ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Thesis for MSc Economics and Business, specialisation Behavioural Economics

From Humans to Machines: Can Artificial Intelligence Outsmart Human Job Applications?

Adorján Bárány (659019)

Supervisor: dr. Sophie van der Zee

Second assessor: dr. Jan Stoop

23 June 2023

"The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam."

Abstract

The present study aims to investigate the impact of artificial intelligence (AI) on candidates' employment prospects, specifically by examining people's perceptions of a ChatGPT-assisted cover letter. This is a topic of considerable relevance, as imperfect information already characterises job applications. With the recent technological progress that the public release of ChatGPT meant, AI might provide an even more efficient tool for deception. This can be heavily detrimental to a firm, as human resources as they key drivers of today's economic progress, and therefore a subpar hiring decision can be very costly. The data collection involved 128 participants who rated both cover letters for hiring likeliness and offered starting salary. The data was analysed using paired samples t-tests and linear regression models, considering control variables such as age, education level, and hiring experience. The main findings point towards the ChatGPT-assisted cover letter having a clear edge over the human-written one. It received a 7.10% higher hiring likeliness rating and a 6.62% higher offered starting salary as well. These findings suggest that the use of AI does increase the chances of employment for an applicant and questions the effectiveness and the validity of the hiring processes in place at most of the companies.

Keywords: ChatGPT, AI, deception, workplace.

Table of contents

Table of contents **4**

I. Introduction **6**

II. Literature Review **9**

II/A. The advent of artificial intelligence *9*

II/B. The issue of asymmetric information in hiring *12*

II/C. Deception during the job application process *13*

II/D. The importance of finding the right candidate *15*

II/E. The added value of the study at hand *16*

III. Methodology **18**

III/A. Pilot experiment *18*

III/B. The revision of the experimental design *19*

III/C. Experimental design *19*

III/D. Sample *20*

III/E. Procedure and stimuli *22*

III/F. Analysis *24*

III/G. Ethical considerations *26*

IV. Results **27**

IV/A. Descriptive statistics *27*

IV/B. Statistical analysis *29*

IV/C. Content analysis ... *33*

V. Discussion ... **35**

V/A. Main results ... *35*

V/B. Limitations ... *35*

V/C. Implications ... *37*

VI. Conclusion ... **38**

VII. References ... **40**

VIII. Appendix ... **54**

Appendix A ... *54*

Appendix B ... *55*

Appendix C ... *62*

I. Introduction

The question of whether computers can think like humans or not has been a prevalent topic of discussion since the pioneering work of the renowned computer scientist Alan Turing more than 80 years ago (Turing, 1950). Consequently, it is no surprise that opinions on artificial intelligence (AI) range from considering utilising its capabilities and mitigating the risks connected to it the main challenge that society will face in the near future (Makridakis, 2017), all the way to the more extreme viewpoint of it being the final invention of humanity (Barrat, 2013). According to Stephen Hawking (2017), both ends on the spectrum are plausible:

The rise of powerful AI will be either the best or the worst thing ever to happen to humanity. We do not yet know which.

When the term AI is mentioned, our minds often gravitate towards how it is portrayed in popular culture, for example as seen on the cinema screen, where humanity either finds itself enslaved by intelligent machine overlords or facing the looming threat of extinction (Gurkaynak et al., 2016). Consequently, it is paramount to emphasise that AI is a multifaceted technology with many layers and a myriad of potential applications, which includes the "intelligent" assistants like Apple's Siri that we carry around every day in our pockets and potentially life-changing technologies alike (Urban, 2015). Moreover, it is imperative to establish a precise understanding of the term 'artificial intelligence' prior to proceeding with the research. In line with scholarly consensus, this paper adopts the definition provided by Kaplan and Haenlein (2019), who describe AI as follows: *"a technology system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"*. By adopting this widely accepted definition, the ensuing discussion can be grounded in a shared conceptual framework.

A notable advancement in recent times has been the introduction of large language models (LLMs) such as ChatGPT that took Natural Language Processing (NLP) to a new level (Min et al., 2021), and are able to comprehend and generate language that closely resembles human communication (Alshater, 2022). The name already signalled forward-thinking and change, as

GPT stands for “Generative Pre-trained Transformer” (Wiggers & Stringer, 2023). According to Sam Altman, co-founder and CEO of Open AI, the parent company of ChatGPT, we should expect the magnitude of the revolution being on par with the release of the first iPhone 16 years ago (Bello, 2023). However, it is not only the creators of the tool who are expecting a large-scale change as a result of the release of ChatGPT, and more broadly, AI in general (Posner & Fei-Fei, 2020). This is an especially relevant field to research, after the best-known LLM currently available, ChatGPT (Gruetzemacher, 2022), set a new record for reaching a million visitors in only five days subsequent to its launch in November 2022 (Milmo, 2023). By February 2023, the website was globally known and had over 100 million active users (The Economist, 2023a). The usage numbers clearly show that the technological advancements have been recognised not just by academics and professionals, but everyday people as well. This underlines a clear advantage of the service, namely that the website is freely accessible to anyone. Building on the surging relevance of ChatGPT, this study focuses on this field within the context of AI, and aims to examine the impact of the recent drastic technological progress of LLMs.

There are numerous use cases of ChatGPT. This is partially fuelled by its ease of use and its wide accessibility. Companies are eager to enhance their own productivity by utilising its data-processing and analytical capabilities (Alshater, 2022; Rodney et al., 2019). Other than business usage, ChatGPT has already been made use of in other facets of life, such as for educational purposes (Azaria, 2022; Kasneci et al., 2023) or in the healthcare industry (Elkassem & Smith, 2023; Yang et al., 2023). However, there are already documented examples of malicious ChatGPT use, such as students handing in assignments written by the AI (Ventayen, 2023). This resulted in a growing concern in the field of academia regarding the correct evaluation of the capabilities of students, and thus the integrity of the currently used assessment methods (Anders, 2023; Cotton et al., 2023; Kasneci et al., 2023; King & ChatGPT, 2023; Susnjak, 2022). Consequently, conducting further research is paramount into what implications LLMs such as ChatGPT might have on plagiarism and deception, especially in stressful, high-stake environments where such practices are more common (Ventayen, 2023). Workplaces, and particularly job applications are such scenarios. Consequently, the use of deception during the hiring process is already prevalent (Feldman et al., 2002; Feldman & Weiss, 2006; Melchers et al., 2020; Robinson et al., 1998; Roulin et al., 2015; Roulin et al., 2016; Roulin & Krings, 2016; Roulin & Bourdage, 2017; Wood et al., 2007). These deceptive practices can have a strong negative impact on the hiring effectiveness of recruiters (Knouse et al., 1988; Roulin et al., 2016). Academic and HR professionals are in agreement on the fact that gathering correct information on the skills, qualifications and motives of a given candidate is difficult due to the imperfect information that characterises job application processes (Carranza & Pimkina, 2017). It is therefore imperative to study how novel technologies such as ChatGPT might change the landscape of job applications as it opens up new possibilities of deception.

This a considerable issue, as hiring the right applicant for a job vacancy is critical for organisational success. Selecting the right candidate is not only a time-consuming process, but it also requires a significant number of resources, including financial and human capital. Moreover, the recruitment procedure suffers heavily from imperfect information, which makes finding the ideal fit for the company difficult (Carranza & Pimkina, 2017; Falk et al., 2013; Finkin, 2001). The nature of the situation provides an opportunity for deception, which poses a serious threat to the effectiveness and the validity of the process (Roulin et al., 2016). A bad hire can be costly for an organisation in terms of productivity, time, turnover rate and morale (Cable & Judge, 2017; Hausknecht, et al., 2004). Consequently, conducting research on hiring effectiveness and best practices is beneficial to all firms, as the already problematic topic of assessing candidate competence can become impossible due to the difficulty of distinguishing human-written text from that generated by ChatGPT (The Economist, 2023b).

These are very relevant topics today, given the rapid changes and the increased competitiveness in the global economy and the labour landscape (Knouse et al., 1988). With the advancements in the field of AI, discussions surrounding the future of work have intensified (Dunlop, 2016). The already prominent role of AI in the workplace is only expected to grow: 39% of companies are already using artificial intelligence in their recruitment practices and this number will double over the coming years (van Esch et al., 2021). The true power of LLMs, however, is largely yet to be discovered and firms find themselves at a crossroads regarding whether to adopt or restrict the usage of such tools in the workplace (Bloomberg, 2023). While the benefits of using AI in these processes are numerous, such as reducing human bias and increasing efficiency, there is also concern that candidates may use AI to deceive potential employers during the application process, especially with the emergence of sophisticated LLMs chatbots such as ChatGPT. In other words, the playing field has been tilted in a segment of professional environments where deception is already ubiquitous.

Building on the already existing difficulties in the hiring process, the well-documented prevalence of candidates misrepresenting themselves during job applications and the potential worsening of effective hiring through the malicious usage of AI; this paper will examine the role that LLMs technologies play and might play in the future in the context of deception in the workplace. The abovementioned reasons underline the importance of the current study, as there is a significant need for a comprehensive analysis of people's perceptions of job applications written by artificial intelligence and their respective success rate, when compared to human-written counterparts. In order to answer the question: *"are job applications written with the aid of artificial intelligence more likely to succeed than their human-produced counterparts?",* the current paper aims to bridge the gap between the fields of deception research, the job application and the hiring process, as well as the advent of AI in connection to the public release of LLMs such as ChatGPT. Although the topics by themselves are not novel, the relationship between them has changed. Due to the ability of ChatGPT to generate human-like content in seconds, there is a very realistic possibility that this piece of technological progress will impact many other areas of life, and therefore it is imperative to study the interdisciplinary developments it might bring.

II. Literature Review

II/A. The advent of artificial intelligence

Considering the pace at which its user base grows at, the relevancy of researching ChatGPT cannot be overstated. It reached a million visitors in a record time of only 5 days following its November 2022 launch and had over 100 million active users in February already (Milmo, 2023; The Economist, 2023a). Although the term 'Artificial Intelligence' was already introduced in 1955 by John McCarthy who described it as intelligent computer programmes

(Gurkaynak et al., 2016), the current pertinence of the topic stems from the recent public release of Large Language Models (LLMs), such as ChatGPT, that have the potential to "transform humans' relationship with computers, knowledge and even with themselves" (The Economist, 2023a). The research of Alshater (2022) examined the benefits and drawback connected to such models, more specifically to ChatGPT. The paper states that advanced AI chatbots offer advantages such as increased efficiency and speed, greater flexibility, improved consistency, accuracy and objectivity.

Proponents of LLMs often highlight its potential to develop output that is "indistinguishable from human-written text" (The Economist, 2023b). However, the benefits of AI are multifaceted. It can enhance productivity by providing assistance with low-value-added activities, so that the human labour force can focus on high value tasks (Rodney et al., 2019). It can also handle significantly larger datasets than humans would be able to analyse, thus leading to streamlined and cost-effective processes (Rodney et al., 2019). It can be used for educational purposes, for example to explain concepts on a multitude of levels or to quickly solve mathematical problems (Azaria, 2022; Kasneci et al., 2023). There are a number of potential healthcare applications of ChatGPT as well, such as medical imaging (Yang et al., 2023) and radiological reporting (Elkassem & Smith, 2023).

Even in its current, arguably imperfect form, artificial intelligence has received an enormous amount of attention recently from professionals, members of academia and the media alike, with its proponents considering it a life-changing piece of technological progress (Posner & Fei-Fei, 2020). According to Makridakis (2017), the transformation it holds within itself could be more substantial than that of the Industrial Revolution. It has the potential to tackle the key issues of humanity currently, such as diseases by the development of new drugs or climate change by designing new materials (The Economist, 2023a). Consequently, its supporters are campaigning for openness both in mindset and in regulations (Dirican, 2015).

Nevertheless, there is scepticism regarding the notion that artificial intelligence can comprehensively address all of the challenges faced by humanity. There are two categories of doubt that lead to this division on the topic. Firstly, a smaller group lacks faith in the technology itself, and consider AI to be human skill and knowledge “re-formatted and re-cycled” with the help of unconscious machines that are by themselves incapable of learning (Gurkaynak et al., 2016, p. 750). This signals that there is scepticism whether computers will ever be able to think for themselves (Makridakis, 2017) and even if they are, there is more to life than the Cartesian supremacy of logic and mathematics (Ormandy, 2015). Furthermore, even if we accept the idea of sophisticated AI, it still does not come without limitations, such as reliance on data availability and quality as well as carrying a potential for misuse and an overly-technology dependent future (Alshater, 2022). Mostak (2023) emphasised a limitation connected to the common idea that the main focus of AI research should be training machines to formulate ideas and make decisions on their own (Makridakis, 2017). This concern stems from the fact that the technology itself is developed by humans, therefore it is fallible: “just like the humans who build AI algorithms, AI can be biased” (Mostak, 2023).

The second source of distrust towards AI lies in the belief that its triumph might mean the end of human supremacy (Makridakis, 2017). Contrary to the previous group of academics and professionals, who contest computers’ ability to formulate thoughts, the basis of this idea stems from the assumptions that computers will come close to human intelligence as soon as over the course of the next two decades (Makridakis, 2017). Consequently, the worry might arise in some that AI will render a significant segment of the jobs available today obsolete (Brynjolfsson & McAfee, 2015) and therefore they urge governments to impose regulations to mitigate the risks that AI holds within itself (Clarke, 2019). The thought of technological progress causing unemployment has already been formulated in the 1800s by the Luddites in Great Britain; however, the fear is rather novel that new jobs will not be created in parallel, considering that the range of tasks that machines can carry out now extend beyond unskilled ones with the emergence of LLMs such as ChatGPT (The Economist, 2023a).

Naturally, many argue for the irreplaceability of human intellect, at least in high-end occupations. While on one hand this would certainly increase social inequality, on the other hand an interesting thought to consider is one of the famous French economists, Say’s view on cars. He famously wrote in the 19th century that no machine would ever be able to exert performance akin to that of the worst horse (Say, 1843; as cited in Makridakis, 2017). Nobel laureate Wassily Leontief presented a similar idea in 1983, comparing humans to horses (Brynjolfsson & McAfee, 2015). Building on this concept, Brynjolfsson and McAfee (2015) recognise the possibility that human labour will not remain the key driver of productivity and consequently decline in relevance.

Econometric models suggest a variety of numbers in terms of jobs at the risk of automation, ranging from 47% in the case of the USA to only 9% for OECD member states (Hunt et al., 2022). However, it is important to keep in mind that the industrial revolution and digitalisation in fact decreased unemployment (Makridakis, 2017); and therefore, it can be argued that technological progress does not necessarily results in higher unemployment levels (Whitley & Wilson, 1982).

Additionally, there is a segment of experts who declare a certain level of existential risk in connection with AI. Almost half of the AI researchers who partook in a 2022 survey believed that there is at least 10% chance of "extremely bad" impact, which the study defined as on par with human extinction (The Economist, 2023a). According to the paper, the general root of this fear is not necessarily that AI will have malicious aspirations, but rather that the aims of it will not align with that of their creators.

II/B. The issue of asymmetric information in hiring

The job application process suffers heavily from imperfect information (Carranza & Pimkina, 2017). This asymmetry stems from the fact that on the one side, the employer does not have a clear understanding of the candidates' capabilities, while on the other side, the candidate does not know the exact responsibilities they would need to take on, their day-to-day tasks and often not even the financial compensation (Falk et al., 2013; Finkin, 2001). In such high-stake situations, the job applicants will often utilise impression management tools to create a controlled image of their own capabilities in the prospective employer's eyes (Knouse et al., 1988).

When applying for a position, candidates have to persuade the hiring managers that they are more competent and higher performing than the others (Knouse et al., 1988), which in the case of asymmetric information can be done via signalling (McCormick, 1990). Usually, the first contact between an applicant and the recruitment department of an organisation is through the resume and the cover letter (Pennington et al., 2014), which already serves as a tool of the former to convince the latter to grant them a place in the next round of the process (McDowell, 1987), which is usually an interview. Papers on the topic urge applicants to pay careful attention to their resumes and cover letters in order to make a positive first impression (Knouse et al., 1988). A good cover letter is crucial for success, as companies receive up to tens of thousands of applications, and therefore firms will have to reject most of the candidates based off of that and only invite a small percentage to an interview (Waung et al., 2017).

From the recruitment standpoint, the hiring team aims to predict job performance through the skills and qualifications of the candidate, for which information they often have to rely on how the applicants present themselves (Roulin et al., 2015; Twyman et al., 2018). Although the findings Gneezy (2005) of show that not all people are willing to lie to achieve their preferred outcome; in a Darwinian manner rational human will try their best to use every technique and tool at their disposal to increase their chances of employment (Roulin & Krings, 2016). Consequently, it is paramount to conduct research on how AI might be used to write job applications to uncover whether this poses a threat to the validity of the system.

Furthermore, research has shown that many believe that a certain level of exaggeration is advisable (Knouse et al., 1988) and expected by the hiring managers, due to the frequency of it happening (Robinson et al., 1998). In other words, truthful candidates could be at a disadvantage similarly to those who do not wish to deceive the recruiters by using AI to enhance their applications, provided that this would increase their chances of receiving a job offer.

II/C. Deception during the job application process

Deception is a complex social phenomenon that is prevalent in everyday interactions (Debey et al., 2015). Research suggests that there is a connection between deception and self-presentation, and that people tend to lie more often when they aim to appear competent or likeable (Feldman et al., 2002). Professional environments are often characterised by these two factors. The job application process is a critical aspect of organisational recruitment as it helps to identify whether the applicant is an optimal match for the position (Ryan & Tippins, 2004). The job application process, especially the first step as it usually consists of a resume and a cover letter (Knouse et al., 1988; Pennington et al., 2014), is a high-stakes, self-presenting scenario, which means that candidates have both motive and opportunity to falsify information to their own benefit.

Accordingly, it is not surprising that it is relatively well-documented that applicants often delve into deceptive practices (Wood et al., 2007). According to a study by Feldman and Weiss (2006) job applicants are likely to engage in deceptive behaviour to create a positive image of themselves during job interviews. The paper suggests that recruiters are only somewhat effective in detecting these impression management techniques (Feldman & Weiss, 2006). Melchers et al., (2020) came to similar conclusions in terms of the prevalence of deceptive self-presentation during the job application process. With the routine occurrence of misrepresentation, employers should be aware of such practices and develop tactics to detect it (Melchers et al., 2020). There is also evidence of frequent applicant faking in personality tests (Roulin & Krings, 2016).

It is however important to note that not only applicants can employ deception. Norton et al. (2004) found that people will often use casuistry when justifying their hiring decisions. They defined this phenomenon as the practice of usage of seemingly logical and moral, but untrue reasoning to legitimise their unethical criteria. This can be common in such scenarios, as both parties have an incentive to appear in a favourable light. Candidates will try to convince employers to hire them, while recruiters will try to justify their own decisions in a socially acceptable way and mask their biased decisions.

The extent of faking is difficult to measure this accurately. Self-reported studies (either built on hypothetical scenarios or past behaviour) and field experiments differ in estimates. Additionally, another issue stems from the unclear concept of what constitutes deception, for example if a candidate omits a detail from their application, it is often impossible to judge whether it was because they did not deem it relevant or because they wanted to conceal that piece of information (Wood et al., 2007). Consequently, precise statistics are unavailable;

however, low estimates suggest that anywhere between 40 and 70% of applicants misrepresent themselves on their CVs (Wood et al., 2007). Higher estimates put this number in the region of 81 to 99% (Roulin & Krings, 2016). Surveys among recent college graduates suggest that the willingness to deceive is even more prominent: in one, almost all respondents are willing to tell at least one false statement to get a job and over 40% of them have admitted to already doing so (Wood et al., 2007); while in the other, 90% of the sample stated they are willing to misrepresent personal information (Robinson et al., 1998).

Social validation can be another important reason behind rational candidates submitting deceptive job applications, aside from to boost their own chances. This phenomenon is described by Cialdini and Goldstein (2002) as the tendency of people to follow and mimic the behaviour of their peers. Accordingly, the more commonplace deceptive practices in the workplace get, the more it encourages others to take part in them. Additionally, a certain level of exaggeration in terms of skills and expertise is not only allowed but even encouraged by some (Knouse et al., 1988). Many recruiters are aware of the techniques that candidates employ, such as deception and impression management. Frequently, they aim to adjust their hiring decisions accordingly (Knouse, et al., 1988) and possibly detect deception through tools such as integrity tests, behavioural consistency checks, and situational judgment tests (Melchers, et al., 2020). However, their efforts are only moderately successful, as studies continue to prove the frequent presence of deception during job applications.

II/D. The importance of finding the right candidate

The gravity of human capital has increased over the past decades, to "arguably the most important asset that an organisation can have" (Furnham & Palaiou, 2017, p. 71). The reason behind this is that people are the drivers behind intangible assets, which today account for the majority of the value of a business enterprise. Consequently, the weight of effective recruitment and hiring has grown (Dineen et al., 2002; Knouse et al., 1988; van Esch et al., 2021).

However, the key importance of finding the right candidate for organisational success is not a newfound piece of information. Subpar hiring decisions and ineffective selection processes can be expensive for businesses and have a detrimental effect on their profitability by increasing attrition and decreasing productivity (Cable & Judge, 1997; Hausknecht et al., 2004). Hiring the right candidate is essential for creating a positive work environment and fostering employee engagement, satisfaction, and commitment (Kristof, 1996). Employees that are a good fit for their position are more likely to be content with their employment, stay loyal to the company, and deliver higher-quality work (Judge et al., 1995). Furthermore, organisations that hire the right candidate can benefit from increased innovation and creativity (Goncalo & Staw, 2006). In conclusion, hiring should be a priority to any company, as it is one of the key drivers of organisational success today.

Even though signalling one's qualifications and suitability for a job is of utmost importance in the hiring process for a candidate (McCormick, 1990), empirical research indicates that recruiters only possess limited information regarding the mechanisms and nuances of it (Celani & Singh, 2011). Although there is extensive research on hiring, HR managers have restricted knowledge of the best practices and strategies (Ryan & Tippins, 2004). This deficiency in information is a general issue in recruitment, as it can potentially hinder the accurate assessment of candidates' competencies and fit for the job. Additionally, hiring a candidate who has misrepresented themselves during the recruitment process or falsified information on their application can have substantial negative effects on the firm in general (Wood et al., 2007). These factors further underline the importance of the applicant selection process in relation to organisational success (Knouse et al., 1988; van Esch et al., 2021).

II/E. The added value of the study at hand

Deception during job interviews is a prevalent phenomenon that can have a significant impact on hiring decisions (Babcock, 2003). Applicants use deception as a rational strategy to increase their chances of being hired (Feldman et al., 2002; Feldman & Weiss, 2006; Knouse et al., 1988; Melchers et al., 2020; Robinson et al., 1998; Roulin et al., 2015; Roulin et al., 2016; Roulin & Krings, 2016; Roulin & Bourdage, 2017; Wood et al., 2007). Applicant faking is an important issue as it can affect the ranking of the candidates and the potentially threatens the validity of the selection process (Roulin et al., 2016).

However, with the wide availability of LLMs that are able to deliver text that is indistinguishable from human-written ones (The Economist, 2023b), the playing field has been changed perhaps forever. The extremely fast response rate and the remarkable capabilities of LLMs can easily be abused to create a false first impression of a candidate, as it can perform white-collar tasks such as generating cover letters or resumes based on a few pieces of information within seconds (The Economist, 2023a). This opens up new avenues for deception in a segment of life that was already plagued by it (Wood et al., 2007).

Having carried out the initial literature review, a number of interlinked factors were identified that are of key importance in shaping the future of workplace deception. The emergence of publicly available LLMs meant that people have access to tools that have considerable utility in a variety of use cases, such as education, healthcare and data analytics (Azaria, 2022; Elkassem & Smith, 2023; Kasneci et al., 2023; Yang et al., 2023). However, the advent of AI simultaneously presents a novel tool that can be harnessed for malicious endeavours. Such an example is the documented use of ChatGPT by students for assignments (Ventayen, 2023). If candidates deem the use cases and the prior achievements of ChatGPT convincing enough, they may be motivated to exploit AI in an attempt to enhance their prospects of securing employment; especially considering the prevalence of deception in job applications (Feldman et al., 2002; Feldman & Weiss, 2006; Melchers et al., 2020; Robinson et al., 1998; Roulin et al., 2015; Roulin et al., 2016; Roulin & Krings, 2016; Roulin & Bourdage, 2017; Wood et al., 2007). Consequently, it is of paramount importance to study whether job applications written with the help of artificial intelligence are perceived better by employers.

Considering the remarkable capabilities of ChatGPT, we expect a positive correlation between its usage and job applicant performance. The main independent variable of the model will be therefore cover letter type, operationalised by a human-written and an AI-assisted cover letter. Job applicant performance, the main variable of interest will be expressed by two dependent variables, namely hiring likeliness and offered starting salary. Consequently, the two hypotheses are devised as follows:

H1A: A ChatGPT-assisted cover letter achieves a higher likelihood of hiring in comparison to a solely human-written one.

H1B: A ChatGPT-assisted cover letter receives a higher offered starting salary in comparison to a solely human-written one.

III. Methodology

To examine the impact AI has on a candidates' chances of employment, this study examines people's perceptions of a ChatGPT-assisted cover letter. The choice fell on the cover letter for the experiment, given that it is a key driver of first impressions and an instrumental part of the application process (Knouse et al., 1988; Pennington et al., 2014); as well as a useful and effective sales tool of the applicant (McDowell, 1987). In the following sections, the rationale and the academic backing for the chosen experimental design is provided as well as the outline of the procedures for participant recruitment, data collection, and data analysis.

III/A. Pilot experiment

For the success of this study, it is crucial that the stimuli are similar in terms of qualifications, skills and knowledge but different enough that participants can distinguish between them. The first factor is paramount for comparability and the validity of the study, while the second allows the analysis of the differences between human and AI language usage and their respective perception in a high-stake professional scenario, such as a job application. Moreover, as providing monetary compensation to the participants was not an option, the survey had to be short and easily understandable to maximise the number of participants.

Consequently, prior to the main experiment, a pilot experiment was conducted to gather feedback on the experimental design and survey instrument. The pilot experiment aimed to assess the feasibility and effectiveness of a 2x2 design experiment, consisting of four cover letters: human-written (control group), AI-written, human-written enhanced by AI, and AI-written enhanced by a human. The pilot experiment involved a sample of 8 participants, who were selected based on their availability to complete the survey and provide valuable feedback as well as their familiarity with the job application process. Each participant was briefed about the purpose of the study and provided informed consent before their participation.

After the pilot experiment, participants were asked to review the survey instrument and provide their opinions on various aspects of the experimental design. Specifically, they were asked to evaluate the length of the survey (the energy and time required to complete it) and the ease of differentiating between the different cover letters.

The feedback obtained from the pilot experiment was analysed to gain insights into the participants' perceptions and to perform necessary modifications to the experimental design. The results of the pilot experiment showed a clear indication of the need for revisions: participants unanimously reported that the survey was excessively time-consuming and they expressed difficulty in differentiating between the cover letters due to their similarities.

III/B. The revision of the experimental design

Based on the feedback received from the pilot experiment, the original 2x2 design was adapted for the subsequent main experiment. In response to participants' concerns, the researcher decided to streamline the survey and focus on two cover letter types: the human-written (control group) and the AI-written cover letter. This modification aimed to enhance the feasibility and clarity of the experiment, addressing the concerns raised by the participants of the pilot experiment.

The revised experimental design retains the fundamental objective of investigating the impact of artificial intelligence on job applicant performance. By simplifying the design, we aimed to mitigate potential participant burden and improve the clarity of the experimental conditions. Both the former and the latter are of key importance in any experiment, but even more so in the case of a paper written as part of a university degree, as finding participants can be often difficult.

III/C. Experimental design

To test whether the use of AI impacts job application performance, we conducted an online experiment. As offering monetary incentive to the participants was not possible, the survey was kept as short as possible and took approximately 2 minutes to fill out. Employing a within-subject experimental design, participants were presented with a task after providing informed consent and demographic information. They were presented with a job description and a list of required skills and qualifications. Afterwards, the respondents were asked to read cover letters and decide which applicant was most suitable for the job opening. The key difference between the two cover letters was that one was human made, while the other one was written by AI. The aim is to investigate how the use of AI, which is our main variable of interest, influences the outcome, job applicant performance. Job applicant performance is operationalised by two variables, hiring likeliness and offered starting salary. Other variables included age, highest level of completed education and hiring experience. Additionally, an open question at the end of survey is aimed to understand the rationale behind the choices of the respondents. The survey then ended with a short debriefing message that included contact details and thanked the participants for their time.

III/D. Sample

Before conducting the experiment, an a priori power calculation was conducted in G*Power. As the experiment employs a within-subject design with all participants rating both cover letters, a t-test was chosen as the most appropriate method of analysis as it can show the difference between two dependent means. For a matched pairs t-test, the required number of participants needed for an α error probability of 0.05 is 45. For the detailed breakdown of the power calculation please refer to Appendix A. To encourage answering the questions, the consent, the demographic and the candidate rating questions were set as mandatory. The question asking the participants to explain the rationale behind their choices was left as optional, as that required considerably more time and effort than the other questions. In order to achieve the required number of responses, the survey was circulated on social media such as Facebook, Instagram and LinkedIn, as well as sent to WhatsApp groups. The data collection period lasted for two weeks in June 2023.

In total, 230 participants started the survey. The 102 abandoned and incomplete surveys will not be taken into account. Therefore, the sample size is 128 for the compulsory questions. All questions were compulsory, apart from the one on the rationale for the participant's choices, for which 99 participants provided some sort of input. The average age of the participants was 27.66 years, with a standard deviation of 10.89. The minimum and maximum ages were 18 and 63 respectively. The respondents were relatively highly educated individuals on average, as three quarters of the respondents completed a higher education degree (Bachelor's, Master's, PhD etc.). This is relevant because these participants likely have a better understanding of white-collar job application procedures. The share of participants with highest completed level of education being primary or secondary was low, 2 and 30 respondents chose these options respectively. Another factor that signals that the participants were relatively well versed to answer questions on hiring is the fact that over half of the participants (51.56%) stated that they have some sort of background in recruitment. Respondents with HR experience were also more likely to provide rationale as 80.30% of them did so, while the same ratio was 74.19% for the respondents without recruitment experience.

Table 1: Demographics of the sample

	Count	Percentage
Education		
Primary	2	23.44
Secondary	30	1.56
Higher	96	75.00
HR experience		
No	62	48.44
Yes	66	51.56

This table shows the highest level of completed education and hiring experience of the participants.

III/E. Procedure and stimuli

The survey first presented information on the general purpose of the study and asked for informed consent. Then demographic questions followed, that can later be used for purposes of summary statistics, data visualisation, and as control variables. Afterwards, instructions were provided on how to proceed as well as a job description and requirements. Then the stimuli, the two cover letters were presented and the participants were asked to rate both applicants and provide rationale for their choices.

The survey commenced with obtaining informed consent from the participants. The study was presented as research aiming to understand people's perceptions on job applicant and how they make hiring decisions. This ensured that while the participants are not being deceived, they do not have a clear understanding of the true aim of the survey, and consequently they will not try to guess which cover letter was AI-written and adjust their answers accordingly.

Next, demographic questions were presented to collect information for summary statistics, data visualisation, and as control variables. These questions included age, highest level of education completed (primary, secondary, or higher education), and whether the participants had hiring experience. These control variables are in line with those used by academics in similar studies, such as Bell and Klein (2001), Louvet (2007) and Nordstrom et al. (1998). Prior research indicates that a substantial number of commonly used control variables lack proper theoretical justification and are incorporated simply because of their widespread usage (Bernerth & Aguinis, 2016). The use of a parsimonious approach was followed to avoid survey fatigue and increase participant completion rates.

Afterwards, the participants received a concise job description similar to the studies of Bell and Klein (2001) and Louvet (2007). Additionally, they were given a list of desirable skills and qualifications that they should look for. This ensured that even participants without a deeper understanding of the industry of management consulting will have an idea of what traits a good candidate should possess, and consequently what they should look for in the two cover letters. Both the job description and the requirements were based on real job advertisements for similar positions in the industry, with the main inspiration being the Business Analyst listing of

McKinsey & Company. The instructions, the job description and the list of desirable skills and qualifications can be found in Appendix B alongside the survey in full.

The cover letters are the same in terms of content. All applicant characteristics were kept the same across the two letters, such as level of education, previous work experience and skills. To examine the effect of the use of ChatGPT, differences between the two cover letters were only stylistic and grammatical. To ensure comparability, ChatGPT received specific instructions in terms of what details to build the cover letters on, with the produced text later being checked over diligently. The original prompt was changed a few times, because ChatGPT deviated from the core information and added other details, until the texts were identical in content. A new node was opened for each effort, to guarantee that the output is not influenced by the previous prompts. The prompt used can be seen in Appendix C.

The order in which the cover letters were presented was randomised to further combat any potential bias or order effects, in line with the methodology of Stone and Wright (2013) and Wood et al. (2007). To achieve anonymity and avoid any name-based discrimination, two generic English names were chosen with no difference in socio-economic or gender background (Åslund & Skans, 2012). This was also highlighted in the survey itself. The two names were Stanley Scott and Michael Hudson for the human-written and the ChatGPT-assisted cover letters respectively. The carefully safeguarded equivalency in terms of skills and qualifications allows for a fair comparison between the human cover letter and that of the artificial intelligence.

For each cover letter, participants rate the job applicant's performance based on two Likert-type scale questions. The first question measures hiring likeliness, ranging from 1 (extremely unlikely to recommend for hire) to 5 (extremely likely). The second question assesses the proposed yearly starting salary in euros, with values ranging from 20,000 to 60,000. There are precedents for an experimental design based on a binary outcome variable, e.g., whether the applicant progresses to the next stage of the hiring process or not (Bjørnshagen, 2021; Carlsson & Eriksson, 2019; Ravaud et al., 1992; Stone & Wright, 2013; Thorat & Attewell, 2007). While that is a rational choice when sending out applicants to real vacancies, asking participants to provide their opinions on some form of a scale is considered to be the more appropriate method for such a survey-based experiment (Bell & Klein, 2001; Louvet, 2007; Nordstrom et al., 1998).

Afterwards, participants were asked to provide rationale for their choices. This is paramount, firstly to have a deeper understanding of why one cover letter might have a higher chance at employment than the other, and secondly to counter potential casuistry. Casuistry refers to the phenomenon when people deceive themselves by providing a morally acceptable argument for a decision they made based on a factor that might be considered unethical (Norton et al., 2004). As this question requires significantly more time and effort than the other ones, it was left as the only non-mandatory part of the survey to encourage the participation of those who do not have the time or do not feel competent to answer this question. For the purposes of analysis therefore we will consider the survey without an answer to the rationale question complete. A reminder message was put in place though in Qualtrics, to ask participants to answer the question if they have not done so already. With a qualitative component added to the survey, new avenues of analysis have opened up, namely more in-depth information became available on how the participants think and behave. This input is especially useful, considering that qualitative data is a meaningful and imperative part of behavioural economics research (Gordon, 2011).

Finally, the respondents were thanked for their time and participations and received a debriefing explaining the purposes of the experiment and what exactly was tested. A contact email address was also included in case the participants had any questions or feedback regarding the survey or the research in general and informed that they can also reach out, should they want to receive the results of the study.

III/F. Analysis

As discussed previously, this study aims to measure the impact of artificial intelligence on job applicant performance by comparing the results attained by AI- and human-written cover letters. The main variable of interest, job applicant performance, is measured by two metrics in line with the two hypotheses: hiring likeliness and offered starting salary. To analyse the data, paired samples t-tests and linear regression models is employed, as we expect the underlying assumptions of these models to hold. These models consider the within-subject design and accounts for the dependency between the ratings provided by the same participant. The regression includes the following predictors: age, highest level of completed education, hiring experience, and the type of cover letter (human-written or AI-generated). The control variables aim to measure whether there is a difference between older and younger participants, as the former group likely has more professional experience than the latter. The same applies for more educated individuals and those with hiring experience; and sets out to examine whether these variables have any effect on the decision. Additionally, these control variables are in line with similar studies, such as Bell and Klein (2001), Louvet (2007) and Nordstrom et al. (1998). As both hiring likeliness and offered starting salary are variables for job applicant performance, we expect them to be correlated. Consequently, the models employed are similar.

Before starting the analysis, some variables were recoded. Recruitment experience was recoded to 1 for having experience and 0 for not. Highest level of completed education was also recoded between 1 and 3 in an ascending order of educational level.

For H1A (hiring likeliness):

$$hiring\_likeliness\_ij = \beta\_0 + \beta\_1 * type\_of\_cover\_letter\_ij + \beta\_2 * age\_i + \beta\_3 * education\_i + \beta\_4 * hiring\_experience\_i + \varepsilon\_ij$$

For H1B (proposed starting salary):

$$starting\_salary\_ij = \beta\_0 + \beta\_1 * type\_of\_cover\_letter\_ij + \beta\_2 * age\_i + \beta\_3 * education\_i + \beta\_4 * hiring\_experience\_i + \varepsilon\_ij$$

where:

hiring_likeliness_ij represents the hiring likeliness rating for participant i on cover letter j.
starting_salary_ij represents the proposed starting salary for participant i on cover letter j.
type_of_cover_letter_ij refers to the type of the cover letter j that participant i rates. As this is a within-subject experiment and therefore each participant serves as their own control group,

this variable will represent the ratio between the salaries and the hiring likeliness ratings that each cover letter received, respectively.

age_i represents the age of participant i.

$education_i$ represents the highest level of completed education for participant i.

$hiring\_experience_i$ is a binary variable indicating whether participant i has hiring experience (0 for no, 1 for yes).

β_0 represents the intercept, which captures the average hiring likeliness or starting salary when all other predictors are zero.

β_1, β_2, β_3, and β_4 are the regression coefficients corresponding to the type of cover letter, age, education, and hiring experience, respectively. These coefficients correspond to the weights attached to each variable when predicting the outcome variable.

ε_{ij} represents the random error term accounting for unexplained variability in the ratings.

Additionally, an open question on the motivation behind the participants' choices was included in the survey in order to gain deeper insights into their decision-making process. The responses were subjected to content analysis, which involved both manual examination and the use of Nvivo software (Durian, 2002; Feng & Behar-Horenstein, 2019; Hilal & Alabri, 2013; Loughran & McDonald, 2016; Salmona et al., 2015; Wong, 2008). This approach provided a comprehensive understanding on the data and led to valuable insights.

Overall, the paper assesses the effects of cover letter type on job applicant performance, measured by hiring likeliness and offered starting salary as well the effect of the control variables on the outcome. The study at hand examines this via t-tests, regression and a content analysis of the respondents' rationale for their choices.

III/G. Ethical considerations

Careful attention has been paid to ensure that the study is carried out in an ethical manner. To safeguard this, the four key pillars of ethical research outlined by Diener and Crandall (1978) were followed. Firstly, all participants had to give explicit and informed consent to their data being used for research purposes before starting the experiment. Secondly, apart from questions on factors suspected to be important, namely education, age and recruitment experience, no personal data were collected. The survey is completely anonymous to ensure that the privacy of the respondents is respected. This was also communicated to the participants beforehand, as part of the privacy disclaimer. Thirdly, participants were not deceived either intentionally or unintentionally. No false information was presented to participants, and they were aware that they are taking part in an experiment and their answers will be used for research purposes. Contrary to this, members of academia usually sent job applications to real companies looking to fill existing vacancies when conducting similar experiments (Bjørnshagen, 2021; Carlsson & Eriksson, 2019; Ravaud et al., 1992; Thorat & Attewell, 2007). That is often a useful technique when exploring delicate topics, such as discrimination, as this method provides transparency in connection to a topic where alternative approaches might not yield accurate results (Riach & Rich, 2010), as people might be inclined to give socially desirable answers in a survey setting for example, where there are no consequences (Rich & Riach, 2004). In this case however, there are no socially desirable answers, therefore this issue is not present. Consequently, the ethically superior survey-based experiment approach is expected to yield similarly accurate results to handing in actual job applications. The fourth and final pillar of ethical research was facilitated through the first three factors, ie. that no harm was done to the participants. Finally, filling out and passing the MSc ethical check ensured that the survey was ready for distribution.

IV. Results

IV/A. Descriptive statistics

The answers to the core questions of the experiment – namely rating the candidates on a 5-point Likert-type scale in order of likelihood of recommending hiring them, giving a prospective yearly starting salary and providing justification for the above choices – allows us to study the relative strengths of the job applications. In terms of the hiring question, the differences appear relatively minor at first glance, with the exception of the highest category. As Table 2 shows, the candidate with the AI-written cover letter was deemed *extremely likely* to be recommended for hiring by 25% respondents, whereas this ratio is only 15.62% for the solely human-written version.

Table 2: Likeliness of hiring

	Human-written		AI-written	
	Frequency	Percentage	Frequency	Percentage
Extremely unlikely	7	5.47	3	2.34
Somewhat unlikely	20	15.62	17	13.28
Neither likely nor unlikely	20	15.62	18	14.06
Somewhat likely	61	47.66	58	45.31
Extremely likely	20	15.62	32	25.00
Sum	**128**	**100**	**128**	**100**

This table shows the frequency and the percentage of the answers for the hiring likeliness question in the case of the two cover letters respectively.

A more in-depth analysis of the numbers shows a noticeable difference when converting the textual responses to the 1-5 Likert-type scale design. As table 2 shows, the cover letter written with the assistance of ChatGPT achieved a 0.25 higher average score (3.77) compared to the human (3.52). This is a difference of 7.10%. Moreover, the standard deviation (SD) is lower in the case of the AI-written cover letter (1.04 compared to 1.10), which suggests that respondents' opinion was more homogeneous in that case. It is important to note however, that the median (4) is the same for both groups. This suggests that overall, both the human and the AI candidate is 'likely' to be recommended for hiring, according to the participants of the experiment.

Table 3: Likeliness of hiring

	Mean	Median	Standard deviation	Minimum	Maximum
Human-written	3.52	4	1.10	1	5
AI-written	3.77	4	1.04	1	5

This table shows the mean and the median likeliness of hiring score in the case of the two cover letters respectively.

In terms of the proposed yearly staring salary, the slightly better performance of the AI cover letter over the human one holds as well. The former received on average 2,359.80 € a month more than the latter, which is a difference of 6.62%. The standard deviation in this case however is slightly higher for the AI version.

Table 4: Offered yearly starting salary (in Euros)

	Mean	Standard deviation	Minimum	Maximum
Human-written	35,645.55	8,225.40	20,000	60,000
AI-written	38,005.35	8,633.38	20,000	60,000

This table shows the mean offered yearly salary as well as the standard deviation and the minimum and maximum values for the two cover letters respectively.

The following segment will take a closer look at the differences between the cover letters by utilising statistical analysis, as well as interpret the rationale provided by the respondents for their choices.

IV/B. Statistical analysis

To examine H1A, namely whether a cover letter written with the help of ChatGPT has a higher hiring likeliness compared to a human written one, a t-test was employed. The AI-assisted cover letter received a higher hiring likeliness rating (M: 3.77, SD: 1.04) compared to the human-written one (M: 3.52, SD: 1.10), $t = -1.87$, $p<0.05$. The results of the t-test suggest that H0A of there being no difference between the mean hiring likeliness ratings of the AI-assisted and the human-written cover letters can be rejected. Table 5 shows the detailed results below.

Table 5: T-test for hiring likeliness

Paired t test : likely1 likely2

	obs	Mean1	Mean2	dif	St Err	t value	p value
likely1 - likely2	128	3.523	3.774	-.25	.134	-1.85	.064

This table shows the results of the t-test conducted on the hiring likeliness rating.

To examine the effect of the demographic variables on the hiring likeliness ratings, we ran a regression for each cover letter type. We found no statistically significant correlations at the 5% statistical significance level. Tables 6 and 7 show the detailed results of the regressions.

Table 6: Regression for hiring likeliness, human cover letter

Linear regression

likely1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
age	.004	.009	0.43	.666	-.014	.022	
newedu	-.146	.217	-0.67	.503	-.575	.283	
newhr	-.212	.202	-1.05	.296	-.612	.188	
Constant	3.92	.585	6.70	0	2.762	5.078	***

Mean dependent var	3.523	SD dependent var	1.101
R-squared	0.016	Number of obs	128
F-test	0.666	Prob > F	0.574
Akaike crit. (AIC)	392.813	Bayesian crit. (BIC)	404.221

*** *p<.01*, ** *p<.05*, * *p<.1*

This table shows the results of the regression conducted on the hiring likeliness rating for the human cover letter.

Table 7: Regression for hiring likeliness, AI cover letter

Linear regression

likely2	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
age	.016	.009	1.91	.058	-.001	.034	*
newedu	.028	.202	0.14	.89	-.371	.427	
newhr	.263	.188	1.40	.165	-.11	.635	
Constant	3.106	.544	5.71	0	2.029	4.183	***

Mean dependent var	3.773	SD dependent var	1.044
R-squared	0.053	Number of obs	128
F-test	2.294	Prob > F	0.081
Akaike crit. (AIC)	374.361	Bayesian crit. (BIC)	385.769

**** p<.01, ** p<.05, * p<.1*

This table shows the results of the regression conducted on the hiring likeliness rating for the AI cover letter.

To examine H1B, namely whether a cover letter written with the help of ChatGPT receives a higher offered starting salary compared to a human written one, a t-test was employed, similarly to the case of H1A. The AI-assisted cover letter received a higher offered starting salary (M: 35645.55, SD: 8225.40) compared to the human-written one (M: 38005.35, SD: 8633.38), $t = -3.25$, $p<0.05$. The results of the t-test suggest that H0B of there being no difference between the mean hiring likeliness ratings of the AI-assisted and the human-written cover letters can be rejected. Table 8 shows the detailed results below.

Table 8: T-test for offered starting salary

Paired t test : salary_1 salary_2

	obs	Mean1	Mean2	dif	St Err	t value	p value
salary 1 - salary ~	128	35645.554	38005.352	-2359.797	730.008	-3.25	.002

This table shows the results of the t-test conducted on the offered starting salary.

To examine the effect of the demographic variables on the hiring likeliness ratings, we ran a regression for each cover letter type. We found that that age is positively correlated with the offered starting salary for AI-written cover letter. An additional year of age of the participant is predicted to increase the yearly offered starting salary of the human cover letter by € 177.05 rating points, ceteris paribus. This effect is statistically significant at the 5% level. Apart from this, we found no other statistically significant correlation. The detailed results of the regressions can be seen below in Tables 9 and 10.

Table 9: Regression for offered starting salary, human cover letter

Linear regression

salary_1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
age	78.119	69.261	1.13	.262	-58.968	215.206	
newedu	400.486	1618.937	0.25	.805	-2803.843	3604.815	
newhr	-1387.577	1510.085	-0.92	.36	-4376.458	1601.304	
Constant	33105.472	4369.232	7.58	0	24457.538	41753.407	***

Mean dependent var	35645.555	SD dependent var	8225.397
R-squared	0.016	Number of obs	128
F-test	0.693	Prob > F	0.558
Akaike crit. (AIC)	2675.953	Bayesian crit. (BIC)	2687.361

*** *p<.01,* ** *p<.05,* * *p<.1*

This table shows the results of the regression conducted on the offered starting salary for the human cover letter.

Table 10: Regression for offered starting salary, AI cover letter

Linear regression

salary_2	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
age	177.049	71.268	2.48	.014	35.989	318.108	**
newedu	701.875	1665.855	0.42	.674	-2595.319	3999.07	
newhr	-186.052	1553.849	-0.12	.905	-3261.555	2889.45	
Constant	31285.596	4495.858	6.96	0	22387.033	40184.158	***

Mean dependent var	38005.352	SD dependent var	8633.376
R-squared	0.055	Number of obs	128
F-test	2.394	Prob > F	0.072
Akaike crit. (AIC)	2683.267	Bayesian crit. (BIC)	2694.675

**** p<.01, ** p<.05, * p<.1*

This table shows the results of the regression conducted on the offered starting salary for the AI cover letter.

IV/C. Content analysis

To gain a better understanding of the thought process of the respondents and the rationale behind their choices, a question about motivation was asked. Conducting a content analysis both manually and with the software Nvivo yielded a range of interesting results (Durian, 2002; Feng & Behar-Horenstein, 2019; Hilal & Alabri, 2013; Loughran & McDonald, 2016; Salmona et al., 2015; Wong, 2008). The trends uncovered showed that the AI cover letter was preferred due to it being more professional and better worded than the human counterpart overall. Other advantages that the participants' perceived the AI cover letter had over the human one was a more comprehensive structure. However, a number of candidates mentioned that the human-written letter gives the impression of a more approachable, more passionate, more 'human' candidate while the other was criticised for being robotic and even narcissistic at times. Respondents also rationalised their decision by stating that their candidate of choice – most commonly the AI one – had more professional experience. This rationalised the need for such a question due the occurrence of casuistry, as the cover letters included equal work experience (Norton et al., 2004). Overall, the participants generally highlighted the positives and rationalised their choices by focusing on the advantages one cover letter had over another instead of emphasising the disadvantages. This is also reflected in the rating the candidates received, as the median hiring likeliness rating for both groups is '*somewhat likely*' to recommend for hiring. It is also important to note that a number of candidates expressed that they are undecided between the candidates or that even though they preferred one over the other, the difference between the cover letters was marginal.

In terms of the software-based analysis, Nvivo presented the most frequent words which were later filtered (to omit the candidates' names and generic English words) and divided into two categories: words regarding skills and qualifications and that to personal characteristics. The words are also grouped together by meaning for the purposes of analysis, e.g., 'qualifications' includes 'qualified' as well. This revealed the key factors that influenced the decisions of the respondents, therefore what characteristics resulted in the preference of the AI cover letter over the human counterpart in general among the sample. The following table presents the words mentioned in the responses and their respective number of occurrences.

Table 11: Most common words explaining the respondents' decisions

Skills and experience		Attitude	
Word	#	Word	#
experience	29	motivation	14
skills	23	confident	5
professional	13	humble	5
qualifications	8	generic	4
communication	7	nice	2

V. Discussion

V/A. Main results

To summarise, the results showed that the AI-written cover letter received higher ratings in terms of hiring likelihood, with 25% of respondents deeming it *extremely likely* to recommend for hiring compared to 15.62% for the human-written version. There was also a considerable difference in the average hiring likeliness rating, with the human-made and the AI-written cover letters receiving 3.52 and 3.77 respectively. The AI-written cover letter also resulted in a 6.62% higher average offered starting salary compared to the human-written one. Moreover, when participants provided rationale for their choices, they highlighted the AI cover letter's professionalism, wording, and comprehensive structure. However, some participants expressed a preference for the human-written letter due to its perceived human qualities, such as being more approachable and passionate. Content analysis of respondents' explanations further supported the preference for the AI cover letter. Overall, the study suggests that AI assistance in cover letter writing can improve hiring chances and starting salary prospects.

V/B. Limitations

Despite the thought-provoking insights revealed by this study, several limitations should be acknowledged and further research to address these should be conducted. First, the sample size and its composition warrant consideration. With a sample of 128 participants, the generalisability of the findings may be limited, especially considering that the sample mainly consists of highly educated young people. This certain extent of lack of heterogeneity might limit the value of the findings. Moreover, as monetary incentive was not provided to the participants, some might have answered the questions carelessly, without exerting the needed effort to make an informed decision (Ward et al., 2017).

Secondly, the online survey distribution method introduces potential issues related to non-response bias and sampling bias, raising concern regarding the representativeness of the sample (Bethlehem, 2010; Evans & Mathur, 2005; Ward et al., 2017). We do not have information on the 102 participants who left the survey without completing it and those who chose to participate may possess certain characteristics that differ from the larger population. Berg (2005) defines this bias as “the mistake researchers expect to make in estimating a population characteristic based on a sample of survey data in which, due to non-response, certain types of survey respondents are underrepresented”. The paper concludes that solving this issue is often difficult, therefore being aware of this potential bias might be the best solution to this problem. The validity of participants' opinions should be considered. While more than half of the participants had prior experience in hiring, it might be beneficial to include a broader range of experienced recruiters and hiring managers, to obtain a more comprehensive understanding of their perspectives. Conducting a larger experiment with a more diverse and representative sample could enhance the robustness of the results.

Thirdly, gender was not measured in the survey. This was to keep the survey as short as possible, which is especially important in the case of no monetary incentive. Additionally, gender was not expected to be correlated with the outcome, therefore was not included. This however results in limited information regarding the sample. Moreover, one respondent admitted to gender bias, more specifically to preferring Stanley Scott, the human candidate, as they believed Stanley to be a female name. Although explicit efforts were made to combat any gender or socioeconomic bias by choosing generic names of the same gender for both candidates, the conclusion can be drawn that this attempt was not entirely successful.

Fourthly, a key limitation of the current paper is that it focuses on how AI-assisted job applications are perceived. While the results show an advantage in favour of the capabilities of ChatGPT, we have no information on how common its usage might be among job applicants. As ChatGPT and other LLMs are relatively novel, the data on their usage for deception in workplace environments is limited. Future research on the topic would add a useful dimension to the results of the study at hand.

Additionally, the content analysis was not checked over by a second rater, but instead it was coded by one person. To limit potential bias, two methods were employed, namely manual coding and software-aided with Nvivo.

Finally, the limitations of the materials used in the study should be acknowledged. The cover letters utilised may not fully represent the diversity of real-world job applications. Employing a wider range of cover letter examples from various industries and positions could provide a more comprehensive assessment of the impact of AI assistance in cover letter writing. A potential avenue of research could be a comparative study that employs a similar design but in a number of industries, thus examining whether the results of this paper are industry-specific or not. Moreover, as the two cover letters were similar in terms of content, the experiment might feel artificial and there is a chance that the participants realised the true aim of the survey. Addressing these limitations in future research could contribute to a more robust understanding of the effects of AI-written cover letters on hiring outcomes and salary offers.

V/C. Implications

We found a clear advantage in favour of artificial intelligence over a human-written job application. A cover letter written with the help of ChatGPT resulted in an increase both in terms of hiring likelihood and in offered starting salary compared to a solely human-written one. The differences are both considerable in size and statistically significant, thus increasing the importance of this finding. Consequently, these results have a number of implications for various fields, especially considering that this is the first study on the specific topic.

The comprehensive literature review conducted as part of the study showed a clear tendency of job applicants to deceive their prospective employers for an increased chance at a job offer. By proving that AI can be a prolific tool even for malicious use such as for deceptive applications, it is very likely that techniques similar to what was employed during the research will be utilised by candidates. Consequently, employers either need to look into ways to detect applicant faking through the use of AI or develop new methods to assess candidate skills. Considering the current pace of AI evolution, the latter might be a longer-term solution. Moreover, an additonal implication stems for this same line of thought but on the side of job applicants. While such deceptive practices are unethical, this study shows the benefits of utilising AI enhanced cover letters during the job application process and uncovers a new use case for AI.

Finally, AI developers and researchers should look further into the outputs of large language models and invest time into developing detection software in order to combat faking. The study at hand is set in a professional environment, however, the workplace is not the only premise of life where people can employ AI for deception. With other fields such as academia expecting a potentially enormous impact due to the release of sophisticated and competent LLMs to the public, developers should look further into the risks their technology might pose and measures they can devise to mitigate the mentioned risks.

VI. Conclusion

The study seeks to bridge the gap between deception research, the job application and hiring process, and the emergence of AI technologies like ChatGPT. As the first study to examine the effect of AI on job applicant performance, it underscores the urgency of comprehensively analysing people's perceptions of AI-written job applications and their relative success rates. With the rapid development of AI, discussions on the future of work have intensified, and firms face the dilemma of adopting or restricting AI usage in the workplace. The potential for candidates to use AI to deceive employers during the application process further adds complexity to an already challenging hiring landscape. Understanding these dynamics becomes increasingly crucial as AI technology continues to shape various aspects of life and work.

This study demonstrates a significant advantage of artificial intelligence (AI) over human-written job applications. Cover letters assisted by ChatGPT led to higher hiring likelihood and offered starting salary compared to solely human-written ones, with both differences being substantial and statistically significant. Job applicants should be mindful of ethical considerations when using AI technology during the application process. While AI-enhanced cover letters may offer benefits in terms of hiring likelihood and salary offers, resorting to deceptive practices is unethical and may lead to negative consequences in the long run.

The comprehensive literature review revealed a tendency of job applicants to deceive employers for better chances at job offers. The study underlines the need for ethical consideration and proactive measures in the evolution and application of large language models to address potential misuse. Similarly, the study sheds light on the lack of efficiency and validity of the current applicant assessment methods in place.

In conclusion, this study provides novel insights into the impact of AI-assisted cover letters on hiring outcomes and offers valuable implications for job applicants, employers, and AI developers alike. With the growing importance of artificial intelligence in almost every domain, it is essential to take into account the potential for both positive and negative aspects of AI and to work toward ensuring fair, transparent, and ethical procedures in its implementation. Future studies should investigate strategies to address the difficulties and opportunities brought about by this developing technology as well as the usage of AI in the job application process.

VII. References

Alshater, M. (2022). Exploring the role of artificial intelligence in enhancing academic performance: A case study of ChatGPT. *SSRN Electronic Journal,* https://doi.org/10.2139/ssrn.4312358

Anders, B. A. (2023). Is using ChatGPT cheating, plagiarism, both, neither, or forward thinking? *Patterns, 4*(3), 100694. https://doi.org/10.1016/j.patter.2023.100694

Åslund, O., & Skans, O. N. (2012). Do anonymous job application procedures level the playing field? *ILR Review, 65*(1), 82-107. https://doi.org/10.1177/001979391206500105

Azaria, A. (2022). ChatGPT usage and limitations.

Babcock, P. (2003). Spotting lies. *HRMagazine, 48*, 46–52.

Barrat, J. (2013). *Our final invention: Artificial intelligence and the end of the human era*. Macmillan.

Bell, B. S., & Klein, K. J. (2001). Effects of disability, gender, and job level on ratings of job applicants. *Rehabilitation Psychology, 46*(3), 229-246. https://doi.org/10.1037/0090-5550.46.3.229

Bello, C. (2023, 25 January). *ChatGPT: AI will shape the world on a scale not seen since the iPhone revolution, says OpenAI boss.* Euronews.

https://www.euronews.com/next/2023/01/25/chatgpt-ai-will-shape-the-world-on-a-scale-not-seen-since-the-iphone-revolution-says-opena

Berg, N. (2005). Non-response bias. *Encyclopedia of social measurement* (pp. 865-873). Elsevier Inc. https://doi.org/10.1016/B0-12-369398-5/00038-4

Bernerth, J. B., & Aguinis, H. (2016). A critical review and best-practice recommendations for control variable usage. *Personnel Psychology, 69*(1), 229-283. https://doi.org/10.1111/peps.12103

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review / Revue Internationale De Statistique, 78*(2), 161-188. http://www.jstor.org/stable/27919830

Bjørnshagen, V. (2021). The mark of mental health problems. A field experiment on hiring discrimination before and during COVID-19. *Social Science & Medicine, 283*, 114181. https://doi.org/10.1016/j.socscimed.2021.114181

Brynjolfsson, E., & McAfee, A. (2015). Will humans go the way of horses? labor in the second machine age. *Foreign Affairs, 94*(4), 8-14. http://www.jstor.org/stable/24483811

Cable, D. M., & Judge, T. A. (1997). Interviewers' perceptions of person-organization fit and organizational selection decisions. *Journal of Applied Psychology, 82*(4), 546-561. https://doi.org/10.1037/0021-9010.82.4.546

Carlsson, M., & Eriksson, S. (2019). Age discrimination in hiring decisions: Evidence from a field experiment in the labor market. *Labour Economics, 59*, 173-183. https://doi.org/10.1016/j.labeco.2019.03.002

Carranza, E., & Pimkina, S. (2017). *Overcoming information asymmetry in job search*

Cialdini, R. B., & Goldstein, N. J. (2002). The science and practice of persuasion. *Cornell Hotel and Restaurant Administration Quarterly, 43*(2), 40-50.

Clarke, R. (2019). Regulatory alternatives for AI. *Computer Law & Security Review, 35*(4), 398-409. https://doi.org/10.1016/j.clsr.2019.04.008

Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International,* , 1-12.

Debey, E., De Schryver, M., Logan, G. D., Suchotzki, K., & Verschuere, B. (2015). From junior to senior pinocchio: A cross-sectional lifespan investigation of deception. *Acta Psychologica, 160*, 58-68. https://doi.org/10.1016/j.actpsy.2015.06.007

Diener, E., & Crandall, R. (1978). *Ethics in social and behavioral research*. U Chicago Press.

Dineen, B. R., Ash, S. R., & Noe, R. A. (2002). A web of applicant attraction. *Journal of Applied Psychology, 87*(4), 723-734. https://doi.org/10.1037/0021-9010.87.4.723

Dirican, C. (2015). The impacts of robotics, artificial intelligence on business and economics. *Procedia - Social and Behavioral Sciences, 195*, 564-573. https://doi.org/10.1016/j.sbspro.2015.06.134

Dunlop, T. (2016). *Why the future is workless*. NewSouth.

Durian, D. (2002). Corpus-based text analysis from a qualitative perspective: A closer look at NVivo. *Style, 36*(4), 738-742.

Elkassem, A. A., & Smith, A. D. (2023). Potential use cases for ChatGPT in radiology reporting. *American Journal of Roentgenology,* , 1-4. https://doi.org/10.2214/AJR.23.29198

Evans, J. R., & Mathur, A. (2005). The value of online surveys. *Internet Research, 15*(2), 195-219.

Falk, S., Hammermann, A., Mohnen, A., & Werner, A. (2013). Different degrees of informational asymmetry on job markets and its impact on companies' recruiting success. *Zeitschrift Für Betriebswirtschaft, 83*(4), 295-317. https://doi.org/10.1007/s11573-013-0654-8

Feldman, R. S., Forrest, J. A., & Happ, B. R. (2002). Self-presentation and verbal deception: Do self-presenters lie more? *Basic and Applied Social Psychology, 24*(2), 163-170. https://doi.org/10.1207/S15324834BASP2402_8

Feldman, R. S., & Weiss, B. (2006). Looking good and lying to do it: Deception as an impression management strategy in job interviews. *Journal of Applied Social Psychology, 36*(4), 1070-1086. https://doi.org/10.1111/j.0021-9029.2006.00055.x

Feng, X., & Behar-Horenstein, L. (2019). Maximizing NVivo utilities to analyze open-ended responses. *The Qualitative Report, 24*(3), 563-571.

Finkin, M. W. (2001). Introduction on informational asymmetries in the labor market regulation of information in the labor market: What employees may learn about employers. *Comparative Labor Law and Policy Journal, 22*(4), 433-436. https://heinonline-org.eur.idm.oclc.org/HOL/P?h=hein.journals/cllpj22&i=441 https://heinonline-org.eur.idm.oclc.org/HOL/PrintRequest?handle=hein.journals/cllpj22&collection=0&div=28&id=441&print=section&sction=28

Furnham, A., & Palaiou, K. (2017). Applicant attraction to organizations and job choice. *The wiley blackwell handbook of the psychology of recruitment, selection and employee retention* (pp. 71-90)https://doi.org/10.1002/9781118972472.ch5

Gneezy, U. (2005). Deception: The role of consequences. *American Economic Review, 95*(1), 384-394.

Goncalo, J. A., & Staw, B. M. (2006). Individualism–collectivism and group creativity. *Organizational Behavior and Human Decision Processes, 100*(1), 96-109. https://doi.org/10.1016/j.obhdp.2005.11.003

Gordon, W. (2011). Behavioural economics and qualitative research – A marriage made in heaven? *International Journal of Market Research, 53*(2), 171-185. https://doi.org/10.2501/IJMR-53-2-171-186

Gruetzemacher, R. (2022, -04-19). The power of natural language processing. *Harvard Business Review,* https://hbr.org/2022/04/the-power-of-natural-language-processing

Gurkaynak, G., Yilmaz, I., & Haksever, G. (2016). Stifling artificial intelligence: Human perils. *Computer Law & Security Review, 32*(5), 749-758. https://doi.org/10.1016/j.clsr.2016.05.003

Hausknecht, J. P., Day, D. V., & Thomas, S. C. (2004). Applicant reactions to selection procedures: An updated model and meta-analysis. *Personnel Psychology, 57*(3), 639-683. https://doi.org/10.1111/j.1744-6570.2004.00003.x

Hilal, A. H., & Alabri, S. S. (2013). Using NVivo for data analysis in qualitative research. *International Interdisciplinary Journal of Education, 2*(2), 181-186.

Hunt, W., Sarkar, S., & Warhurst, C. (2022). Measuring the impact of AI on jobs at the organization level: Lessons from a survey of UK business leaders. *Research Policy, 51*(2), 104425. https://doi.org/10.1016/j.respol.2021.104425

Judge, T. A., Cable, D. M., Boudreau, J. W., & Bretz Jr, R. D. (1995). An empirical investigation of the predictors of executive career success. *Personnel Psychology, 48*(3), 485-519. https://doi.org/10.1111/j.1744-6570.1995.tb01767.x

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? on opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

King, M. R., & ChatGPT. (2023). A conversation on artificial intelligence, chatbots, and plagiarism in higher education. *Cellular and Molecular Bioengineering, 16*(1), 1-2. https://doi.org/https://doi.org/10.1007/s12195-022-00754-8

Knouse, S. B., Giacalone, R. A., & Pollard, H. (1988). Impression management in the resume and its cover letter. *Journal of Business and Psychology, 3*(2), 242-249. https://doi.org/10.1007/BF01014492

Kristof, A. L. (1996). Person-organization fit: An integrative review of its conceptualizations, measurement, and implications. *Personnel Psychology, 49*(1), 1-49. https://doi.org/10.1111/j.1744-6570.1996.tb01790.x

Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research, 54*(4), 1187-1230. https://doi.org/10.1111/1475-679X.12123

Louvet, E. (2007). Social judgment toward job applicants with disabilities. *Rehabilitation Psychology, 52*(3), 297-303. https://doi.org/10.1037/0090-5550.52.3.297

Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures, 90*, 46-60. https://doi.org/10.1016/j.futures.2017.03.006

McCormick, B. (1990). A theory of signalling during job search, employment efficiency, and "stigmatised" jobs. *The Review of Economic Studies, 57*(2), 299-313. https://doi.org/10.2307/2297383

McDowell, E. E. (1987). Perceptions of the ideal cover letter and ideal resume. *Journal of Technical Writing and Communication, 17*(2), 179-191. https://doi.org/10.2190/BK23-74U3-333Q-0T86

Melchers, K. G., Roulin, N., & Buehl, A. (2020). A review of applicant faking in selection interviews. *International Journal of Selection and Assessment, 28*(2), 123-142. https://doi.org/10.1111/ijsa.12280

Milmo, D. (2023, 2 February). *ChatGPT reaches 100 million users two months after launch.* https://www.theguardian.com/technology/2023/feb/02/chatgpt-100-million-users-open-ai-fastest-growing-app

Min, B., Ross, H., Sulem, E., Veyseh, A. P. B., Nguyen, T. H., Sainz, O., Agirre, E., Heintz, I., & Roth, D. (2021). Recent advances in natural language processing via large pre-trained language models: A survey. *ACM Computing Surveys,*

Mostak, T. (2023, 1 May). *For artificial intelligence to change the world for the better, we must fight AI bias.* Forbes. Retrieved Jun 5, 2023, from https://www.forbes.com/sites/forbestechcouncil/2023/05/01/for-artificial-intelligence-to-change-the-world-for-the-better-we-must-fight-ai-bias/

Nordstrom, C. R., Huffaker, B. J., & Williams, K. B. (1998). When physical disabilities are not liabilities: The role of applicant and interviewer characteristics on employment interview outcomes. *Journal of Applied Social Psychology, 28*(4), 283-306. https://doi.org/10.1111/j.1559-1816.1998.tb01707.x

Norton, M. I., Vandello, J. A., & Darley, J. M. (2004). Casuistry and social category bias. *Journal of Personality and Social Psychology, 87*(6), 817-831. https://doi.org/10.1037/0022-3514.87.6.817

Ormandy, R. (2015, *Google and elon musk to decide what is good for humanity.* https://www.wired.com/insights/2015/01/google-and-elon-musk-good-for-humanity/

Pennington, R., Delano, M., & Scott, R. (2014). Improving cover-letter writing skills of individuals with intellectual disabilities. *Journal of Applied Behavior Analysis, 47*(1), 204-208. https://doi.org/10.1002/jaba.96

Posner, T., & Fei-Fei, L. (2020). AI will change the world so it's time to change AI. *Nature, 588*

Ravaud, J., Madiot, B., & Ville, I. (1992). Discrimination towards disabled people seeking employment. *Social Science & Medicine, 35*(8), 951-958. https://doi.org/10.1016/0277-9536(92)90234-H

Riach, P. A., & Rich, J. (2010). An experimental investigation of age discrimination in the english labor market. *Annales d'Économie Et De Statistique,* (99/100), 169-185. https://doi.org/10.2307/41219164

Rich, J., & Riach, P. (2004). Deceptive field experiments of discrimination: Are they ethical? *Kyklos (Basel), 57*(3), 457-470. https://doi.org/10.1111/j.0023-5962.2004.00262.x

Robinson, W. P., Shepherd, A., & Heywood, J. (1998). Truth, equivocation concealment, and lies in job applications and doctor-patient communication. *Journal of Language and Social Psychology, 17*(2), 149-164. https://doi.org/10.1177/0261927X980172001

Rodney, H., Valaskova, K., & Durana, P. (2019). The artificial intelligence recruitment process: How technological advancements have reshaped job application and selection practices. *Psychosociological Issues in Human Resource Management, 7*(1), 42-47. https://doi.org/10.22381/PIHRM7120194

Roulin, N., Bangerter, A., & Levashina, J. (2015). Honest and deceptive impression management in the employment interview: Can it be detected and how does it impact evaluations? *Personnel Psychology, 68*(2), 395-444. https://doi.org/10.1111/peps.12079

Roulin, N., & Bourdage, J. S. (2017). Once an impression manager, always an impression manager? antecedents of honest and deceptive impression management use and variability across multiple job interviews. *Frontiers in Psychology, 8*, 29. https://doi.org/10.3389/fpsyg.2017.00029

Roulin, N., & Krings, F. (2016). When winning is everything: The relationship between competitive worldviews and job applicant faking. *Applied Psychology, 65*(4), 643-670. https://doi.org/10.1111/apps.12072

Roulin, N., Krings, F., & Binggeli, S. (2016). A dynamic model of applicant faking. *Organizational Psychology Review, 6*(2), 145-170. https://doi.org/10.1177/2041386615580875

Ryan, A. M., & Tippins, N. T. (2004). Attracting and selecting: What psychological research tells us. *Human Resource Management, 43*(4), 305-318. https://doi.org/10.1002/hrm.20026

Salmona, M., Kaczynski, D., & Smith, T. (2015). Qualitative theory in finance: Theory into practice. *Australian Journal of Management, 40*(3), 403-413. https://doi.org/10.1177/0312896214536204

Stone, A., & Wright, T. (2013). When your face doesn't fit: Employment discrimination against people with facial disfigurements. *Journal of Applied Social Psychology, 43*(3), 515-526. https://doi.org/10.1111/j.1559-1816.2013.01032.x

Susnjak, T. (2022). ChatGPT: The end of online exam integrity? *arXiv Preprint arXiv:2212.09292,* https://hal.science/hal-03913837

The Economist. (2023a, 20 April). *How to worry wisely about artificial intelligence.* The Economist. Retrieved 1 May 2023, from https://www.economist.com/leaders/2023/04/20/how-to-worry-wisely-about-artificial-intelligence

The Economist. (2023b, 22 April). *Large, creative AI models will transform lives and labour markets.* The Economist. https://www.economist.com/interactive/science-and-technology/2023/04/22/large-creative-ai-models-will-transform-how-we-live-and-work

Thorat, S., & Attewell, P. (2007). The legacy of social exclusion: A correspondence study of job discrimination in india. *Economic and Political Weekly, 42*(41), 4141-4145. http://www.jstor.org/stable/40276548

Turing, A. M. (1950). Computing machinery and intelligence. *Readings in cognitive science* (pp. 6-19). Elsevier Inc. https://doi.org/10.1016/B978-1-4832-1446-7.50006-6

Twyman, N. W., Pentland, S. J., & Spitzley, L. (2018). Deception detection in online automated job interviews. *HCI in business, government, and organizations* (pp. 206-216). Springer International Publishing AG. https://doi.org/10.1007/978-3-319-91716-0_16

Urban, T. (2015, 22 Jan). *The AI revolution: The road to superintelligence.* https://waitbutwhy.com/2015/01/artificial-intelligence-revolution-1.html

van Esch, P., Black, J. S., & Arli, D. (2021). Job candidates' reactions to AI-enabled job application processes. *AI and Ethics, 1*(2), 119-130. https://doi.org/10.1007/s43681-020-00025-0

Ventayen, R. J. M. (2023). ChatGPT by OpenAI: Students' viewpoint on cheating using artificial intelligence-based application. *Available at SSRN 4361548,* https://doi.org/http://dx.doi.org/10.2139/ssrn.4361548

Ward, M. K., Meade, A. W., Allred, C. M., Pappalardo, G., & Stoughton, J. W. (2017). Careless response and attrition as sources of bias in online survey assessments of personality traits and performance. *Computers in Human Behavior, 76*, 417-430. https://doi.org/10.1016/j.chb.2017.06.032

Waung, M., McAuslan, P., DiMambro, J. M., & Mięgoć, N. (2017). Impression management use in resumes and cover letters. *Journal of Business and Psychology, 32*, 727-746.

Whitley, J. D., & Wilson, R. A. (1982). Quantifying the employment effects of micro-electronics. *Futures, 14*(6), 486-495. https://doi.org/10.1016/0016-3287(82)90034-9

Wiggers, K., & Stringer, A. (2023, 25 May). *ChatGPT: Everything you need to know about the AI-powered chatbot.* TechCrunch. https://techcrunch.com/2023/05/24/chatgpt-everything-you-need-to-know-about-the-open-ai-powered-chatbot/?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAAJkSCFRpT0K39i5bm035Jr7Xxmr_clstlmQWC4WHz58cUHypq2OGo_tm9oGWYyNThhxSQwfV_g9tG_k_lYlDKUwp2kro75mLgLL419tqatoTZL6A_ovhzH6qRdQr2rWs_fhdDnrNLm35mV4xiNHBuaeZbNbX14aCP_8cn1ntF3xI

Wong, L. P. (2008). Data analysis in qualitative research: A brief guide to using NVivo. *Malaysian Family Physician: The Official Journal of the Academy of Family Physicians of Malaysia, 3*(1), 14.

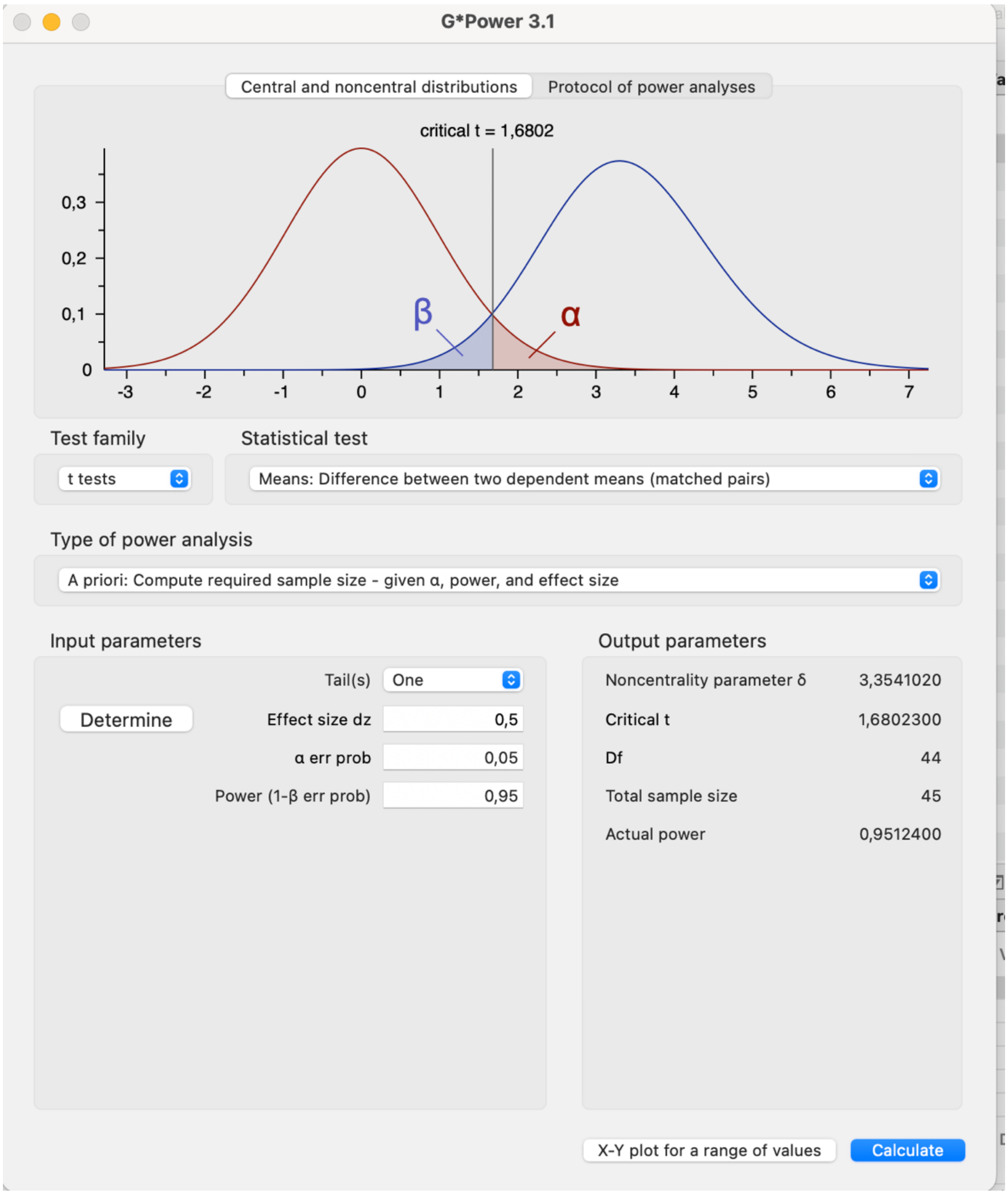
Wood, J. L., Schmidtke, J. M., & Decker, D. L. (2007). Lying on job applications: The effects of job relevance, commission, and human resource management experience. *Journal of Business and Psychology, 22*(1), 1-9. https://doi.org/10.1007/s10869-007-9048-7

Yang, J., Li, H. B., & Wei, D. (2023). The impact of ChatGPT and LLMs on medical imaging stakeholders: Perspectives and use cases. *Meta-Radiology, 1*(1), 100007. https://doi.org/10.1016/j.metrad.2023.100007

VIII. Appendix

Appendix A

Figure 1. Power calculation



Appendix B

[Start of Survey]

[Start of Block: Cover block]

Dear Participant!

As part of my Master's thesis at the Erasmus University Rotterdam, I am conducting a survey to observe people's decisions regarding job applications. I would like to kindly ask you to assist me with that. The survey is anonymous, optional and takes less than 2 minutes to complete.

Thank you very much in advance for your cooperation, should you have any questions or feedback, do not hesitate to contact me at 659019ab@eur.nl.

Please confirm your consent to the following statement:
I hereby confirm that I am older than 18 and voluntarily consent to participate in this survey. I allow my data to be collected anonymously and used for research purposes.

○ Consent

○ Do not consent

[End of Block: Cover block]

[Start of Block: Demographic questions]

Please state your age in years.

____

Please select your highest level of completed education.

- ○ Primary education
- ○ Secondary education
- ○ Higher education (Bachelor's degree, Master's degree, PhD etc.)

Do you have any recruitment experience?

- ○ Yes
- ○ No

[End of Block: Demographic questions]

[Start of Block: Core questions]

In this segment, you will be asked to imagine that you work in the HR department of a company called Management Consulting Firm operating in the Netherlands, overviewing job applications for the position of Consultant. You received two motivation letters, attached below. Please read to following two motivation letters carefully and answer questions about their quality and suitability for the job. Please note that we have anonymised the letters to avoid privacy concerns.

The role:
Analysing client challenges and implementing effective solutions as part of small teams. The role will involve gathering and analysing information, testing hypotheses, and formulating recommendations. The consultant will communicate findings to client management, collaborate with their team members, and implement recommendations.

The requirements for the job are as follows:
- Undergraduate degree or Master's degree or 1+ years of work experience after completing your undergraduate degree
- Ability to work collaboratively in a team and create an inclusive environment with people at all levels of an organisation
- Capability to drive an independent workstream in the context of a broader team project
- Comfort with ambiguous, ever-changing situations
- Ability to break down and solve problems through quantitative thinking and analysis
- Ability to communicate effectively, both verbally and in writing, in English

Motivation Letter - Stanley Scott

Dear Hiring Manager,

I am excited to express my interest in the Consultant position at Management Consulting Firm. As a firm committed to professional excellence, I am impressed by the values, dedication to diversity and inclusion, and the impressive history of your organisation.

My BSc Economics degree from University ABC allowed me to combine problem-solving and critical thinking skills with my knowledge in economics and business, therefore I am confident that I can provide valuable insights and novel ideas. Furthermore, I have also gained relevant experience in fields such as financial analysis and management consulting. My adaptability, communication and organisation skills are key strengths that enable me to work effectively both in a team and independently. Aside from utilising my academic and professional knowledge, I aspire to capitalise on my perseverance and my hardworking mentality.

I am confident that I would be a strong candidate for this position and would make a great addition to your team. Should you have any questions regarding my skills and qualifications, do not hesitate to contact me at the email address or phone number provided above.

Thank you for your time and consideration.

Kind regards,
Stanley Scott

Motivation Letter - Michael Hudson

Dear Hiring Manager,

I am writing to express my sincere interest in the Consultant position at Management Consulting Firm. With a BSc degree in Economics from University ABC, strong problem-solving skills, and a solid understanding of economics and business, I am confident in my ability to contribute to your organization.

My experience in financial analysis and management consulting has provided me with valuable insights into the industry. I am adept at adapting to different work environments and excel both in team collaborations and independent tasks. My effective communication skills allow me to convey complex ideas clearly and foster strong working relationships.

With excellent organisational abilities, I consistently meet deadlines and manage multiple projects efficiently. I approach my work with perseverance and a strong work ethic, always striving for excellence.

As a Consultant, I believe my qualifications and skills make me a great fit for your team. I am eager to contribute my problem-solving abilities, dedication, and insights to drive success for your clients.

Thank you for considering my application. I look forward to the opportunity to discuss how my expertise can benefit Management Consulting Firm.

Sincerely,

Michael Hudson

How likely is it that you would recommend hiring Stanley Scott?

○ Extremely unlikely

○ Somewhat unlikely

○ Neither likely nor unlikely

○ Somewhat likely

○ Extremely likely

How likely is it that you would recommend hiring Michael Hudson?

○ Extremely unlikely

○ Somewhat unlikely

○ Neither likely nor unlikely

○ Somewhat likely

○ Extremely likely

What yearly starting salary (in EUR) would you offer each candidate?

	20000	25000	30000	35000	40000	45000	50000	55000	60000
Stanley Scott									
Michael Hudson									

Please provide rationale for your decisions and explain why you might have preferred one candidate over another.

[End of Block: Core questions]

[Start of Debriefing]

Thank you for your valuable time spent taking this survey! Your response has been recorded and your data will be used for research purposes in line with the agreed terms.

The title of my study is "From Humans to Machines: Can Artificial Intelligence Outsmart Human Job Applications?" and the survey was designed to measure whether participants would prefer the AI-written cover letter (Michael Hudson) over the human counterpart (Stanley Scott).

Should you have any questions or feedback reagrding the survey or the research project as a whole, do not hesitate to contact me at 659019ab@eur.nl. If you are interested in the outcome of the research, you can also request the results via the email address.

[End of Debriefing]

[End of Survey]

Appendix C

Prompt for ChatGPT

I would like you to write a cover letter (also known as motivation letter) for a job application in the name of "Candidate B". The position in question is "Consultant" at a company called "Management Consulting Firm". The industry the firm operates in is management consulting. The aim is to convince the company to hire Candidate B. Below are the skills and qualifications the candidate has, highlight this when formulating your answer. The cover letter should be 180-200 words.

- BSc degree in Economics from University ABC
- Strong problem-solving and critical thinking skills
- Knowledge in economics and business
- Experience in financial analysis
- Experience in management consulting
- Adaptability in different work environments
- Excellent communication skills
- Strong organizational skills
- Ability to work effectively in a team
- Ability to work independently
- Perseverance and a hardworking mentality