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Facial Recognition Technology and Racial Discrimination a Study on the Design of On-Demand-Asynchronous Video Interview Solutions Used in Recruitment

Evans Uhunoma

ABSTRACT: 7% of people of colour in the UK are unemployed as compared to 4% for whites (UK Gov, 2021). While recent breakthroughs in face recognition technology (FRT) have enhanced the process of recruitment through the use of on-demand-asynchronous video interview solutions (Tambe, et al., 2019; Harwell, 2019; Nawaz, 2020), several other studies have however confirmed that FRT and its application in recruitment activities are biased towards people of colour (Izario et al., 2017; Buolamwini, 2019; Simonite, 2019). Consequently, this is predicted to lead to an increased diversity crisis within the workplace as the employment of people of colour may even lessen further (West et al., 2019). The aim of this dissertation was therefore to understand how on-demand-asynchronous video interview solutions (ODAVIS) capture peculiarities in faces. Specifically, how creators of FRT determine candidates' suitability for jobs using FRT's facial analysis, if the data used to train their model is representative of the faces in the world and what reasonable adjustments (if any) are made for people of colour. The major findings include the use of facial landmarks and gaze estimators to analyse candidates' facial expressions and emotions during interviews, the use of non-representative training data that leads to inconsistency in performance, and the inclusion of certain adjustments (like automatic flashlights, data augmentation or bias audit) during the designs of the solutions and implementation, to close the gaps of inconsistent performance observed for different races.

KEYWORDS: Facial Recognition Technology (FRT), On-Demand-Asynchronous Video Interview Solutions (ODAVIS), People of Colour (POC).

INTRODUCTION

1.1 Background of Research

In recent years, there have been significant breakthroughs in the application of technology and artificial intelligence (AI) in the field of human resources (HR). These breakthroughs are transforming the HR field altogether and creating numerous opportunities for businesses to rethink their human resource procedures (Ahmed, 2018). Accordingly, one of the major applications of AI in HR practice today is the use of automated tools to determine a candidate's employability based on face recognition technology (Tambe, et al., 2019; Nawaz, 2020). Through candidates' cameras, facial movements and expressions can be analyzed during an interview, after which a behavioural profile (strengths and weaknesses of the candidate) is generated, 'before ranking them against other applicants based on an automatically generated employability score' (Harwell, 2019, p.2). The facial recognition technology (FRT) tools adopted by companies to do this, is called on-demand-asynchronous video interview solutions, referred to as ODAVIS throughout this dissertation.

The major challenge however is that it is unsure how FRT examines differences in faces, specifically for different races (Merler et al., 2019). This is particularly problematic because the report generated from the solution becomes a basis through which the suitability of candidates for jobs is decided (Izario et al., 2017). And as many other authors believe, FRT and its application in the workplace may consequently worsen diversity-related issues, such as discrimination against certain races, women and neurodivergent people (Tambe et al., 2019; Buolamwini, 2019; West et al., 2019; BBC, 2022). This dissertation however focused on racial discrimination.

1.2 Problem Statement

Several studies have confirmed that AI and FRT are biased towards people of colour (Tambe et al., 2019; Buolamwini, 2019; West et al., 2019). Simonite (2019) opined that even the best algorithms have trouble recognising black faces. However, not much study has been done to understand how creators of FRT, program ODAVIS to generate candidates' behavioural profiles just by analysing their faces and if certain considerations or reasonable adjustments are made for people of colour where inconsistency in the performance of the solution are observed. In addition, not so much has also been done to find out if FRT developers train their models with data that are representative of all races. Consequently, this study's focus is not to confirm or negate if FRT is discriminatory to certain races but to understand how creators of FRT determine candidates' suitability for jobs just by analysing their facial movements, if the data used to train their model is representative of the faces in the world and what reasonable adjustments (if any) are made for people of colour where inconsistencies are observed.

1.3 Research Aim, Objectives, and Questions

Aim: To understand how face recognition technology captures peculiarities in faces when using ODAVIS for hiring.

Objectives:

a) To understand how creators of FRT determine candidates' suitability for jobs just by analysing their facial movements and expressions.
b) To find out if the training data used for FRT models are representative of the face distribution found in the real world.
c) To identify considerations/reasonable adjustments (if any) FRT creators put in place to mitigate bias towards people of colour.

Questions:

a) How do creators of FRT determine candidates' suitability for jobs just by analysing their facial movements and expressions?
b) Do FRT developers use training data for FRT models that are representative of the face distribution found in the real world?
c) What considerations/reasonable adjustments (if any) do FRT creators put in place to mitigate bias towards people of colour?

1.4 Dissertation Structure

The structure of this dissertation was divided into five chapters. **Chapter one** introduced the research and defined the objectives. **Chapter two** reviewed the relevant literature cutting across theories and previous studies on the subject. **Chapter three** discussed the methodology employed and issues around the ethical considerations made. **Chapter four** presented and discussed the key findings with a focus on answering the research questions. **Chapter five** summarised the dissertation, reflected on the limitations and presented some practical recommendations to companies.

LITERATURE REVIEW

2.1 Introduction

This chapter discussed the major theories and previous studies relevant to this dissertation. It started with a brief description of the facial recognition technology and its application in the field of HR, after which the subject of racial discrimination was briefly discussed. Other discussions and analyses in this chapter were on the relevant theories, previous research and identified research gaps.

2.2 Facial Recognition Technology: Applications in HR and Challenges

Artificial Intelligence, otherwise called AI, coined by John McCarthy in 1955 (Doug, 2018) refers to a set of technologies, through which a computer system can execute instructions that would have typically required human intelligence (Tambe et al, 2019). It cuts across several automated activities and applications such as image processing, natural language processing (NLP), robotics, facial recognition technology (FRT) and machine learning (Lee et al, 2018). This suggests that FRT, the focus of this dissertation, is one of the major application areas of AI. According to RecFaces (2021), FRT simply means a collection of algorithms (a set of instructions), used to recognise people in photos or videos. That is, through an FRT tool, an individual can be recognised from a multitude of other people. This has become an opportunity for many businesses to carry out some of their video/imagery-inclined activities that typically would have involved human labour today (Nawaz, 2020). Consequently, FRT is now being applied in many industries today, like health, security, and schools and also in business and HR-related activities such as teleconferencing, ID checks, attendance marking, building access and smarter advertising (Faux and Luthon, 2012; Forbes, 2022).

FRT Application in Human Resources

Facial recognition technology is also applied in human resources management today. Tambe, et al. (2019) noted that one of the major applications of AI and facial recognition technology in HR practice today is using it as a recruitment tool. For example, one of the breakthroughs of a top car manufacturer was the use of FRT to evaluate candidates, through their appearances and facial expressions. Candidates are questioned about their expertise and experiences through the central touchscreen of the car. After the interview, the AI evaluates the candidate's credentials, drive, and social skills using the data acquired. Based on that, it produces an evaluation report that is automatically sent to the human resources division (Jo, 2018). Masud et al. (2020) also opined that through FRT, human and computer collaboration has been enhanced to make selection more seamless for recruiters. HireVue for example is one of the leading facial recognition technology development companies, whose ODAVIS, various companies use to carry out their interview activities (Izario et al., 2017). Through candidates' cameras, facial movements can be analyzed during an interview which forms part of the input for hiring decisions (Harwell, 2019). There are several other similar products used to automatically select candidates through the application of FRT and other AI. They include but are not limited to VidCruiter, Spark Hire, Arctic Shores, Easy Hire and many more (Capterra, 2022). An ODAVIS simply put, is when technology, rather than a traditional interviewer, facilitates pre-determined questions (Sabel, 2018). The technology simply asks the candidate questions, which they are to give responses, while the technology monitors their facial expressions, eye contact and manner of speaking. The rationale of the solution is that it helps decide the best candidate by analysing the applicant's looks and languages, identifying their speaking style, as well as how they respond to each inquiry (Izario et al., 2017; Black and Esch, 2020). This suggests that the use of the FRT tool has made recruitment more seamless for many organisations, as it saves them time, energy, money, and supposedly even helps them select the best candidates.

Challenges of Applying FRT in HR

Although the application of FRT in video interviews has gained so much acceptance over the years, especially with the high adoption from several large companies such as Shell, Unilever, and NHS (Recruiter, 2019; H2B, 2019; Shell, 2022), there have also been several challenges. The primary reason for this is that FRT aims at detecting and understanding human facial features, which comes with various difficulties (Merler et al., 2019). This is because every face has distinct features that make it different from others. And while "computers may be good at following rules, they are bad at pattern recognition" and distinguishing such features (Brynjolfsson and McAfee, 2014, p.4). The features are difficult to distinguish due to the individual morphological differences in the face such as the colour of the eyes, the shape of the nose, and most importantly the skin colour and tone (Faux and Luthon, 2012). This essentially is where the issue of discrimination and unfairness creeps in. One of the leading development companies of ODAVIS for example has been the target of major criticism as many believe it is highly discriminatory towards certain people (Kahn, 2021). Merler et al. (2019) nevertheless argued that recent breakthroughs in neural networking and data-driven deep learning have improved the accuracy of FRT to efficiently identify those morphological distinctions.

2.3 Racial Discrimination

Discrimination in the workplace is the practice of making unwarranted disparities or biased judgements about people, that cannot be substantiated by facts but are made due to the social group they belong to (Kumra and Manfredi, 2012). There are various types of discrimination. In the UK, the Equality Act (2010) covers 9 protected characteristics which when unwarranted disparities are made based on can be seen as discriminatory. They are age, disability, sex, gender reassignment, sexual orientation, race, religion & belief, pregnancy & maternity, and marriage and civil partnership. The focus of this dissertation is on racial discrimination.

Racial Discriminations in Interviews

Issues of discrimination in the application of FRT in the selection of candidates have gotten so much attention lately (Zhao et al, 2017; Lohia et al, 2018; West et al, 2019). It is particularly problematic because the outcomes of the decisions made by the FRT, as in the case of video interviews, can determine who gets hired (Tambe et al, 2019). This, therefore, signals a potential diversity crisis in the workplace, because if some groups can't even be hired by the selection tool, then how would the workplace be diverse? This partly also explains why the unemployment rate for people of colour (POC) is 7% as compared to 4% for white (UK Gov, 2021). Still, while these discriminatory issues encountered by FRT in video interviews and other AI applications in HR generally affect different groups, unfortunately, the discriminatory repercussion is not evenly distributed across all races (West et al, 2019). An intersectional study by Buolamwini and Gebru (2018) shows that Blacks have the highest error rate of FRT applications (See Fig.1 below).

Figure 1 - Error Rate of FRT for Different Races (New York Times, 2018, p.3; Adapted from Buolamwini and Gebru, 2018)

Simonite (2019) also opined that even the best algorithms have trouble recognising black faces. In addition, at the beginning of 2020 in the US, Detroit police detained a black man in front of his family with belief that he was involved in a shoplifting incident nearby which was later found out to be an error made by the FRT app as it could not distinguish Black and White faces (ACLU, 2020; United Nations, 2020). Consequently, these may suggest that the Black race is more significantly affected by the FRT solutions. In addition, one may also conclude that if these issues of discrimination persist in the application of FRT in any given area, it is also suggestive that there is no difference when used as means of selecting candidates through video interviews. Buolamwini states this better.

The main message is to check all systems that analyse human faces for any kind of bias. If you sell one system that has been shown to have bias on human faces, it is doubtful your other face-based products are also completely bias-free

(Buolamwini, 2019, p.15)

Arguments against Racial Diversity

While many may believe that it is a crucial time to be addressing the issues of diversity and systemic discrimination in the application of AI and FRT in various fields including HR (West et al, 2019), some are sceptical of, if not an outright dismissal of the idea that racism exists in the application of AI in any field. For example, several researchers opposed an event idea titled "Black in AI workshop", a renowned machine learning conference with the argument that the event was irrelevant as perceived discrimination against Blacks does not exist (Khan and Bass, 2017). In addition, a more recent argument that seems to be used against racial discrimination in the application of AI and FRT is called cognitive diversity (discussed next). Essentially, this theory has over time been appropriated by opposers of the idea that AI discriminates. They believe that individual peculiarities cutting across perspectives, behaviours and thought processes should be the focal point of diversity issues and not race or gender (West et al, 2019). Williams (2017) went further to propose that even 12 white men from the same background can still be considered a diverse group as long as they think differently. This idea is particularly problematic for authors like Tambe et al. (2019), West et al. (2019) and Buolamwini (2019) who are major believers that AI and FRT are discriminatory towards certain races, especially given that the idea (cognitive diversity) is beginning to circulate among major influencers in the AI industry (Shead, 2019).

Having discussed the concepts of FRT and racial discrimination and how both relate, the next section discusses the major theories adopted in this dissertation.

2.4 Relevant Theories

Cognitive Diversity

Cognitive diversity describes the extent to which a group differs in terms of their thought processes, perspectives, and behaviours (Miller et al., 1998). The assumption is that distinctions among group members may result from characteristics like thinking-pattern, behaviour-manner, skill level, or experiences, as opposed to traditional demographics like race or gender (Miller et al., 1998; West et al, 2019). While several researchers have confirmed that cognitive diversity has a positive relationship with creativity, problem-solving and improved decision-making (Parayitam and Papenhausen, 2016; Meissner and Wulf, 2017; Younis, R., 2019), some other studies believe that it has negative results in respect to teamwork and communication (Miller, 1990; Ness, 2021). As it relates to this dissertation, given the belief that cognitive diversity is beginning to circulate among major influencers in the AI industry (Shead, 2019), it is suggestive that this may influence how FRT creators perceive diversity issues, and consequently have major impacts on the current bias experienced by certain races. This is because race or gender may not (or no longer) be an important consideration for them if they believe cognitive diversity is superior to demographic diversity. Nonetheless, a few authors have recommended an amalgamation of cognitive and demographic diversity categories going forward as it seems a focus on cognitive diversity only may be a double-edged sword (Kang et al. 2006; Tatli and Özbilgin, 2012; Younis, 2019).

Similarity-Attraction Paradigm

Similarity-attraction paradigm has to do with people's preferences for engaging with those who are like them (Byrne, 1971). This essentially implies that people tend to favour others who possess' similar traits or features to them. In the context of this dissertation, the study of Crawford (2016) confirmed this paradigm when he found that one of the reasons why AI may be biased toward people of colour is because most AI and FRT developers are concentrated in the hands of only a few companies, that went to similar elite universities and are usually male and white. That is, most FRT tools are created by white-male people and following the similarity-attraction paradigm, there is, therefore, a tendency for them to create systems that work best for people like them subconsciously. This may also be a possible explanation for why the error rate of FRT is significantly lower for White Males (Buolamwini, 2019).

The Shackled-Runner Analogy

In, the shackled runner analogy, Noon (2010) highlights the challenges in closing the racial discrimination gaps using the story of two runners. In the context of this dissertation, this analogy suggests that, while FRT may be inherently biased as confirmed by various studies discussed so far, it may also be possible to close this gap going forward, if FRT developers give ***special considerations/adjustments*** to how FRT functions for people of colour by looking at the training data used and how ODAVIS is implemented.

Face Dataset

In FRT, the eyes in addition to other facial features help map facial traits from an image or video and then compare the information to a database of known faces (Galterio et al., 2018). This database of known faces is called a face dataset. There are several face datasets available today and some of the popular ones used by most FRT companies are as follows: Facebook dataset, Labelled faces in the wild home (LFW), YouTube faces dataset with facial keypoints, Google facial expression comparison dataset, and Large-scale celebfaces attributes (CelebA) (Ortiz and Becker, 2014; Choudhury, 2020). While humans may be able to identify and remember up to 5000 faces (The Guardian, 2018), these databases can remember hundreds of thousands of faces and cumulatively into millions, as fast as within 0.2 seconds (Barragan-Jason et al, 2015). These images here are often used as training data (data used to train machine learning models) by several FRT systems (Parkhi et al, 2015; Guo et al, 2016; Zhang et al, 2016). In the context of this dissertation, given that most FRT systems use these platforms for their training data, the question is, are the faces in these datasets representative of all faces in the world?

2.5 Previous Research

This section discusses some of the previous research in FRT and racial discrimination subject areas.

One of the earliest research projects in FRT was an Oxford seminar thesis by Kanade (1973). He was interested in understanding how FRT identifies peoples' faces through their morphological traits like the distance between eyes, shape of nose and mouths. Essentially, he focused on understanding the intrinsic variations that may pose problems for FRT in the future.

In the last decade, however, more studies in this area have been on addressing different themes. One of the major themes has been focused on who creates FRT. The focus of this theme has been to understand the source of discrimination in the AI field. West et al (2019) found out that black race representation in most tech companies is around 5% or less. Crawford's (2016) study showed that most developers in tech companies that create AI and FRT are predominantly white males. However, other studies such as Williams (2017) have argued that there is still diversity among AI creators, just not racial or gender inclined but with a focus on cognitive diversity.

Another major theme that previous research has been carried out on is the inherency of AI and FRT to be biased toward certain people. Tambe et al (2019) study showed that AI is inherently biased toward women and people of colour. Buolamwini and Gebru (2018) found that the error rate of FRT is predominantly higher for people of colour than for others. Merler et al (2019) opined that the training data used in FRT are not representative of all races. However, one of the major FRT company's AI head recently claimed that their FRT app (*Amazon Rekognition*) is not discriminatory towards certain races as claimed by other investigators and that their training data cuts across all race and ethnicities (Kleinman, 2019).

Lastly, another major theme previous researchers have focused on has been the application of FRT to specific HR activities in the workplace. Weichselbaumer's (2016) study focused on the application of FRT on job applications, where he found out that application profiles of white people had higher call-back rates than profiles of people of colour. Other studies have focused on the application of FRT for psychometric assessment and IQ testing. Duchaine and Nakayama (2006) found out that the Cambridge Face Memory Test (CFMT), a variation of FRT have no association with standardized IQ tests. Wilmer et al (2010) found out that CFMT has no association with general abilities. Other studies focusing on the application of FRT on one-demand-asynchronous video interviews found that the application of FRT in selecting candidates leads to discrimination (Zhao et al, 2017; Lohia et al, 2018). However, Masud et al (2020) studied opined that irrespective of FRT shortcomings, it nonetheless enhances collaboration between humans and computers to make the recruitment process more seamless. Izario et al (2017) and Black and Esch (2020) also believe that the application of FRT in video interviews helps determine the character and trustworthiness of the best candidates based on their outward appearance, response to answers, and eye contact.

2.6 Research Gaps

As discussed in the previous section, several studies have been done around the themes of who create FRT (Crawford, 2016; West et al, 2019), and why FRT is an inherent bias against certain race (Buolamwini and Gebru, 2018; Tambe et al, 2019), and problems of applying FRT to HR activities (Duchaine and Nakayama, 2006; Weichselbaumer, 2016; Zhao et al, 2017). There have also been studies around the distinctions of eye shapes, noses, and mounts in the application of FRT (Merler et al, 2019). However, much research has not been done to see if developers consider facial characteristics such as skin colour and why it impacts the reported varied performance of FRT systems when applied to ODAVIS. In addition, there hasn't also been so much research into whether FRT developers employ training data that is representative of all races during the development. As a result, the goal of this dissertation is not to prove or disprove whether FRT is discriminatory towards specific races or which race is responsible for it, but to understand how creators of FRT capture peculiarities when using FRT in recruitment.

METHODOLOGY

3.1 Research Philosophy

In this dissertation, the research philosophy adopted is **interpretivism.** Interpretivism is based on "perceiving or comprehending the meanings that people attach to their actions through social constructions such as language, shared meanings, and instruments" (Myers, 2019, p.45). The reasons for adopting this philosophy are, first, it allows researchers to have multiple interpretations, secondly, it helps get responses that are close to the truth through qualitative and primary data, and lastly, it offers a great level of depth on social issues like the subject of this dissertation (Klein and Myers, 1999; Saunders et al, 2012). However, this philosophy has some shortcomings. First, Chowdhury (2014) argued that objective data are difficult to collect using this philosophy as the researcher does not focus on universal truths, hence, it is perceived by many as subjective. In addition, Gill and Johnson (2010) argued this approach may be unreliable as the interpretation and truth differ among researchers. These shortcomings are in contrast with the positivism philosophy which some contend comes with clear evidence and higher reliability given that its approach tends to be more scientific (Cohen et al., 2007; Hammersley, 2013). It is also in contrast with pragmatism philosophy which typically focuses on concrete and practical issues and results (Iaydjiev, 2013). Irrespective of the shortcomings highlighted, the interpretivism approach was still chosen because it enables analysis of stories, narrative or textual-inclined data collected, and most importantly allows multiple interpretation and conclusions, which are all important to answer the research questions of this dissertation.

3.2 Research Approach

The reasoning approach adopted in this dissertation is **induction**. Bryman and Bell (2015, p.27) explained that the induction research approach draws its inferences "by using known premises to generate untested conclusions, which then involves a generalization from specific to general". Some of the criticism against this approach include the tendency to get wrong inferences and its scope limitations (Eisenhardt et al., 2016; Saunders et al., 2019). The opposite of this is the deductive approach, which in contrast focuses on patterns, trends, and causal relationships between variables (Robson, 2002) and unlike the induction approach, deduction inference is usually from general to specific (Bryman and Bell, 2015). Nevertheless, the induction approach was favoured for this study because, first it is more consistent with the interpretivism philosophy (Saunders et al., 2019) and secondly, it is the most appropriate approach for socially inclined subjects like that of this dissertation, which aims to understand the context in which the development of ODAVIS takes place (Easterby-Smith et al., 2021; Thomas et al., 2022). Other advantages of this approach include, opportunity to generate new theories, and ability to offer alternative explanations (Eisenhardt et al., 2016; Saunders et al., 2019).

3.3 Methodological Choice

The methodological choice adopted in this dissertation is **qualitative**. This choice uses qualitative data collection methods (Saunders et al., 2019) which helps collect qualitative data in textual form. This is as opposed to the quantitative method where the focus is on collecting numerical data with single or multiple data collection methods or mixed methods that try to employ both methods (Saunders et al., 2019). Some of the criticism of using the qualitative method include difficulty in measuring causality and insufficient sample size (Taylor, et al., 2015). Nevertheless, a qualitative approach is adopted for this study because it gives the opportunity to generate valuable conversations in textual form, from the target audience of this research that numbers may not be able to. Some of its other benefits include flexibility and the use of small sample size (Choy, 2014).

3.4 Data Collection and Analysis

The choice of data collection method adopted in this dissertation is primary data through **one-on-one interviews**. Interview is one of the most used data collection methods in qualitative research as it allows researchers to gather data through in-depth conversations, stories, and narratives (Saunders et al., 2019). Specifically, semi-structured interview questions (see appendix 2) were developed using an appreciative inquiry guide (Michael, 2008) to collect data from the target audience (FRT creators). A semi-structured interview was adopted because it allows the capturing of emotions and non-verbal cues of the interviewees, gives great deal of flexibility, is open-ended and follows a natural conversational flow (Patton, 2014).

The target audience that the data were collected from were creators of FRT and ODAVIS. Hence, I interviewed FRT developers and other relevant stakeholders who have worked in FRT and have been part of the development of ODAVI solutions. A non-probability sampling technique, specifically **convenience sampling**, was adopted for this dissertation. Although this technique has been thought to be prone to bias (Etikan and Bala, 2017), it was however still chosen because it saves time and cost (Acharya, et al., 2013). In terms of the sample size sufficient for this study, Saunders et al. (2007) argued that qualitative research should typically require a small sample size following the principle of saturation. They, therefore, recommended sample size of 10-20 interviewees. Francis et al. (2010) corroborated this in their study where saturation was achieved after 17 interviews. Consequently, **twelve (12) interviewees** were selected for this study.

Thematic analysis was used in analyzing the data collected. This involved categorizing the textual data collected into themes and then presenting it to answer the research questions (Saunders et al., 2007). This data analysis type was chosen because it helps apply inductive reasoning logic and enables all research questions to be answered (Braun and Clarke, 2012).

3.5 Ethical Considerations

In ensuring that this dissertation is carried out following academic ethical principles, the recommended guidelines of Macfarlane (2010) were adopted. This cut across getting verbal and documented consent as well as informing the interviewees of their rights to anonymity, and withdrawal at any point in time. Saunders et al (2019) also recommend that interviewees' responses should be treated with confidentiality and privacy. Consequently, a consent form and participant information sheet were developed (see appendix 1) and used to inform the interviewees of these rights and the ethical considerations employed in carrying out this research before the interviews.

FINDINGS AND DISCUSSIONS

4.1 Introduction

The objectives of this dissertation were to understand how creators of FRT determine candidates' suitability for jobs using ODAVIS facial analysis, if the data used to train their model is representative of the faces in the world and what reasonable adjustments and considerations (if any) are made for people of colour. After interviewing the twelve (12) creators of FRT, the results were analysed and are presented in this chapter.

The structure of this chapter is divided into five sections. The first section reiterates the research questions and outlines the structure of this chapter. The second section outlines the interviewee's profiles. The last three sections present and discuss the key findings of each of the three research questions.

4.2 Profiles of Interviewees

Following the ethical considerations adopted in this dissertation, all names used in this chapter were pseudonymized. The profiles of the FRT creators interviewed can be seen in Table 1 below.

Table 1 - Interviewees' Profiles

Participants	Pseudonyms	Gender	Region	Role
Participant 1	Aiden Lakshanya	Female	India	Business Psychologist
Participant 2	Beton Kailing	Male	Ireland	Mid-Level Developer
Participant 3	Charles Fabrizo	Male	South Africa	Senior Developer
Participant 4	Daniel Hendriks	Male	UK	Product Manager
Participant 5	Eirene Erik	Male	Nigeria	Junior Developer
Participant 6	Fabio Cyril	Male	US	Junior Developer
Participant 7	Gabriel Gallagher	Male	Nigeria	Junior Developer
Participant 8	Helyette Deekshita	Male	UK	ODAVIS Recruiter
Participant 9	Ibrahim Ishtar	Male	Nigeria	Mid-Level Developer
Participant 10	Jacint Jabir	Male	Canada	Mid-Level Developer
Participant 11	Kalap Baldwin	Male	Nigeria	Junior Developer
Participant 12	Liam Alexander	Male	UK	Researcher

4.3 How FRT Determines Candidate's Traits through Facial Analysis

The first research question of this dissertation was to understand how creators of FRT determine candidates' suitability for jobs using facial analysis. Overall, two major themes were identified as methods utilized by ODAVIS to analyse people's facial expressions and assign an emotion/behaviour to such expressions during interviews. The first theme centred around statistical analysis and the second theme centred on deep learning, specifically, convolutional neural networks (CNN).

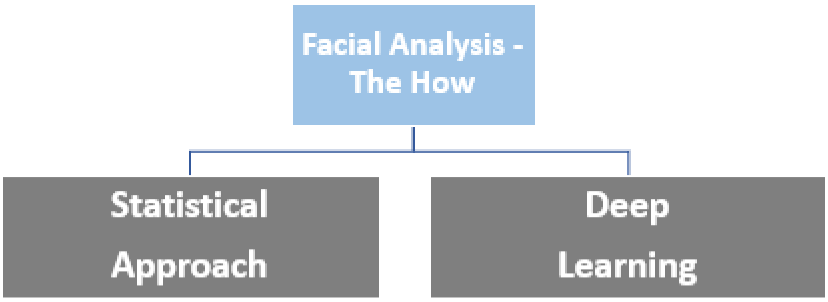

Figure 2 - How FRT Classify Behaviours through Facial Analysis

The statistical approach has to do with resizing and dividing images/videos read into a standard pixel size, before computing certain statistical tests, and then classifying the faces using any of the popular statistical classifiers (Jia, 2017), whereas deep learning uses various sub techniques such as CNN which "captures an input and assigns importance as weights and biases to various aspects and characteristics of an image, such as features of a face as gestures, or age…" (Brito et al., 2021, p.115851). Consequently, in CNN, by learning and identifying these traits as belonging to a specific person, the algorithm can distinguish one feature from another, and classify emotions or behaviour to certain facial features and expressions.

A recurrent response among the interviewees was the reiteration that through CNN, the ODAVIS can identify emotions such as smiling, happiness, sleepiness, tiredness, and even some behaviour such as the focus level of a candidate, or whether a candidate is stressed, distracted, or even cheating. Seven out of twelve of the interviewees focused on this and some examples of their responses can be seen below.

…we can identify these behaviours by classifying certain landmarks on people's faces to different emotions. A hybrid of neural networks measures and classifies the activities over a period. Logic can (then) *be created to define activities based on the classifications made. For example, we can measure candidates' focus or distraction level, by using a gaze estimator, that specifies the direction that the candidate is expected to be looking at. This can be used in addition to NLP* (Natural Processing Language) *to detect distracted audio feedback - like if the candidate is talking to some other person* (Cheating).

…Fabio Cyril, Male, US, Junior Developer

Another interviewee though agreed on how ODAVIS can do this through deep learning, however, said it is dependent on how the machine has been trained and the availability of sufficient data to understand different reactions.

…depends on how you train and adjust your machine (model)*. The application can look through your face and detect certain features like stress level, smiling (enthusiasm), sadness, and various other emotions.* The truth is *humans tend to react the same way, and hence the system is trained to see that. The algorithms can* (even) *be trained to predict or compare candidates to high performers within the organisations using features like haircut, dressing and general presentation.* However, we *need more data on peoples' sitting positions, gestures, and reactions.*

…Beton Kailing, Male, Ireland, Mid-Level Developer

Concerning whether FRT captures inherent face distinctions among different races when determining these traits, how accurate it is and whether the performance of the system is consistent across all races, the responses from interviewees indicated that performance is not the same across races, as certain conditions like skin colour make it difficult to capture the inherent facial distinctions among different races. *Eirene Erik* for example talked about how an ODAVIS like-tool failed to grant a black person access to take their assessment (as the face could not be read properly). *Beton Kailing* also mentioned how the tool was tested with nose masks on, for different races, but didn't work for blacks. *Jacint Jabir* however said it is very accurate and that the performance is consistent across races as different skin and eye colours are used to train the model. Unlike the three other responses above, the response below gave a new light.

Sometimes it's not a racial or diversity-related issue but just physics. Black people have darker skins and (also) *in dark rooms, less light is reflected to the camera. In a dimly light environment, it is naturally easier to see a white person than a black person… (*hence the differences in performance).

…Daniel Hendriks, Male, UK, Product Manager

Use of Facial Landmarks to Classify Candidates' Emotions: A Breakthrough or Recipe for Discrimination?

Facial landmarks are keypoints in people's faces and one of their functions is to detect emotions (Nguyen et al., 2017). One of the major findings presented above is the use of certain facial landmarks to classify certain emotions and traits of candidates during video interviews. On the one hand, this finding is consistent with that of several other authors and seem like a breakthrough. First, Loconsole et al. (2014) discovered that there are 19 major keypoints in human faces and can be used to compute 26 geometrical features for emotion prediction. Secondly, Black and Esch (2020) corroborate this finding when they found that ODAVIS aids in selecting the best candidate by evaluating the applicant's appearances, facial expressions and speaking manner. Also, a top car manufacturer uses FRT to evaluate driving candidates' appearances and facial expressions, based on which an evaluation report is generated and sent to the hiring managers (Jo, 2018).

On the other hand, this does not appear to be the opinions of other researchers and may therefore need to be approached with caution. Faux and Luthon (2012) argued that skin tone and colour are the most difficult morphological difference for FRT to understand. As a result, first, it is unsure if the result of the face analysis will be consistent for different people due to variations in skin colour and shapes of their eyes and noses. This was confirmed by Kahn (2021) who found ODAVIS to have inconsistent performance across races. Secondly, the use of this solution can increase profiling cases when candidate's haircut, dress sense or mood, are used to judge their overall level of competency. Lastly, as pointed out by Buolamwini (2019), given that other FRT application has been seen as discriminatory towards POC in other fields, there is no guarantee that it is any different now. Consequently, companies need to evaluate the risks and rewards of these solutions before adopting them in their recruitment process, as it is illogical to adopt a tool which though brings a benefit, come with 2 problems.

Inconsistency in Performance: A Physics Issue or Just an Excuse?

Another finding of this dissertation is that although humans' facial features are different, humans tend to react the same way (irrespective of skin colour), and hence the system is trained to see that. This suggests that even if the data used to train the ODAVIS model is from one race, it is expected to work the same way for other races because humans react the same way.

While Merler et al. (2019) argued in favour of this by stating that this is one of the major advantages of CNN (efficiency in identifying morphological distinctions across races with little or no bias), however, Brynjolfsson and McAfee (2014) argued that computers are bad at such pattern recognition. Nevertheless, certain facial expressions have been said to be consistent in all parts of the world (Zadeh, 2018). That is, there is a universal expression for certain emotions, and this may imply that even if facial samples of only one race is used to build such model, performance may still be expected to be the same for every other race. Contrary to the above however, this is still not the case in reality, as there is still a high level of the inconsistency of ODAVIS performance across different races. For example, a leading creator of ODAVIS has been heavily criticised as it is believed that the solution is still highly discriminatory towards POC (Kahn, 2021). Simonite (2019) also argued that even the best algorithms have trouble recognising black faces.

Lastly, in a scenario where this is conclusively more of a physics problem, and the perceived discrimination towards POC is unintended, should this then be left unattended? Should the minority groups affected be ignored even though the system analyses them differently because of their skin colour, lighting condition or camera quality? To answer these questions, the story of the shackled runner can be a guide. For the application of this technology to be fair, special considerations may have to be given to the affected race (mostly POC), as a form of justice. This could include, going the extra mile to get more black faces as training data, ensuring that ODAVIS comes with an automatic lighting/ brightening effect or even using more black faces to train some versions of the model to close the inconsistency gaps. However, the attitude of FRT creators in this regard may be problematic. For example, 5 out of the 12 interviewees recommended that NO special consideration whatsoever should be given to any race when building or implementing ODAVIS. This is because, the system is meant to be scientific, and its operations must be standardized across all users.

4.4 Training Data Sources and Representation

The second research question focused on finding out if the data used to train FRT models is representative of the faces in the world. The key findings here are divided into two categories. First, the source of the training data and secondly, the perception of the developers concerning the representativeness of the data. In the first category, three major themes were identified as sources of training data. Fig.4 below shows a summary of these sources.

Figure 3 - Sources of Training Data

Here are some of the responses of interviewees:

…supplied ones (pre-trained dataset) *are not of great use, as the cameras* (data size and quality) *are not the same,* same with *the lighting, the training subjects* (race, gender) *and so on.*

… Charles Fabrizo, Male, South Africa, Senior Developer

Data from previous candidates in the system databases of CVs are used as training data. Previous candidates' ODAVIS videos are also used to train the machine (model).

… Helyette Deekshita, Male, UK, ODAVIS Recruiter

For *Beton Kailing*, they said the reason their organisation uses pre-trained datasets only is that *"training your own algorithm is a very lengthy process". Gabriel Gallagher's* reason was that a *"combination of dataset sources helps to get better representation".*

The second category of findings is concerning FRT creators' perception of the training data representation of faces all over the world. 5 out of the 12 interviewees stated that the training used is not representative (specifically as it relates to race and ethnicities). Another 5 of the 12 interviewees however stated that the training data used are usually represented. Here are some of the main responses from those who believe the training data are not representative.

…Not equal samples (of training data)*, but a proportion of the population is designated for each ethnicity and stated.*

… Eirene Erik, Male, Nigeria, Junior Developer

The training data are not representative enough…more publicly accessible data available, are for whites.

… Fabio Cyril, Male, US, Junior Developer

The dataset is mostly white faces, with little or no representation of the black race. We use customised dataset to fill these gaps.

… Ibrahim Ishtar, Male, Nigeria, Mid-Level Developer

Some other interviewees however thought the data are representative enough. For example.

Black race (people) within the US, UK and Europe are used as part of the training data and hence, function the same way and accurately as black people from Africa.

… Jacint Jabir, Male, Canada, Mid-Level Developer

Having presented the main findings about the second research question, the next sub-sections discuss these findings with relevant literature.

Are the Training Data Used Representative?

In terms of the sources of the data, first, the use of a pre-trained database seems to be a very good use of resources for FRT companies, as these platforms already have thousands of pre-trained data, instead of training their own data which takes time. However, irrespective of the quantity of data available, if it is not representative of all races, it is still not good enough. For example, using the LFW pre-trained database as a case study, even though it has thousands of data sets and is one of the most popular databases used in building FRT-inclined solutions, its data only has a 7% black faces representation (Han and Jain, 2014). Secondly, the use of customized data only, though allows for building the quality of training data needed (including adding specific representations of different races and ethnicities), is however too lengthy a process, and at best will have good but insufficient data samples. This is because training one's own data could take time, hours, days or even years (AI Stack Exchanges, 2019). Nevertheless, datasets from the candidates' profiles or videos of previous candidates who have completed an interview on any of the ODAVIS could be a major form of training data as they made involve the exact samples of what the training model is intended to build. Consequently, the most ideal and recommended training data source is the use of a combination of a pre-trained dataset (large samples) and a customized dataset (used to complement the larger samples and fill the racial inequality gaps). This way, the training data may then be "large enough while also being diverse enough to learn the many ways in which faces inherently differ" to have consistent performance for all faces we see in the world (Merler et al., 2019, p.2)

The second discussion here is centred around the attitude of FRT creators on the representative training model. This is because, understanding whether creators perceive the need to consider having representative training data, may indicate what issues to tackle, whether the gaps in how the machines function only or the creators themselves too. The similarity-hypothesis theory (Byrne, 1971) suggests that people tend to favour others who possess' similar traits or features to them. Crawford (2016) also pointed out that the creation of AI is concentrated in the hands of white males. Consequently, for creators of AI where this theory is true, this may imply that they would rather favour using other "white males" individuals as their training data, as these "types of people" are similar to them. Surprisingly too, only 2 out of the 12 interviewees stated that they won't find it challenging building an FRT solution for a race different from theirs. This suggests most developers may prefer building models for the same or similar race as theirs, hence a possible explanation for using more white males as training data.

To conclude, one of the interviewees said it best:

Your solution is only as good as your data. No matter how strong the model is, the solution cannot function beyond the accuracy of the training data. To build a solution that will be globally acceptable means that the data ought also to be globally inclusive. It must be representative of the entire population.

… Fabio Cyril, Male, US, Junior Developer

4.5 Considerations Made by FRT Creators

The third research objective seeks to understand considerations and reasonable adjustments FRT creators make during the design and implementation of ODAVI solutions. Overall, over 20 different considerations were listed by all 12 interviewees as major considerations made. One of the interviewees stated why these considerations are needed.

…there is a standard we work with. However, reasonable adjustments are made afterwards where gaps are perceived.

… Aiden Lakshanya, Female, India, Business Psychologist

6 major themes were identified cutting across all the highlighted considerations. Figs.6 below presents a summary of the themes.

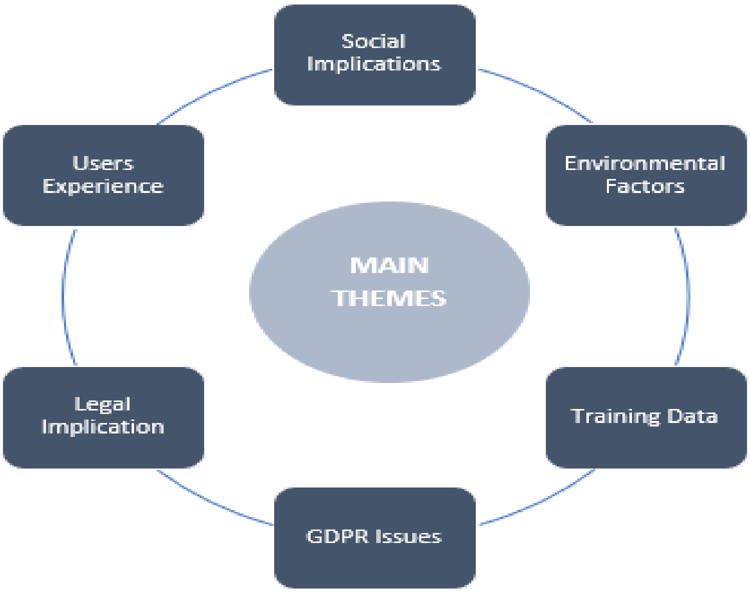

Figure 4 - Thematic Presentations of Considerations Listed

The first two major themes identified were considerations around social implications of ODAVIS and environmental factors that may impact how ODAVIS functions. Considerations under these themes appeared the most, with FRT creators stating the need for them to make considerations around issues like bias in the system (against race or gender), issues around profiling, lighting, camera quality, and device type. For example, two of the interviewees said:

…in a dimly light environment, it is naturally easier to see a white person than a black person. Reasonable adjustments can be made to correct this… the algorithm can be tweaked to work better than it does, for people with darker skins.

… Daniel Hendriks, Male, UK, Product Manager

Some of the problems we have with the FRT solution is that they come with heavy device requirements that people from developing nations or humble backgrounds may not be able to afford.

… Jacint Jabir, Male, Canada, Mid-Level Developer

Commenting on how some of the strategies they use to correct these issues of bias, camera, lighting and profiling, these interviewees said:

Some data augmentation techniques can be used to adjust the model to increase the contrast and brightness of the skin colour before detection and analysis. We can define a metric for specific skin tone and then apply the augmentation. However, this leads to more processing time.

… Ibrahim Ishtar, Male, Nigeria, Mid-Level Developer

Models should be trained with low resolution that would allow people with low-level devices to get the same performance. However, most of the solutions in the market are trained with 4k images, hence a potential issue in having standardized performance.

… Jacint Jabir, Male, Canada, Mid-Level Developer

…most clients are moving away from this (facial analysis) *as most of the data they need to determine a candidate's capability can be gotten from NLP – unless the client specifically requests* (facial analysis report)*. So, we isolate the facial analysis and determine how valid the result is. And if it gives a validity score within the required threshold, then face analysis is no longer necessary for such candidates.*

… Helyette Deekshita, Male, UK, ODAVIS Recruiter

The four other themes were centred around considerations made concerning the quality or quantity of training data, privacy issues, laws of the country of use and others (candidates' experiences, recruiters' experience, system audits). Fig.6 below shows a word cloud of considerations listed by the interviewees in order of appearance.

Figure 5 - Word Cloud of Considerations Listed by Interviewees

Having presented the findings about the third research question, the next sub-section discusses these findings.

Considerations that May Close the Gaps for People of Colour

Among all the considerations listed by the interviewees, 4 of them could help improve the performance of ODAVIS for people of colour. They are lighting, device requirements, ODAVIS bias testing/audit and isolation of facial analysis report.

First, lighting was the most highlighted consideration developers make/believe should be made as it appeared in the lists of 6 of the 12 interviewees. It also came up as part of the major considerations to close the performance gaps of ODAVIS between light and dark skin people. This finding is corroborated Sarda et al.'s (2011) findings that lighting is a major challenge of FRT, and its variation could change how solutions developed from FRT functions. Consequently, to get some similarity in performance of ODAVIS for white and people of colour, it is recommended that all ODAVIS creators set algorithms that can adjust the contrast, and brightness of the skin colour of candidates using the tool, before detection and analysis are made. This could involve ensuring the tools have in-built flashlights and encouraging candidates to be in a well-lighted environment before starting the assessment. This may however still be problematic for candidates living in underdeveloped countries with power and lighting issues and perhaps even for black people having hyper-pigmented skins.

Secondly, the issue of device requirement seems to be a very important consideration all ODAVIS companies should make. If organisations are to achieve a truly diversified workforce, this may mean that they must be able to build their recruitment process around everyone, irrespective of income level or economic background. For example, information from a top ODAVIS creator website shows a high device requirement to take their video interviews, requesting for laptops with a processor speed of 2.0 GHz, Adobe flash player 11.6 version minimum, newer versions of operating systems, large RAM size and more. This may be difficult for individuals with poor income or low-level devices. In terms of income level, Blacks and Hispanics are at the bottom of the list (Statista, 2022). This may suggest that they may be affected the most. Consequently, it is recommended that ODAVIS creators make the solutions to function for low-level devices, so as not to ostracise certain individuals, who may most likely be POC.

Another very important consideration is testing the ODAVIS tool for bias before deployment to the market. This is a very good practice and Deloitte (2021) recommended a periodic subjection of companies hiring tools to an independent audit. This helps spot biases and put some elements of controls to mitigate them.

In addition, isolation of facial analysis from the assessment report can be good practice for all ODAVIS creators to adopt. That is, the video is put off, and the candidate is assessed with the audio only through NLP. And if the validity of the result falls within the required threshold, then face analysis is no longer necessary for such candidates. This approach seems quite logical also, as an individual's skill level can be assessed via their responses to questions only as confirmed by Wilkinson (2021). Nguyen et al. (2014)

however argued that non-verbal cues are a very great way to determine a candidate's *hirability*, hence the justification for the need to observe the candidate's face as they talk. Nevertheless, a co-founder of the AI Now Institute, a research centre in New York still argued otherwise saying:

It's a profoundly disturbing development that we have proprietary technology that claims to differentiate between a productive worker and a worker who isn't fit, based on their facial movements, their tone of voice, and their mannerisms.

…Meredith Whittaker (Harwell, 2019)

Lastly, it is also important to state that some interviewees still believed that the solutions' operation should be standardized completely, and no consideration or reasonable adjustments should be made. In addition, even some who stated some considerations or adjustments should be made believed none should be made regarding POC. A possible explanation for this is the role of cognitive diversity theory in the AI industry. In enquiring where these FRT creators stand in the cognitive diversity school of thought, 4 out of the 12 interviewees believed cognitive diversity is superior to demographic diversity. This may mean that such creators see little or need to include racial, gender or other demographic-related indicators in their decision-making process. This confirms the findings of Shead (2019) who believed that cognitive diversity may be getting adopted by some major influencers in the AI industry. This is particularly problematic because, if AI creators do not see the need for demographic diversity considerations when creating solutions, there is only so much external stakeholders can do.

CONCLUSION

5.1 Summary

This dissertation aimed to understand how FRT determines candidates' suitability for jobs through ODAVIS' facial analysis. A one-on-one interview was conducted with 12 creators of FRT including software developers, business psychologists and other stakeholders to understand this process and the considerations they make in the development and implementation phases of such solutions. One of the major findings is the use of facial landmarks and gaze estimators to recognize and analyze candidates' emotions during the interview. This is used in addition to NLP, after which a report assessment is then generated recommending to the recruiter if such candidates are suitable for the jobs. Inconsistency in the performance of the solution for different races was however found, confirming the findings of previous researchers. Another major finding is that the data used to train the ODAVIS model was not representative. While some interviewees opined that the data needed not to be representative for the solution to be effective, some interviewees observed inconsistencies in performance and put measures and considerations in place to mitigate such gaps. Some of these considerations included augmentation of the training data, optimizing the lighting effect, reducing the device requirement, isolating facial analysis for some clients, and carrying out a periodic audit of the solution.

5.2 Practical Recommendations

Following the findings and discussions from the last chapter, here are some practical recommendations for companies.

1. Companies that create ODVI solutions:
   a. Ensure the data used in training their model has a representation of all faces found in the real world (Han and Jain, 2014; Merler et al., 2019). This cuts across taking time to train the model before selling the solutions to clients, using a combination of a pre-trained database and customized sources (CVs and videos of existing candidates)
   b. Augmenting the data where there is a need. This sometimes may involve increasing the data of people of colour and reducing that of the main population for some versions.
   c. Reduce the requirements of the devices.
   d. Carry out numerous tests of the solution before deployment to clients (test the solution for different ethnicities, observe the performance before launch).
   e. Take a second look at the diversity composition of the solution design team. This may involve intentionally hiring people of colour or people from other minority groups to get domain knowledge to help in mitigating bias.
2. Companies that use ODVI solutions for recruitment:
   a. Exercise caution when deciding which ODAVIS tool to use for their recruitment activities or whether to even use one at all. This may involve requesting a demo, and bias reports from multiple ODAVIS vendors before deciding. It may also involve confirming if the vendors' system can isolate facial analysis and use NLP only to determine the suitability of the candidates. It may also involve evaluating the cost and benefit of the system for their recruitment activities, and where the costs outweigh the benefits, they may decide not (Buolamwini, 2019; Simonite, 2019).
   b. Carry out periodic independent bias audits on the solution if adopted.

5.3 Limitations, Way Forward and Future Research Directions

This dissertation is subject to certain limitations. First, the data used was gathered through interviews, which was insufficient to gather all the facts. Researchers carrying out similar future studies, may in addition to interviews, consider experimenting with the ODAVI solution itself and subjecting it to an independent audit. This may provide more insights. A second limitation is the interview subject. While the subjects gave as much information as they could, there were still gaps in certain areas. For subsequent studies, it is recommended that interviews be conducted on other subjects like the recruiters, candidates and even the decision makers of the ODAVIS companies like the CEOs. This should give more robust insights into missing pieces. A third limitation is the sampling technique used (convenience sampling). Future research may need to consider stratified sampling techniques that could allow the researcher to get proportionate opinions from the different stakeholders (like software developers, business psychologists, market researchers, and others) or country of application (which can help compare the result of one country to another and see if the laws of the different countries impact the way ODAVIS work for them). Lastly, while reflecting, another possible bias in this dissertation may be the researcher's philosophy and race. This may have affected how the research was approached. Consequently, researchers with different philosophies (pragmatic or post-modernists) and those from neutral races are encouraged to carry out similar research and compare the results.

5.4 Personal Reflection

As a black immigrant in the UK, I recognise that living here comes with its challenges. Challenges that sometimes make me ponder on giving it all up and returning to my home country, Nigeria. If wishes were horses though.

Still, Nigeria is a beautiful place. A place where I didn't have to walk for a few minutes before seeing a familiar face. A place where I can talk to someone and anyone without holding back from fear of being judged as a caveman. And most importantly, a place where no one ever has to think of the implications of their skin colour while trying to get a job.

The UK is a beautiful country too. But dunno if I can say the same thing. Here, I probably would have to 'whiten' my CV before even being shortlisted for an interview. When I get the interview, the least expectation is to be assessed just like everyone else. However, I fear that the expression of eagerness shown on my face may be interpreted as intense anger by recruitment robots?

No one enjoys being treated differently from their counterparts, not even the goose and the gander. Equal opportunity requires consistency in decisions for both whites and blacks. Until then, the diversity mantra by UK companies unfortunately will remain only a sham.

…Evans Uhunoma

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REFERENCES

1) Acharya, A.S., Prakash, A., Saxena, P. and Nigam, A. 2013. Sampling: Why and how of it. Indian Journal of Medical Specialties. **4**(2), pp.330-333.
2) ACLU, 2020. Wrongfully Arrested Because Face Recognition Can't Tell Black People Apart [Online]. [Accessed 23 May 2022]. Available from: https://www.aclu.org/news/privacy-technology/wrongfully-arrested-because-face-recognition-cant-tell-black-people-apart/
3) Ahmed, O. 2018. Artificial intelligence in HR. International Journal of Research and Analytical Reviews. **5**(4), pp.971-978.
4) AI Stack Exchanges. 2019. How long it takes to train face recognition deep neural network? [Online]. [Accessed 18 July 2022]. Available from: https://ai.stackexchange.com/questions/12513/how-long-it-takes-to-train-face-recognition-deep-neural-network-rough-estimati
5) Barragan-Jason, G., Cauchoix, M. and Barbeau, E.J. 2015. The neural speed of familiar face recognition. Neuropsychologia. **75**, pp.390-401.
6) BBC, 2022. Job hunting for neurodivergent people: 'AI recruitment means I've got zero chance' [Online]. [Accessed 23 May 2022]. Available from: https://www.bbc.co.uk/bbcthree/article/c62bcab6-db6f-4026-90bb-7f508705a65b
7) Bell, D. 1973. The Coming of Post-Industrial Society. New York: Basic Books.
8) Black, J.S. and Esch, V.P., 2020. AI-enabled recruiting: What is it and how should a manager use it? Business Horizons. **63**(2), pp.215-226.
9) Braun, V. and Clarke, V. 2012. Thematic analysis. APA Handbook of Research Methods in Psychology. **2**, pp.57-71.
10) Bryman A. and Bell, E. 2015. Business Research Methods. 4th ed. Oxford: Oxford University Press.

11) Brynjolfsson, E. and McAfee, A. 2014. The second machine age: Work, progress, and prosperity in a time of brilliant technologies. New York: WW Norton & Company.
12) Buolamwini, J. 2019. Response: Racial and Gender bias in Amazon Rekognition — Commercial AI System for Analyzing Faces. [Online]. [Accessed 09 May 2022]. Available from: https://medium.com/@Joy.Buolamwini/response-racial-and-gender-bias-in-amazon-rekognition-commercial-ai-system-for-analyzing-faces-a289222eeced
13) Buolamwini, J. and Gebru, T. 2018. Gender shades: Intersectional accuracy disparities in commercial gender classification. In Conference on fairness, accountability and transparency. pp. 77-91.
14) Byrne, D. 1971. The attraction paradigm. New York: Academic Press.
15) Capterra. 2022. Video Interview Software for the United Kingdom? [Online]. [Accessed 27 May 2022]. Available from: https://www.capterra.co.uk/directory/30821/video-interviewing/software
16) Choudhury, A. 2020. 10 Face Datasets to Start Facial Recognition Projects. [Online]. [Accessed 29 May 2022]. Available from: https://analyticsindiamag.com/10-face-datasets-to-start-facial-recognition-projects/
17) Chowdhury, M. F. 2014. Interpretivism in aiding our understanding of the contemporary social world. Open Journal of Philosophy. **4**(3). pp.327-347.
18) Choy, L.T. 2014. The strengths and weaknesses of research methodology: Comparison and complimentary between qualitative and quantitative approaches. IOSR journal of humanities and social science. **19**(4), pp.99-104.
19) Cohen, L., Manion, L. and Morrison, K. 2002. Research methods in education. London: Routledge.
20) Crawford, K. 2016. Artificial Intelligence's White Guy Problem. The New York Times. [Online]. [Accessed 09 May 2022]. Available from: https://www.nytimes.com/2016/06/26/opinion/sunday/artificial-intelligences-white-guy-problem.html
21) De Brito, A.C.V., Mascarenhas, A.P.F.M., de Souza, J.R., de Campos, J.A.P., Simões, M.A.C. and da Silva, R.M. 2021. Face recognition in Service robotics: Analysis of the padding effect according to people age Reconhecimento facial em robótica de serviço: análise do efeito de preenchimento de acordo com a idade das pessoas. Brazilian Journal of Development, **7**(12). pp.115849-115865.
22) Deloitte. 2021. Challenges of fairness in AI decisions [Online]. [Accessed 04 January 2022]. Available from: https://ukfinancialservicesinsights.deloitte.com/post/102ftmq/challenges-of-fairness-in-ai-decisions/
23) Doug, R. 2018. Artificial Intelligence for Business: What you need to know about Machine Learning and Neural Networks, 2018. Chicago Lakeshore Press: Beaverton.
24) Duchaine, B. and Nakayama, K. 2006. The Cambridge Face Memory Test: results for neurologically intact individuals and an investigation of its validity using inverted face stimuli and prosopagnosic participants. Neuropsychologia. **44**, pp.576–585.
25) Easterby-Smith, M., Jaspersen, L.J., Thorpe, R. and Valizade, D. 2021. Management and business research. Newcastle: Sage.
26) Eisenhardt, K.M., Graebner, M.E. and Sonenshein, S., 2016. Grand challenges and inductive methods: Rigor without rigor mortis. Academy of management journal. **59**(4), pp.1113-1123.
27) Equality Act. 2010. Statutory Code of Practice Employment. Equality and Human Rights Commission.
28) Etikan, I. and Bala, K. 2017. Sampling and sampling methods. Biometrics and Biostatistics International Journal. **5**(6), p.00149.
29) Faux, F. and Luthon, F. 2012. Theory of evidence for face detection and tracking. International Journal of Approximate Reasoning. **53**(5), pp.728-746.
30) Forbes. 2022. Five Ways the Future Of Facial Recognition Will Become More Prevalent In Business And Life In 2022 [Online]. [Accessed 27 May 2022]. Available from: https://www.forbes.com/sites/forbestechcouncil/2022/05/03/five-ways-the-future-of-facial-recognition-will-become-more-prevalent-in-business-and-life-in-2022
31) Francis, J.J., Johnston, M., Robertson, C., Glidewell, L., Entwhistle, V., Eccles, M.P., and Grimshaw, J.M. 2010. What is an adequate sample size? Operationalising data saturation for theory-driven interview studies. Psychology and Health. **25**, pp.1229–1245.
32) Galterio, M.G., Shavit, S.A. and Hayajneh, T. 2018. A review of facial biometrics security for smart devices. Computers. **7**(3), p.37.
33) Gill, J. and Johnson, P. 2002. Research methods for managers. Newcastle: Sage.
34) Guo, Y., Zhang, L., Hu, Y., He, X. and Gao, J. 2016, October. Ms-celeb-1m: A dataset and benchmark for large-scale face recognition. In European conference on computer vision. pp.87-102. Copenhagen: Springer Cham.

35) H2B. 2019. NHS Graduate Scheme Video Interview: Secure Your NHS Career! [Online]. [Accessed 28 May 2022]. Available from: https://www.how2become.com/blog/nhs-graduate-scheme-video-interview
36) Hammersley, M. 2013. The myth of research-based policy and practice. Newcastle: Sage.
37) Han, H. and Jain, A.K. 2014. Age, Gender and Race Estimation from Unconstrained Face Images. MSU Technical Report. [Online]. [Accessed 30 May 2022]. Available from: http://biometrics.cse.msu.edu/Publications/Face/HanJain_UnconstrainedAgeGenderRaceEstimation_MSUTechReport2014.pdf.
38) Harwell, D. 2019. A face-scanning algorithm increasingly decides whether you deserve the job [Online]. [Accessed 15 July 2022]. Available from: https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/
39) Iaydjiev, I. 2013. A pragmatic approach to social science. E-International Relations Students. [Online]. [Accessed 03 June 2022]. Available from: https://www.e-ir.info/2013/03/01/a-pragmatic-approach-to-social-science/
40) Izario, D., Izario, B., Castro, D. and Iano, Y. 2017. Face Recognition Techniques Using Artificial Intelligence for Audio-Visual Animations. SET International Journal of Broadcast Engineering. **2017**(3), pp.78-82.
41) Jia, M. 2017. Statistical Learning Methods for Facial Recognition [Online]. [Accessed 17 July 2022]. Available from: https://openscholarship.wustl.edu/cgi/viewcontent.cgi?article=2075&context=art_sci_etds
42) Jo, S. 2018. Volvo Uses Car's A.I. To Conduct Job Interviews [Online]. [Accessed 18 July 2022]. Available from: https://autoconversion.net/blog/automotive/news-brief-volvo-uses-cars-a-i-to-conduct-job-interviews/
43) Kahn, J. and Bass, D. 2017. Black AI Workshop Becomes Latest Flashpoint in Tech's Culture War. Bloomberg. [Online]. [Accessed 30 May 2022]. Available from: https://www.bloomberg.com/news/articles/2017-10-20/black-ai-workshop-becomes-latest-flashpoint-in-tech-s-culture-war/
44) Kanade, T. 1973. Picture processing system by computer complex and recognition of human faces. Doctoral dissertation. Kyoto: Dept. of Information Science, Kyoto Univ.
45) Kang, H.R., Yang, H.D. and Rowley, C. 2006. Factors in team effectiveness: cognitive and demographic similarities of software development team members. Human Relations. **59**, pp.1681–1710.
46) Kaur, P., Krishan, K., Sharma, S.K. and Kanchan, T. 2020. Facial-recognition algorithms: A literature review. Medicine, Science and the Law. **60**(2), pp.131-139.
47) Klein, H.K. and Myers, M.D. 1999 A set of principles for conducting and evaluating interpretive field studies in information systems. MIS Quarterly. **23**, pp.67–93.
48) Kleinman, Z. 2019. Amazon: Facial recognition bias claims are 'misleading' [Online]. [Accessed 29 May 2022]. Available from: https://www.bbc.co.uk/news/technology-47117299
49) Kumra, S. and Manfredi, S. 2012. Managing Equality and Diversity: Theory and Practice. Oxford: Oxford University Press.
50) Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett. 2016. Advances in Neural Information Processing Systems. Curran Associates. **29**, pp.3315–3323.
51) Loconsole, C., Miranda, C.R., Augusto, G., Frisoli, A., and Orvalho, V. 2014. Real-time emotion recognition novel method for geometrical facial features extraction. Proceedings of the International Conference on Computer Vision Theory and Applications (VISAPP). pp. 378-385.
52) Lohia, P.K., Ramamurthy, K.N., Bhide, M., Saha, D., Varshney, K.R. and Puri, R. 2019. Bias mitigation post-processing for individual and group fairness. In Icassp 2019-2019 ieee international conference on acoustics, speech and signal processing (icassp). pp. 2847-2851). IEEE.
53) Macfarlane, B. 2010. Researching with integrity: The ethics of academic enquiry. London: Routledge.
54) Masud, M., Muhammad, G., Alhumyani, H., Alshamrani, S. S., Cheikhrouhou, O., Ibrahim, S., & Hossain, M. S. 2020. Deep Learning-Based Intelligent Face Recognition in IoT-Cloud Environment. Computer Communications. **152**, pp.215-222.
55) Meissner, P. and Wulf, T. 2017. The effect of cognitive diversity on the illusion of control bias in strategic decisions: An experimental investigation. European Management Journal. **35**(4), pp.430-439.
56) Merler, M., Ratha, N., Feris, R.S. and Smith, J.R. 2019. [Pre-Print]. Diversity in faces. IBM AI Research. New York: J. Watson Research Centre.
57) Michael, S. 2008. The promise of appreciative inquiry as aninterview tool for field research. Development in Practice. **15**(2), pp. 222-230.

58) Miller, C. 1990. Cognitive diversity within management teams: Implications for strategic decision processes and organizational performance. Texas: Graduate School of Business, University of Texas.
59) Miller, C., Burke, L., & Glick, W. 1998. Cognitive diversity among upper echelon executives: implications for strategic decision processes. Strategic Management Journal. **19**, pp.39-58.
60) Myers, M.D. 2019. Qualitative research in business and management. Newcastle: Sage.
61) Nawaz, N. 2020. Artificial intelligence applications for face recognition in recruitment process. Journal of Management Information and Decision Sciences. **23**, pp.499-509.
62) Ness, I. 2021. Mind the Gap: Creative Knowledge Processes Within Interdisciplinary Groups in Organizations and Higher Education. Creativity and Learning. 9, pp.195-217.
63) New York Times. 2018. Facial Recognition Is Accurate, if You're a White Guy - Lohr, S [Online]. [Accessed 26 May 2022]. Available from: https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html
64) Nguyen, B.T., Trinh, M.H., Phan, T.V. and Nguyen, H.D. 2017, April. An efficient real-time emotion detection using camera and facial landmarks. In 2017 seventh international conference on information science and technology (ICIST). pp. 251-255
65) Nguyen, L.S., Frauendorfer, D., Mast, M.S. and Gatica-Perez, D. 2014. Hire me: Computational inference of hirability in employment interviews based on nonverbal behavior. IEEE transactions on multimedia, 16(4). pp.1018-1031.
66) Noon, M. 2010. The shackled runner: Time to rethink positive discrimination? Work, Employment and Society. **24**(4), pp.728–739.
67) Ortiz, E.G. and Becker, B.C. 2014. Face recognition for web-scale datasets. Computer Vision and Image Understanding. **118**, pp.153-170.
68) Parayitam, S., and Papenhausen, C. 2016. Agreement-seeking behavior, trust, and cognitive diversity in strategic decision-making teams: Process conflict as a moderator. Journal of Advances in Management Research. **13**(3), pp.292-315.
69) Parkhi, O.M., Vedaldi, A. and Zisserman, A., 2015. Deep face recognition. Oxford: University of Oxford.
70) Patton, M.Q. 2014. Qualitative research and evaluation methods: Integrating theory and practice. Newcastle: Sage publications.
71) RecFaces. 2021. What Is AI Facial Recognition Tech and How does It Work? [Online]. [Accessed 27 May 2022]. Available from: https://recfaces.com/articles/ai-facial-recognition
72) Recruiter. 2019. The rise of the Robo-recruiter [Online]. [Accessed 26 May 2022]. Available from: https://recruiter.co.uk/2019/12/rise-robo-recruiter
73) Robson, C. 2002. Real World Research. Oxford: Blackwell.
74) Sabel, J.M. 2018. One-Way, On-Demand and Self-Paced Interview Guide [Online]. [Accessed 28 May 2022]. Available from: https://www.hirevue.com/blog/hiring/video-interviewing-guide
75) Sardar, S., Tewari, G. and Babu, K.A. 2011, November. A hardware/software co-design model for face recognition using cognimem neural network chip. In 2011 International Conference on Image Information Processing. pp. 1-6).
76) Saunders, M., Lewis, P. and Thornhill, A. 2007. Research methods for business students. 4th ed. London: Pearson.
77) Saunders, M., Lewis, P. and Thornhill, A. 2012. Research methods for business students. 6th ed. Harlow: Pearson Education Limited.
78) Saunders, M., Lewis, P. and Thornhill, A. 2021. Research methods for business students. 8th ed. London: Pearson.
79) Shead, S. 2019. Google A.I. Panel Member Says Google 'Pulled The Plug Rather Than Defend Themselves'. Forbes. [Online]. [Accessed 30 May 2022]. Available from: https://www.forbes.com/sites/samshead/2019/04/05/google-a-i-panel-member-says-google-pulled-the-plug-rather-than-defendthemselves/#27d051439554
80) Shell. 2022. 7 tips to prepare students & graduates for an online video interview? [Online]. [Accessed 28 May 2022]. Available from: https://www.shell.com/careers/candidate-resource-centre/seven-tips-to-prepare-you-for-an-online-interview.html
81) Simonite, T. 2019. The Best Algorithms Struggle to Recognize Black Faces Equally. [Online]. [Accessed 09 May 2022]. Available from: https://www.wired.com/story/best-algorithms-struggle-recognize-black-faces-equally/
82) Statista. 2022. Poverty rate in the United States in 2020, by ethnic group [Online]. [Accessed 19 July 2022]. Available from: https://www.statista.com/statistics/200476/us-poverty-rate-by-ethnic-group/
83) Tambe, P., Cappelli, P. and Yakubovich, V. 2019. Artificial intelligence in human resources management: Challenges and a path forward. California Management Review. **61**(4), pp.15-42.

84) Tatli, A. and Özbilgin, M.F. 2012. An emic approach to intersectional study of diversity at work: A Bourdieuan framing. International Journal of Management Reviews. **14**(2), pp.180-200.
85) Taylor, S.J., Bogdan, R. and DeVault, M. 2015. Introduction to qualitative research methods: A guidebook and resource. John Wiley and Sons.
86) The Guardian. 2018. Psychologists' face off reveals humans can recognise 5,000 people. [Online]. [Accessed 29 May 2022]. Available from: https://www.theguardian.com/science/2018/oct/10/how-many-faces-average-person-recognises-5000
87) Thomas, J.R., Martin, P., Etnier, J. and Silverman, S.J. 2022. Research methods in physical activity. Oxford: Human kinetics.
88) UK Gov. 2021. Unemployment: Main facts and figures [Online]. [Accessed 22 June 2022]. Available from: https://www.ethnicity-facts-figures.service.gov.uk/work-pay-and-benefits/unemployment-and-economic-inactivity/unemployment/latest
89) United Nations. 2020. Bias, racism and lies facing up to the unwanted consequences of AI [Online]. [Accessed 05 January 2022]. Available from: https://news.un.org/en/story/2020/12/1080192/
90) Weichselbaumer, D. 2016. Discrimination against female migrants wearing headscarves. Institute of Labor Economics. Bonn: IZA Discussion Paper.
91) West, S.M., Whittaker, M. and Crawford, K., 2019. Discriminating systems. AI Now. [Online]. [Accessed 09 May 2022]. Available from: https://cdn.vox-cdn.com/uploads/chorus_asset/file/16125391/discriminating_systems_041519_2.pdf
92) Wilkinson, M. 2021. The 6 Different Types of Interviews [Online]. [Accessed 04 January 2022]. Available from: https://www.coburgbanks.co.uk/blog/assessing-applicants/6-different-types-of-interview/
93) Williams, B.A. 2017. Tech's Troubling New Trend: Diversity Is in Your Head. The New York Times. [Online]. [Accessed 09 May 2022]. Available from: https://www.nytimes.com/2017/10/16/opinion/diversity-tech-women-silicon-valley.html
94) Wilmer, J. B., Germine, L., Chabris, C. F., Chatterjee, G., and Williams, M., Loken, E. 2010. Human face recognition ability is specific and highly heritable. Proc. Nat. Acad. Sci (PNAS). **107**(11), pp.5238–5241.
95) Younis, R. 2019. Cognitive diversity and creativity: the moderating effect of collaborative climate. International Journal of Business and Management. **14**(1), pp.159-168.
96) Zadeh, S. 2018. Are there universal expressions of emotion? [Online]. [Accessed 29 May 2022]. Available from: YouTube https://www.youtube.com/watch?v=-hr58Yu0yDs
97) Zhang, X., Fang, Z., Wen, Y., Li, Z. and Qiao, Y., 2017. Range loss for deep face recognition with long-tailed training data. In Proceedings of the IEEE International Conference on Computer Vision. pp. 5409-5418.
98) Zhao, J., Wang, T., Yatskar, M., Ordonez, V. and Chang, K.W. 2017. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. arXiv preprint arXiv:1707.09457.