.17705/1CAIS.03828

Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion. *ECIS. Proceedings of the 28th European Conference on Information Systems,* 1-16. URL: https://aisel.aisnet.org/ecis2020_rp/168/

Kaplan, D. M., & Fisher, J. E. (2009). A rose by any other name: Identity and impression management in résumés. *Employee Responsibilities and Rights Journal, 21,* 319-332. DOI: 10.1007/s10672-009-9127-1

Kidwell, R. E. (2004). “Small” Lies, Big Trouble: The unfortunate consequences of résumé padding, from Janet Cooke to George O'Leary. *Journal of Business Ethics, 51,* 175-184. DOI: https://doi.org/10.1023/B:BUSI.0000033611.50841.55

Kim, B. H. (2011). Deception and applicant faking: Putting the pieces together. In G. P, Hodgkinson., & J. K, Ford (Eds). *International review of industrial and organizational psychology 2011* (1st Ed., pp. 239-292). Wiley-Blackwell. DOI:10.1002/9781119992592

Kuhn, K. M. (2014). Selecting the good vs. rejecting the bad: Regulatory focus effects on staffing decision making. *Human Resource Management, 54,* 1-20. DOI:10.1002/hrm.21625

Kuhn, K. M., Johnson, T. R., & Miller, D. (2013). Applicant desirability influences reactions to discovered resume embellishments. *International Journal of Selection and Assessment*, *21*(1), 111-120. DOI: https://doi.org/10.1111/ijsa.12021

Lacroux, A., & Lacroux, M. C. (2022). Should I trust the artificial intelligence to recruit? Recruiters' perceptions and behavior when faced with algorithm-based recommendation systems during resume screening. *Frontiers in Psychology, 13*, 1-13. DOI: 10.3389/fpsyg.2022.895997

Langer, M., König, C. J., Back, C., & Hemsing, V. (2023). Trust in artificial intelligence: Comparing trust processes between human and automated trustees in light of unfair bias. *Journal of Business and Psychology, 38,* 493-508. DOI: https://doi.org/10.1007/s10869-022-09829-9

Lee, N. T. (2018). Detecting racial bias in algorithms and machine learning. *Journal of Information, Communication and Ethics in Society, 16*(3), 252-260. https://doi.org/10.3390/sci6010003

Liu, S. Y. (2020). Artificial intelligence (AI) in agriculture. *IT professional, 22*(3), 14-15. DOI: http://dx.doi.org/10.1109/MITP.2020.2986121

Low, J. (2019). A Pragmatic definition of the concept of theoretical saturation. *Sociological Focus*, *22,* 1–9. DOI:10.1080/00380237.2018.1544514

Lowery, M. R., & Blinebry, A. (2014). Résumés. In T. R, Levine (Eds). Encyclopedia of deception (1st Ed., pp. 1514-1518). Sage Publications.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change, 175*. DOI: https://doi.org/10.1016/j.techfore.2021.121390

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120,* 262-273. DOI: https://doi.org/10.1016/j.jbusres.2020.07.045

Marcoux, A. M. (2006). A counterintuitive argument for résumé embellishment. *Journal of Business Ethics, 63*, 183-194. DOI: 10.1007/s10551-005-2412-5

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics, 160,* 835-850. DOI: https://doi.org/10.1007/s10551-018-3921-3

McCarthy, J. (2007). What is artificial intelligence. Available from 〈http://jmc.stanford.edu/artificial-intelligence/what-is-ai/index.html〉 Accessed 05.09.24.

Mihalcea, A. (2017). Employer branding and talent management in the digital age. *Management Dynamics in the Knowledge Economy, 5*(2), 289-306. DOI: 10.25019/MDKE/5.2.07

Miller, A. (2019). The intrinsically linked future for human and artificial intelligence interaction. *Journal of Big Data, 6*, 1-9. DOI: https://doi.org/10.1186/s40537-019-0202-7

Mishra, H., & Venkatesan, M. (2021). Blockchain in human resource management of organizations: An empirical assessment to gauge hr and non-hr perspective. *Journal of Organizational Change Management, 34*(2), 525-542. DOI: https://doi.org/10.1108/JOCM-08-2020-0261

Mohanty, B., Manipal, A., & Mishra, S. (2023). Role of artificial intelligence in financial fraud detection. *Academy of Marketing Studies Journal, 27*(4). URL: https://t.ly/An_Artificial_Intelligence_Approach_to_Financial_Fraud_Detectionunder_IoT_Environment

Nelson, G. S. (2019). Bias in artificial intelligence. *North Carolina Medical Journal, 80*(4), 220-222. DOI: 10.18043/ncm.80.4.220

Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M. E., Ruggieri, S., Turini, F., Papadopoulos, S., Krasanakis, E., Kompatsiaris, I., Kurlanda, K. K., Wagner, C., Karimi, F., Fernandez, M., Alani, H., Berendt, B., Kruegel, T., Heinze, C., Broelemann, K., Kasneci, G., Tiropanis, T., & Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(3), 1-14. DOI: 10.1002/widm.1356

O'Rourke, J. S. (1995). The ethics of résumés and recommendations: When do filler and fluff become deception and lies? *Business Communication Quarterly, 58*(1), 54-56. https://doi.org/10.1177/108056999505800115

Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis, 30*(6), 1771-1782. DOI: 10.1108/IJOA-07-2020-2291

Paauwe, J., & Boon, C. (2018). Strategic hrm: A critical review. In D. G, Collings., G. T, Wood., & L. T, Szamosi (Eds). *Human resource management: A Critical approach* (2nd Ed., pp. 49-73). New York: Routledge. URL: https://mis.kp.ac.rw/admin/admin_panel/kp_lms/files/digital/Core%20Books/Management%2

0books/Human%20Resource%20Management_%20A%20Critical%20Approach%20(%20PDFDrive%20)%20(3).pdf#page=68

Perreault, W. D. (1975). Controlling order-effect bias. *The Public Opinion Quarterly, 39*(4), 544–551. DOI: https://doi.org/10.1086/268251

Prokopenko, M. (2014). Grand challenges for computational intelligence. *Frontiers in Robotics and AI, 1*. DOI: https://doi.org/10.3389/frobt.2014.00002

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review, 33*, 1-19. DOI: https://doi.org/10.1016/j.hrmr.2022.100925

Russell, J. A., Brock, S., & Rudisill, M. E. (2019). Recognizing the impact of bias in faculty recruitment, retention, and advancement processes. *Kinesiology Review, 8*, 291-295. DOI: https://doi.org/10.1123/kr.2019-0043

Saarijärvi, M., & Bratt, E. L. (2021). When face-to-face interviews are not possible: Tips and tricks for video, telephone, online chat, and email interviews in qualitative research. *European Journal of Cardiovascular Nursing, 20*, 392–396. DOI: 10.1093/eurjcn/zvab038

Saberikamarposhti, M., Why, N. K., Yadollahi, M., Kamyab, H., Cheng, J., & Khorami, M. (2024). Cultivating a sustainable future in the artificial intelligence era: A comprehensive assessment of greenhouse gas emissions and removals in agriculture. *Environmental Research*, *250*, 1-17. DOI: https://doi.org/10.1016/j.envres.2024.118528

Shahhosseini, V., & Sebt, M. H. (2011). Competency-based selection and assignment of human resources to construction projects. *Scientia Iranica*, *18*(2), 163-180. DOI: https://doi.org/10.1016/j.scient.2011.03.026

Shen, J., Chanda, A., D'Netto, B., and Monga, M. (2009). Managing diversity through human resource management: An international perspective and conceptual framework. *The International Journal of Human Resource Management, 20* (2), 235-251. https://doi.org/10.1080/09585190802670516

Soleimani, M., Intezari, A., & Pauleen, D. J. (2022). Mitigating cognitive biases in developing AI-assisted recruitment systems: a knowledge-sharing approach. *International Journal of Knowledge Management, 18*(1), 1-18. DOI: 10.4018/IJKM.290022

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review, 61*, 15-42. DOI: 10.1177/0008125619867910

Trziszka, M. (2023). Artificial intelligence in employee recruitment. *In European Conference on Knowledge Management, 24*(2), 1729-1731. DOI: http://dx.doi.org/10.34190/eckm.24.2.1782

Turing, A. M. (1950). Computing machinery and intelligence. *Mind a Quarterly Review, 59*, 433-460. DOI: https://doi.org/10.1093/mind/LIX.236.433

Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior, 90*, 215-222. DOI: https://doi.org/10.1016/j.chb.2018.09.009

Varma, A., Toh, S. M., & Pichler, S. (2006). Ingratiation in job applications: Impact on selection decisions. *Journal of Managerial Psychology, 21*, 200-210. DOI: 10.1108/02683940610659551

Visvikis, D., Cheze Le Rest, C., Jaouen, V., & Hatt, M. (2019). Artificial intelligence, machine (deep) learning and radio (geno) mics: Definitions and nuclear medicine imaging applications. *European Journal of Nuclear Medicine and Molecular Imaging, 46*(13), 2630-2637. DOI: https://doi.org/10.1007/s00259-019-04373-w

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2021). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management, 33*(6), 1237-1266. DOI: https://doi.org/10.1080/09585192.2020.1871398

Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence, 10*(2), 1-37. DOI: 10.2478/jagi-2019-0002

Wexler, M. (2006). Successful resume fraud: Conjectures on the origins of amorality in the workplace. *Journal of Human Values, 12*(2), 137-152. DOI: 10.1177/097168580601200203

Wood, J. L., Schmidtke, J. M., & Decker, D. L. (2007). Lying on job applications: The effects of job relevance, commission, and human resource management experience. Journal of Business and Psychology, *22*, 1–9. DOI: 10.1007/s10869-007-9048-7

Xu, B., & Margevica-Grinberga, I. (2021). A discourse on innovation of English teaching in China from the perspective of artificial intelligence. *Cypriot Journal of Educational Sciences*, *16*(5), 2313-2323. DOI: https://doi.org/10.18844/cjes.v16i5.6347

Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering*, *2*(10), 719-731. DOI: https://doi.org/10.1038/s41551-018-0305-z

Zhou, Y., Cheng, Y., Zou, Y., & Liu, G. (2022). E-HRM: A meta-analysis of the antecedents, consequences, and cross-national moderators. *Human Resource Management Review, 32*, 1-21. DOI: https://doi.org/10.1016/j.hrmr.2021.100862

Zou, J., & Schiebinger, L. (2018). AI can be sexist and racist—it's time to make it fair. *Nature, 559*, 324-326. DOI: https://doi.org/10.1038/d41586-018-05707-8

Zvi, L., & Shtudiner, Z. (2021). Resume fraud and counterproductive behavior: The impact of narcissism in the labor market. *Journal of Behavioral and Experimental Economics, 93*, 1-8. DOI: https://doi.org/10.1016/j.socec.2021.101715

Annexes

Annex A – Interview Script

Informed consent

Greetings,

my name is Gonçalo Almeida, and I am a 2nd year student on the 'Human Resources Development Policies' course at Iscte - Instituto Universitário de Lisboa. This interview is being carried out as part of my master's thesis and aims to deepen my knowledge of the use of resume fraud.

All information provided during the interview will be treated with the utmost confidentiality. Your name will not be associated with any answer you provide. You are also guaranteed the possibility of cancelling your participation in the academic study at any time during the interview and your data will be deleted at that moment, without any personal harm being caused. I also require an audio and video recording of the interview to facilitate future content analysis.

All responses will be treated with the utmost confidentiality and will only be used in the context of the academic study in question, for the period of time strictly necessary to carry it out.

I would like to thank you for your time and presence during the interview.

Thank you for your co-operation.

Kind regards,

Gonçalo Nobre Martins Almeida

Do you declare that you have understood the content?

Do you authorize the audio and video recording of the interview?

(Sample Characterization)

QA1: Would you introduce yourself and share a bit about your role and experience as a recruiter?

QA2: What is your level of education?

QA3: What is your current occupation/profession?

QA4: How long have you worked in selection?

QA4.1: (If the candidate is not currently working in selection/recruitment): When was the last time you worked in selection?

(Resume Focus – What is most valued in the Resume analysis)

QB1: What do you value in the resumes?

(Experience with Resume Fraud – Types of fraud most commonly found; How are the frauds presented; where on the resume do people tend to commit the most fraud?)

QC1: Have you encountered instances of resume fraud in your career as a recruiter? **(If Yes go to QC2; If No go to QC1.1)**

QC1.1: (If the candidate says they have never encountered resume frauds): What about your colleagues or people close to you? **(If Yes go to QC2; If No, go to QC3.1)**

QC2: If so, could you share a specific example (without disclosing confidential information)? **(If the participant says their colleagues have encountered resume fraud and they not, go to QC4.1)**

QC3: What types of resume fraud do you commonly come across in your role?

QC3.1: (**If the participant says he does not know anyone that have encountered resume frauds)** So, hypothetically, if you were to find resume frauds, where in the resume you think you would be most likely to find it? **(Then go to QC6)**

QC4: When encountering a resume fraud, have you noticed if it tends to be a standalone issue or if it is often combined with other frauds?

QC4.1**: (If the participant says their colleagues have found resume frauds)** When encountering a resume fraud, did your colleagues noticed if it tends to be a standalone issue or if it is often combined with other frauds?

QC5: What types of fraud do you, or your colleagues, find most difficult to identify in resumes?

QC6: **(Only ask if the candidate says that never encountered any resume fraud)** What types of resume fraud do you think could be the most find most difficult to identify?

I would like to express my sincere gratitude for your valuable participation in our recent interview. Your insights and experiences have provided invaluable perspectives on the challenges and complexities associated with resume fraud in the recruiting field. Your contributions will significantly enhance the depth and quality of our research.

Is there anything else you would like to add or any final thoughts on the topic?

Thank you for your time and expertise. Once again, I reiterate that the data is strictly confidential and will only be used within the scope of the study. I look forward to the opportunity to share the findings with you and the broader community. You can send me your email in the chat, or you can contact me by e-mail (gnmaa@iscte-iul.pt) if you have any questions or would like information about the results of the interview.

Annex B – Experimental Conditions

Experimental Condition “Control Resume” – CV Control

Spencer Evans

I'm a 30-year-old who has 8 years of experience in the IT field. Already worked at 3 firms and have accumulated much knowledge. I am a very organized person who likes to never let to tomorrow what can be done today. I am highly motivated to work with great colleagues, to grow in the organization and to achieve greatness together. I can help a business stay in order and perfectly organized.

Contacts

(+351) 21 124 8796
spencerevans__1994@gmail.com
linkedin.com/in/spencer-evans-4565489902
Lisbon, Santa Justa Street, 110

Soft Skills

Willingness to learn and improve
Knows how to listen
Organized
Good communication
Good Stress Management
Creativity and Problem Solving
Flexibility

Hard Skills

Performance with C and C++
Excel proficiency
Computer Skills

Languages

English
Hindi
Spanish

Academic Background

Bachelor's degree in Informatics Engineering at University of Lisbon I 2014 - 2017
Graduation Average: 15/20

Master’s degree in Informatics and Computer Engineering at Higher Technical Institute (IST) I 2018 - 2020
Graduation Average: 16/20

Past experiences

Software Engineer at Sonae | 2016- 2018
Software Programmer at HashiCorp | 2018- 2022
Cyber Risk professional Okta | 2023 - to date

Other Activities

Gym Enthusiast
Reading
Vounteer work at SosAnimal | 2022- 2023

Experimental Condition “Mirrored Resume” – CV Mirror

Cedar Smith

I'm a 34-year-old with experience in the finance and accountability area that can help your business grow. I worked with the best firms. In addiction to my voluntary work I am capable of creating a psychological safety environment. With skills like emotional intelligence, computer skills and creativity I will make sure the employer's goals are achieved while helping all my coworkers achieve greatness in the organization.

Contacts

(+351) 21 018 4527
cedarsmith_1990@gmail.com
linkedin.com/in/cedar-smith-849027495
Lisbon, Admiral Reis Avenue, 261

Soft Skills

Willingness to learn and improve
Ethics at work
Knows how to listen
Spirit of Adventurer and challenger (love to be outside of my comfort zone
Good communication
Leadership Spirit

Hard Skills

Data Analytics
Analysis Skills
Excel Experience
Simplify Expertise

Languages

English
German
Spanish

Academic Background

Bachelor's degree in Accounting at DePaul University | 2009-2013
Graduation average: B/A+

Master's Degree in Finance & Investment at Berlin School of Business and Innovation | 2019 - 2021
Graduation average: B+/A+

Past experiences

Accounting Assistant at Allstate Corp | 2011-2012
Accounting and finance technician at Munich Re | 2012-2015
Corporate Finance Analyst at Selby Jennings | 2016 - 2021
Leader of the Finance team at Capital One | 2022 - to date

Other Activities

Jogging
Sports Enthusiast
Voluntary work at All Hands and Hearts | 2015-2018

Experimental Condition “Fraudulent resume with invented degree fraud” – CV Fraud 1

Riley Taylor

I am a 30-year-old with a degree in Electrical and Computer Engineering and a Master's in Information and Computer Sciences at Princeton. I would be an asset to any organization, as I have excellent computer and programming skills which allow me to be a good worker. As an undergraduate I had experience with many Internships in different organizations. I will strive to accomplish the organizations goal while doing my best to progress in my career.

Contacts

(+351) 21 901 6994
rileytaylor_1994@gmail.com
linkedin.com/in/riley-taylor-782348694
Lisbon, Carmo Street, 103

Soft Skills

Good Communicator
Ability to deliver results under pressure (good time management)
Willingness to learn and improve
Colaborative Spirit
Ethics at work
Critic Spirit

Hard Skills

Computer Skills
Excel Proficiency
Data Analytics
Pascal Knowledge

Languages

English
Portuguese
Spanish

Academic Background

Bachelor's Degree in Electrical and Computer Engineering at Maastricht University| 2014-2018
Graduation average: B/A+

Master's Degree in Software Engineering at Princeton| 2020-2023
Graduation average: B/A+

Past experiences

Internship at Cisco as software engineer | 2019-2020

IT Technical Support at Roff | 2020-2021

Internship at Valtech as a software programmer | 2022-2024

Other activies

Sports Enthusiast
Blog Writter
Voluntary work at Food Bank | 2022-to date

Experimental Condition “Fraudulent resume with invented organizations fraud” – CV Fraud 4

Shelby Dominique

I'm a thirty five-year-old with a lot of experience in Informatic Technology. I saw how many organizations operate and what mistakes they did so I can be sure to never do it. I love to travel to get out of my comfort zone, I love challenges and I am willing to learn and improve even more. I want to work in a organization that gives me a chance to grow with challenging goals and a good remuneration. I believe I can be of help to any business. I helped many firms grow with consultancy and systems and app development. I am highly motivated and have great potential.

Contacts

(+351) 21 054 6215
shelbydominique_1989@gmail.com
linkedin.com/in/shelby- dominique-5739348506
Lisbon, Portas de Santo Antão Street, 188

Soft Skills

Willingness to learn and improve
Time Management (results under pressure)
Knows how to listen
Spirit of Adventurer and challenger (love to be outside of my comfort zone
Good communication
Creativity

Hard Skills

C and C++ Expertise
Java Expertise
Computer skills
Excel knowledge

Languages

English
French
Portuguese
Spanish

Academic Background

Bachelor degree in Computer Engineering at Georgia Institute of Technology | 2010-2014
Graduate Average: B/ A+

Master’s degree in Computer Science at University of California, Berkeley | 2016 -2018
Graduate Average: B/ A+

Past experiences

- IT HelpDesk at NexInnovate Solutions | 2009 -2010
- IT Business Partner at Global Data SC | 2011-2014
- IT Consultant at Tata Consultancy Services| 2014- 2016
- IT Project Manager at Infosys | 2017- 2023
- PHP Developer at Appen | 2024 - to date

Other activites

Skydiving
Travelling
Bungee jumping
Volunteer work for Habitat for Humanity | 2020 - 2022

Experimental Condition “Fraudulent resume with exaggerating languages fraud” – CV Fraud 2

Sidney Wallace

I'm a 35-year-old highly skilled and results-driven IT professional with more than 15 years of expertise in software development, network administration, and cybersecurity. I have a proven track record of delivering innovative IT solutions and driving business success through technology initiatives. Due to my adventurous spirit I have travelled to many countries and worked with different cultures. Since then I strongly developed my language skills. I believe I can be an addiction to any global organization.

Contacts

(+351) 939 011 952
sidneywallace_1989@gmail.com
linkedin.com/in/sidney-wallace-860476035
Lisbon, Garrett Street, 121

Soft Skills

Willingness to learn and improve
Ethics at work
Knows how to listen
Analytical skills
Good communication

Hard Skills

Java Script Expertise
Java Experience
Pascal Proficiency
GO Competence

Languages

Chinese
Danish
English
French
Germany
Japanese
Spanish

Academic Background

Bachelor's degree in Computer Science and Engineering at Massachusetts Institute of Technology | 2017-2021
Graduation average: B+/A+

Master's Degree in Software Engineering at University of Oxford | 2021 - 2023
Graduation average: B/A+

Past experiences

IT Risk intern at Larsen & Toubro Infotech | 2009- 2011
IT Support at Hexaware Technologies | 2011 - 2014
Outsystems Developer at Mphasis | 2015 - 2021
IT Project Manager at Mindtree | 2021 - to date

Other Activities

Blog Writter
Swimming
Volunteering at Portuguese Red Cross with blood donation and elderly homecare | 2019 - to date

Annex C – Survey Script

Start of Block: Pre-Survey

Informed Consent Dear participant, my name is Gonçalo Almeida, and I am a 2nd year student in the master's Programme in "Human Resources Development Policies" at Iscte - Instituto Universitário de Lisboa. This survey is being carried out as part of my master's thesis which aims to investigate CV analysis. This survey will take approximately 12 minutes to complete. You are guaranteed the option to withdraw your participation in this study at any time, without any consequences. All responses will be treated with the utmost confidentiality and will only be used within the context of this academic study. Thank you very much for your time and cooperation.

Should you wish to contact me, I am available at gnmaa@iscte-iul.pt. Gonçalo Nobre Martins Almeida

End of Block: Pre-Survey

Start of Block: Filtering

Do you have current or previous experience in reviewing and evaluating CVs?

○ Yes, I have current or past experience in CV screening.

○ No, I do not have experience in CV screening.

○ I do not have any experience in CV screening, but I am studying for a degree or a master's in human resources management

End of Block: Filtering

Start of Block: Filtering Ending

Display This Question:

If Do you have current or previous experience in reviewing and evaluating CVs? = No, I do not have experience in CV screening.

Unfortunately, you do not match the specific criteria we are looking for in this survey. However, if you know someone who has experience with CV screening, either currently or in the past, we would greatly appreciate it if you could share this survey with them.

Skip To: End of Survey If Unfortunately, you do not match the specific criteria we are looking for in this survey. However,... Displayed

End of Block: Filtering Ending

Start of Block: Job offer

IT Job Offer
Please consider the following job vacancy. You will then be asked to assess some CVs for this position:

QuantumHorizon Solutions · European Union
Remote · Full time · 201-500 Employees · Telecommunication services activities
Skills: Technical support, IT provisioning, People Development, IT operations management, Technical support.

QuantumHorizon Solutions is a big firm with headquarters in Netherlands, with 4 international hubs with employees working, remotely, from +20 countries around the world. We aim to provide the best solutions for networks and communications to every business in this new digital era. We were founded in 1984. Since 2016, the firm showed a tremendous growth, and we are one of the fewer firms who are positively implementing AI in the firm's operations in the global market.

We are looking for a Head of ITS team to oversee and manage the back-office infrastructure and other important operations in the corporate environment. You would also be responsible for the company's internal information technology systems, processes. We are looking for someone with strong experience in enterprise architecture work, and that understands the requirements of the operational IT work and have superior project and people management skills.

Your primary responsibilities will include:

- Assessing departmental needs and enhancing productivity;
- Evaluating processes, technologies, and vendors for improvement;
- Managing essential IT infrastructure and procurement;
- Directing business initiatives and projects;

- Ensuring business-critical IT operations;
- Monitoring hardware and software inventory;
- Developing IT continuity plans to prevent downtime;

Qualifications required:

- Minimum 2 years of experience as IT engineer or similar role, with a focus on managing IT operations and systems;
- Proficiency in written and verbal English and Spanish, with an upper-intermediate level of English;
- Strong cross-functional collaboration skills;
- Excellent verbal and written communication skills;
- Strong analytical and problem-solving abilities.

End of Block: Job offer

Start of Block: Little Introduction

During the next segments we will present you with a number of CVs that you should evaluate, for the former job vacancy, in many aspects. You can use all the means you would use when doing a CV screening, even outside of the survey.

End of Block: Little Introduction

Start of Block: CV Control

CV Control (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Control

Start of Block: CV Mirror

CV Mirror (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Mirror

Start of Block: CV Fraud 1

CV Fraud 1 (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Fraud 1

Start of Block: CV Fraud 2

CV Fraud 2 (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Fraud 2

Start of Block: CV Fraud 3

CV Fraud 3 (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Fraud 3

Start of Block: CV Fraud 4

CV Fraud 4 (image)

Evaluate the former CV characteristics from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Academic qualifications	○	○	○	○	○	○	○
Professional experience	○	○	○	○	○	○	○
Soft skills	○	○	○	○	○	○	○
Hard skills	○	○	○	○	○	○	○
Languages	○	○	○	○	○	○	○
Other activities	○	○	○	○	○	○	○
Clarity and presentation of resume	○	○	○	○	○	○	○

To which extent, from 1 (does not match at all) to 7 (Perfect Match), do you find these statements about the former CV, true?

	1	2	3	4	5	6	7
Claimed work experience that they do not actually have	○	○	○	○	○	○	○
Claimed overlapping work experiences	○	○	○	○	○	○	○
Invented degrees they do not have	○	○	○	○	○	○	○
Invented higher education institutions	○	○	○	○	○	○	○
Included things that were exaggerated	○	○	○	○	○	○	○
Suppressed information that may not look favorable	○	○	○	○	○	○	○

Evaluate the former CV, in general, from 1 (Inadequate) to 7 (Exceptional)

	1	2	3	4	5	6	7
Overall Impression	○	○	○	○	○	○	○

What is the probability of selecting the candidate to an interview, from 0 to 100%?

	0 10 20 30 40 50 60 70 80 90 100
Interview Probability	

End of Block: CV Fraud 4

Start of Block: Demographic Characteristics

What is your age?

____

What is your Nationality?

○ Specify in the item box

____

○ Prefer not to say

Which gender do you identify most?

- ◯ Man
- ◯ Woman
- ◯ Non-binary
- ◯ Other, specify in the item box ____________________
- ◯ Prefer not to say

For how long have you been working with CV Screening? / Studying for a degree or master's in human resources management (please answer in years)

____

What is your education level?

- ◯ Less than Highschool
- ◯ Highschool or equivalent
- ◯ Bachelor's Degree
- ◯ Post-Graduation
- ◯ Master's Degree
- ◯ Doctorate's Degree (PhD)
- ◯ Prefer not to say

End of Block: Demographic Characteristics

We thank you for your time spent taking this survey.
Your response has been recorded.