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# Who Am I Impressing?

A qualitative study assessing AI-enabled recruitment's impact on graduating students' job applications

**Abstract**

*With the growing importance of AI screening tools in recruitment and selection, an important consideration becomes how job applicants adapt to this change. Previous research has produced insights on why applicants present themselves in certain ways and how these applicant presentations are perceived by a human recruiter. However, there is a deficit in research that focuses on how applicants adjust the impression that they make towards an AI recruiter. Additionally, whether the applicant actually knows if they are impressing a human or AI has been questioned. Our study therefore asked the question: How do applicants' assessments of AI use in recruitment inform the adjustments they make to their job applications? Through a qualitative research approach, data was gathered from 24 job-seeking university students. A motivational and legal perspective were applied to understand how applicants' assessments of AI affected how they adjusted their application documents. Our analysis concluded that in the absence of effective AI transparency, applicants' experiences determined their beliefs which took a paramount role in whether they assumed AI use in the screening process. Further, given that AI use was assumed, the applicant's motivation to adjust informed both whether and how they adjust. Due to limited AI transparency and motivation to adjust, the final application adjustments made were modest, if existent. Our study contributes to the gap in literature at the intersection of applicant self-presentation, AI use in screening, and AI transparency. It further contributes to AI developers and recruiters considering the use and disclosure of AI recruitment tools in terms of greater understanding regarding the impact on how applicants present themselves accordingly.*

**Keywords**

Artificial intelligence, Human resource management, Job applications, AI-enabled recruitment, Impression management, Motivation

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## Definitions

| | |
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| ARTIFICIAL INTELLIGENCE (AI) | Technological components that collect, process, and act on data in ways that simulate human intelligence (Canhoto & Clear, 2020) |
| APPLICATION DOCUMENTS | The resume, cover letter, transcripts, application form, and any other information submitted with the initial application (Newell, 2005) |
| SCREENING | The initial stage of the recruitment and selection process in which companies assess and analyze candidates' experience, skills, and characteristics from the application documents for role fit (Bogen & Rieke, 2018; Nikolaou, 2021) |
| SELECTION | The second stage of the recruitment and selection process in which assessments are used to further narrow amongst candidates (Nikolaou, 2021) |
| AI LITERACY | A data subject's ability to understand the explanations provided of an AI's decisions (Al-Sulaiti et al., 2023) |
| AI TRANSPARENCY | Concerns not only applicants' right to know *when* AI is being used but also *how* it is being used. As defined in the GDPR Art. 5(1)(a), transparency encompasses both a prospective and retrospective element (Regulation 2016/679) |
| PROSPECTIVE TRANSPARENCY | Providing information upfront about how an algorithm processes data in general, ensuring data subjects can consent or object to their data being processed (Al-Sulaiti et al., 2023; Felzmann et al., 2019; Paal & Pauly, 2018) |
| RETROSPECTIVE TRANSPARENCY | An explanation of how a specific algorithmic decision was made, and it is provided in hindsight (Felzmann et al., 2019; Paal & Pauly, 2018) |
| EXPLAINABLE AI | AI that is able to provide explanations of its decisions (Vishwarupe et al., 2022) |
| VALENCE | The strength of one's preference toward a second-level outcome (Vroom, 1964). For our study, the belief that the specific role is preferred among other options such that it will bring personal satisfaction |
| INSTRUMENTALITY | The belief in the likelihood that achieving a good first-level outcome will actually result in a second-level outcome (Vroom, 1964). For our study, the belief that making case-by-case adjustments for AI (i.e., first-level outcome) is critical for advancing through screening to the next stage of the process (i.e., second-level outcome) |
| EXPECTANCY | The belief in the likelihood that one's effort will result in a good first-level outcome (Vroom, 1964). For our study, the belief that one is able to make adjustments successfully and thereby submit an application that AI would screen favorably |
| JOB DESIRABILITY | How attractive the applicant finds a particular role |
| ROLE FIT | How well a role aligns with an applicant's skill set and background |
| TIME IN SEARCH | How long an applicant has been searching for a position |

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# 1. Introduction

Digitalization has led to a seismic shift in the sources of firm value from tangible to intangible assets, with people now at the forefront. As a result, recruitment and selection have evolved into a strategic concern for business executives, and artificial intelligence (AI) in hiring has gone from a nice-to-have to a necessity (Black & van Esch, 2020). There are many strategic reasons for the rise of this technology in selecting talent. Online job postings have increased the visibility of vacancies, leading to a vast increase in applicants for a single position. Additionally, higher rates of advanced education lead to more qualified applicants applying for the same number of roles (Bogen & Rieke, 2018; OECD, 2022; Zeman & Frenette, 2021). Furthermore, the rise in discussions around diversity and inclusion demands objective and consistent tools to reduce bias in hiring (Black & van Esch, 2020). These trends necessitate the use of automated filtration tools to handle large amounts of high-quality applications and make predictions similar to, or better than, ones that a recruiter could make. This leads to the introduction of AI, defined as "technological components that collect, process, and act on data in ways that simulate human intelligence," to recruitment and selection (Canhoto & Clear, 2020, p. 184). With increasingly automated selection, the job applicant is now faced with a changing recruitment process.

This changing job application process also increasingly demands a good strategy from the applicant entering a job search. It takes a job seeker an average of six applications to receive one interview and making it to the interview stage still does not guarantee a job offer (Dalton & Groen, 2020). The AI tools designed to help recruiters filter through applications may feel less impressive to applicants whose applications never meet the human eye (Fuller et al., 2021). When applicants want to make a good impression, they may apply impression management to control the impressions that others form about them (Schlenker, 1980). This can include both emphasizing legitimate positive qualities as well as creating false impressions or hiding deficiencies (Leary & Kowalski, 1990). Traditionally, research on how and why such self-presentation occurs has been based on the assumption of a human recipient. Nevertheless, as individuals will adapt to new technologies to benefit from their use (Want et al., 2015), it is important to consider how job seekers behave to advance through screening technology.

Alongside the growth of automation in recruitment, job seekers are seeing a rise in tips and tools for adjusting to AI. Articles by practitioners are being published on adjusting resume content to make it through screening technology (e.g. Casey, 2021; Gardiner, 2022; Liu, 2019), and entire businesses are specializing in automating and optimizing the AI-screened job search for applicants (e.g. *About Us*. 2023). Thereby, AI use in application screening is emerging together with increased incentives and tools at job applicants' disposal to help them respond. As an AI algorithm develops and analyzes the data set it knows (Apte & Spanos, 2022), it is highly relevant for both AI developers and recruiters applying this technology to know how the increasing presence of AI in recruitment may prompt a change in inputted data.

However, whether job seekers actually know if AI or a human is screening them is often unconsidered. In the context of recruitment, applicants have had varied responses to AI in the different stages of recruitment (Acikgoz et al., 2020; van Esch et al., 2019; Wesche & Sonderegger, 2021 compared to Langer et al., 2019; Langer, König, & Scheuss, 2019). Whether recruiters benefit from disclosing AI use is therefore a contested topic (Wesche & Sonderegger, 2021), yet mentioned literature still assumes disclosure. Additionally, and more importantly, Art. 5(1)(a) in the European General Data Protection Regulation (GDPR) requires disclosure of the use of AI to the applicant whose data is being processed (Regulation 2016/679). However, legal scholars have criticized the legislation's effectiveness in achieving this AI transparency and note that disclosure in practice can be both ineffective (Ben-Shahar & Schneider, 2014; Solove, 2013) and intentionally occluding (Ananny & Crawford, 2018). The uncertainty regarding requirements and incentives for AI transparency from recruiters and AI developers may create a discrepancy between theory and the reality it is applied to. As a result, we are left with a fundamental gap in understanding of increasing importance - the informedness of the modern job applicant and their subsequent application adjustments in response to AI in recruitment.

## 1.1. Purpose and research question

In search of answers to how the possibly uniformed job applicant approaches AI in the screening process, this study takes the perspective of the applicant while avoiding the common assumption that AI use in recruitment is transparent to them. Our research question accordingly asks:

***How do applicants' assessments of AI use in recruitment inform the adjustments they make to their job applications?***

First, the purpose of our study is to understand how applicants make assessments of *if* and *how* AI is screening their applications. We remain open to the possibility that the applicant is explicitly informed about the use of AI but do not assume it. Second, we wish to study the possible adjustments that applicants make to their applications depending on their assessments of this AI use. Applicants' assessments of AI and their application adjustments are studied in conjunction because when AI transparency is not taken for granted, applicants' assessments and how these are formed constitute the context for decision-making. Studying possible behavioral adjustments of applicants without considering the assessments that may prompt them could ignore an important context.

## 1.2. Expected contribution

By answering the research question, this thesis aims to make multiple contributions. First, while most literature studying how applicants present themselves in recruitment focuses on interpreting this from the recruiter's perspective, we are adding to the smaller body of literature focused on interpreting this from the applicant's perspective of self-presentation. Second, as AI is a relatively new concept and limited research exists on how AI impacts the recruitment and selection process, we seek to provide insights into how applicants are responding to the introduction of AI and the effect this has on their applications. Third, to the best of the authors' knowledge, no previous study has combined the perspectives of impression management theory from the applicant's perspective with AI transparency. In conclusion, we wish to explore whether, and in such cases how, both AI and AI transparency could be relevant contextual considerations in studying how applicants self-present in job applications based on what applicants actually experience in recruitment processes.

Outside academics, our research aims to contribute to recruiters' and AI developers' understanding of how usage and disclosure of AI may affect the content this technology screens. Within this topic, there is a potential concern of whether AI in recruitment may create direct adverse effects by altering how applicants represent themselves in ways counterintuitive to recruiters' desires to hire the candidate they think they are hiring. Alternatively, there would also be interest in knowing if it creates positive effects by altering how applicants represent themselves in ways beneficial to recruiters. The goal of this thesis then is to enable a better understanding of how the increase in usage of AI impacts applicants' perspectives and actions, thereby providing added context to recruitment and selection processes.

### 1.3. Scope and delimitations

This study focuses on job applicants' assessments of AI in the screening process and how this relates to their application adjustments. For an in-depth understanding of the applicants' assessments and related adjustments, we used a cross-sectional study research design to study the perspective of a specific set of applicants through semi-structured interviews. The participants selected consisted of students at the Stockholm School of Economics, and the sample consisted of 24 participants, with three additional pilot interviews from students outside thechosen school. In sampling these interview participants, job application experiences through networking and referrals were excluded as they can help applicants bypass AI screening tools (Fernandez & Weinberg, 1997; Tambe et al., 2019). The study focused on the initial screening stage in which companies assess and analyze candidates' experience, skills, and characteristics from the application documents for role fit (Bogen & Rieke, 2018; Nikolaou, 2021), as it commonly utilizes AI (Hoffman et al., 2015) and is the first barrier for any applicant to pass through (Nikolaou, 2021), increasing the relevance for both recruiters and applicants.

### 1.4. Research outline

The study is divided into seven main sections, each beginning with a brief summary of their purpose and sub-sections. Section one, the introduction, provides the background necessary to understand and contextualize the purpose of the study and identifies the research question guiding the study. After the introduction, section two provides an overview of existing theory and research in the areas of applicant behavior in recruitment and selection, AI use in screening, applicant reactions to AI, and AI transparency. The literature review concludes by identifying the research gap that validates the need for this study. Next, in section three, we present the methodology chosen for this study, including the research strategy and approach and the process taken for the data collection and data analysis. The methodology concludes by exploring the considerations taken for data quality. From this, we present our results in section four and then analyze these using a theoretical framework in section five. The analysis first introduces this theoretical framework and culminates in the creation of our theoretical model. Next, in section six, the discussion, we address how our analysis answers our research question, compare our findings to extant research and discuss the analytical limitations of the study. Finally, section seven concludes this thesis by addressing the theoretical contributions and practical implications of our findings, methodological limitations of our study, and areas for future research.

## 2. Literature review

This section provides an overview of the existing literature reviewed in the study. First, we will look at recruitment and selection literature on how applicants act in recruitment processes (2.1). From this, we look at how AI will be defined for this study and how AI is used in the screening stage of the recruitment process (2.2). Looking at general recruitment and selection literature before looking at research on AI in recruitment allows us to understand how applicants navigate traditional recruitment and how AI is potentially changing this. Accordingly, we will next look at the existing research on how applicants react to AI-assisted hiring processes (2.4). As we avoid the assumption of an applicant informed of AI use, we will then examine the literature on AI transparency and why the assumption of transparency can be questioned (2.3). Finally, we will synthesize the literature and identify the research gap that our study will address (2.5).

### 2.1. Applicant behavior in recruitment and selection

As increasing importance is placed on the human capital of a firm, the body of literature on Human Resources Management (HRM) is growing in both academic research (e.g. Anwar & Abdullah, 2021; Enz & Siguaw, 2000; Mahoney & Deckop, 1986; Wright et al., 1994; Wright et al., 2001) and in business publications (e.g. Cappelli & Tavis, 2018; Criddle, 2023; The Economist, 2018). Within HRM, the function of recruitment and selection is a major focus (Markoulli et al., 2017). As recruitment and selection have become increasingly technologically dependent (Bartram, 2000; Hmoud & Laszlo, 2019; Woods et al., 2020), this change and its implications are of increasing academic interest to explore. The fundamental aim of recruitment and selection is to "select the 'right' individuals and reject the 'wrong' ones" (Newell, 2005, p. 115). The recruitment and selection process attempts to achieve this through four main stages: attraction, screening, selection, and onboarding. Our research focuses on the screening stage, where the company assesses and analyzes candidates' experience, skills, and characteristics from the application documents for role fit (Bogen & Rieke, 2018; Nikolaou, 2021). Application documents refer to the resume, cover letter, transcripts, application form, and any other information submitted with the initial application (Newell, 2005). This step and these documents play a major role in determining which candidates progress to an initial interview and therefore are the first way an applicant presents themselves in recruitment (Tyler & McCullough, 2009). Although the screening stage is our focus, research from the selection stage, where assessments are used to further narrow amongst candidates, also provides a potentially relevant lens through which to understand applicant behaviors (Nikolaou, 2021). Regardless of the stage, the applicant is presenting themselves in hopes of being perceived as a good candidate.

Within these screening and selection stages, there is a substantial body of research looking at how applicants present themselves to be perceived as the 'right' candidate. Here, the research field of *impression management* is helpful in explaining how individuals control the impressions that others form about them (Leary & Kowalski, 1990). The study of impression management is based on Erving Goffman's (1956) model of social interaction that he compared to theatrical performances, with the individuals performing to leave positive impressions on their audience. This comparison seems to suggest some sort of face-to-face interaction, but Schlenker (1980) defines impression management as encompassing both real and imagined social interactions. While his work on impression management pre-dates AI technology, this inclusion of imagined interactions suggests that people can engage in impression management even in response to an imagined recipient, such as an undefined AI or human recruiter. This inclusion of an imagined recipient is relevant when considering screening specifically, as neither an AI tool nor a human recruiter is physically present when the applicant submits their application. However, little research has delved into precisely who or what the applicant is imagining when engaging in impression management. Most research on impression management in recruitment and employee selection has instead focused on the context of interviews (Barrick et al., 2009; Buehl & Melchers, 2018; Ellis et al., 2002; Hogue et al., 2013; Kristof-Brown et al., 2002; Levashina & Campion, 2007; Stevens & Kristof, 1995), where the recipient is apparent. While there are some studies exploring its use in resumes and cover letters (Henle et al., 2019; Knouse et al., 1988; Waung et al., 2017), they do not discuss who the applicant is imagining and instead focus on implications for recruiters.

In trying to make positive impressions on recruiters and hiring managers, applicants also look for how to paint themselves positively, which can sometimes be interpreted as being less than truthful. A commonly studied category of impression management, *applicant faking,* focuses on how applicants present themselves in a way that does not accurately reflect their true self-image, usually to create a more favorable impression of themselves (Kiefer & Benit, 2016). This body of work includes research looking at why applicants fake (Griffith et al., 2011) and its impacts on the validity of a type of assessment (Hartman & Grubb III, 2011; Krammer et al., 2017), as well as more specifically if and how applicant faking occurs in personality tests (Hartman & Grubb III, 2011; Tett & Simonet, 2011), resumes (Henle et al., 2019), job interviews (Bill & Melchers, 2023; Hogue et al., 2013; Levashina & Campion, 2007), and more recently and rarely, AI-enabled job interviews (Langer et al., 2020).

Notably, applicant faking typically takes the recruiter's perspective when evaluating if applicants are faking and the resulting implications. There is a tendency to view this behavior as inherently illegitimate or nefarious and outside of the employer's goal for honest responses from candidates. When looking at it from the applicant's perspective, managing the employer's impressions arises out of situational demands to make a good impression on the employer. Applying an interpretation of *self-presentation* instead of applicant faking brings a social context where how applicants get the job and if they want it also plays a role in their decision-making process (Johnson & Hogan, 2006; Marcus, B., 2009). This perspective, where if applicants want the job matters, brings the concept of motivation into the equation.

There is not only a variance in perspectives on the conceptualization of how applicants aim to impress but also a variety of perspectives regarding *why* they aim to impress. Whether you call it self-presentation, applicant faking, or impression management, research can be divided into four major perspectives used separately or in combination to explain why applicants aim to impress: motivation, personality, capability, and perceptions of situational norms. Most researchers using the perspective of self-presentation explain applicants' behavior through motivation, arguing that the value the applicant places on the role influences their likelihood to try to aim to impress (Johnson & Hogan, 2006; Marcus, B., 2009; Schmidt et al., 2022). Other researchers conceptualizing this as applicant faking also take on a perspective of motivation, though often they integrate this with other perspectives such as personality, capability, and perceptions of situational norms (Ellingson & McFarland, 2011; Ellingson, 2012; Griffith et al., 2011; Tett & Simonet, 2011). Personality and capability refer to variable applicant traits such as morals or intelligence to understand individual differences in the likelihood of faking (Arkin & Lakin, 2001; Boyce, 2005; Griffith et al., 2011; Hogue et al., 2013; McFarland & Ryan, 2000; Snell et al., 1999). While these usually are discussed regarding personality traits or capabilities that increase the likelihood of faking, capability can also relate to an applicant's marketability, that is, how well their traits align with a given role or roles, and thereby decrease the likelihood of faking (Cable & Judge, 1996; Ellingson, 2012; Schmidt et al., 2022). Less common but also interesting is research that considers applicants' perceptions of situational norms, taking an approach where if faking is perceived to be common and accepted, the applicant is more likely to believe faking is necessary to compete (Boyce, 2005; Snell et al., 1999).

This study aims to understand applicant assessments and subsequent application adjustments and takes a neutral approach to the objective morality or accuracy of those actions. Therefore, the concept of self-presentation is better suited to explain applicants' behavior than the recruiter-centric concept of applicant faking. According to Tyler & McCullough (2009), a job applicant's resume, cover letter, and other submitted documents are self-presentational vehicles designed to quickly communicate a favorable identity image to the recruiter. Additionally, our goal is to understand how applicants' assessments of AI influence the adjustments they make to these documents, not to assess the quality or validity of the adjustments themselves. Accordingly, a perspective of motivation is well suited for our study. The Valence-Instrumentality-Expectancy (VIE) model of motivation, as initially conceptualized by Vroom (1964), states that motivation is a function of how much people value the reward from a given action over alternative actions. While this is largely used in the context of workplace motivations, it has also been reimagined within the scope of recruitment as a tool for understanding faking behavior in personality assessments (Ellingson & McFarland, 2011) as well as in applicants' self-reported skills and experiences (Schmidt et al., 2022).

## 2.2. How AI is used in screening

Having discussed the literature on applicant behavior in recruitment and selection, we introduce AI technology as the second area of our research topic. Before discussing the potential implications, we start by providing a basic understanding of AI and its use in screening. AI has no widely accepted definition (Wang, 2019), and what technologies are included in the concept is an ongoing revision due to the so-called AI effect: as a type of technology is normalized, it is no longer considered AI (Haenlein & Kaplan, 2019). For this study, we therefore choose to use Canhoto & Clear's (2020) definition of AI as our chosen frame of reference as it provides a simple yet inclusive definition: *"An assemblage of technological components that collect, process, and act on data in ways that simulate human intelligence"* (p. 184). These components in turn consist of input data, a processing algorithm, and an output decision (Canhoto & Clear, 2020). In screening tools, the application documents act as the input data which are processed by an algorithm to produce the output decision of which applicants should be prioritized for closer consideration by a human reviewer (Bogen & Rieke, 2018).

There are multiple types of AI tools whose algorithms focus on different application components as their input data with different purposes. This includes screening tools designed to screen out applicants by using predefined questions, scanning resumes for keywords connected to the job listing (e.g., *Ideal.* 2023; Cowgill, 2020), chatbots that evaluate applicants through individual conversations with AI (e.g., Nordmark, 2022; Webb, 2017), and complex deep learning models less dependent on pre-labeled data (Qin et al., 2020). There are also selection tools designed to predict top performers and candidate "fit" through personality tests, games, or surveys. Most tools rarely make any form of an affirmative hiring decision, instead assisting with the automation of candidate rejection (Bogen & Rieke, 2018). The rationale for using these tools is that AI-based decision-making can accommodate larger data sets with comparatively fast speeds and standardized, highly replicable outcomes compared to human decision-making. Using an AI-to-human decision-making process, where AI is applied to a data set to pass on suitable alternatives for a human decision-maker to select from, has shown potential benefits for the quality of organizational decision-making (Shrestha et al., 2019).

## 2.3. Applicant reactions to AI in recruitment

The use of AI in recruitment and selection raises the question of how applicants respond to this change. In other words, when applicants are self-presenting toward an AI, would they do it differently than toward a human? In the following section, we discuss whether AI in recruitment could matter for how applicants self-present and what existing literature comes closest to answering this question.

Although Schlenker's (1980) definition of impression management includes imagined social interactions, this predates AI technology. Little research has delved into how transferable traditional findings within impression management are when AI enters the picture. AI aims to simulate human intelligence and is constantly developing, though it is still not comparable to the human mind (Brynjolfsson & Mitchell, 2017; Marcus & Davis, 2021). While it excels in speed and decision replicability (Shrestha et al., 2019) and is often used to make quicker and less biased hiring decisions, AI has shown shortcomings in potential bias depending on how it is programmed (D. F. Mujtaba & N. R. Mahapatra, 2019) and still requires an eventual human decision maker (Shrestha et al., 2019). There are hence considerable differences in how AI can screen job applications relative to a human. With different ways of screening, this raises the question of whether there could also be differences in how an applicant chooses to self-present depending on the recipient.

Researchers have begun studying possible differences in how applicants react to AI in recruitment and selection. However, the exploration of applicants' behavioral responses to AI is in an early stage. Research from the perspective of the applicant primarily focuses on applicant reactions to AI (Nikolaou, 2021), with these reactions including "the attitudes, affect, or cognitions applicants might have about a hiring process or selection tools" (Ryan & Ployhart, 2000, p. 566). Notably, applicant behavior is not included in the aforementioned definition. Many of these reactions are indeed well proven to correlate with certain behavior (Hausknecht et al., 2004; Konradt et al., 2013; McCarthy et al., 2017), and are also possible to study through applicants' intent to behave a certain way (van Esch et al., 2021). However, having a starting point in perception and intention, reaction literature is not ideal for providing richer descriptions of behavior, such as how and why applicants may adjust their applications for an AI screening tool.

Although literature integrating applicants' self-presentation and AI is sparse, a recent study taking a more behavioral approach to AI in the selection stage of recruitment was published by Langer et al. (2020). The study concluded that automated interviews conducted by AI decreased applicants' efforts of deceptive impression management (applicant faking) while on the other hand, limited their opportunities to perform. These findings support the notion that automated recruitment tools can indeed affect how applicants present themselves. The dual effects of automation discovered in Langer et al.'s article also reflect a lack of academic consensus regarding whether the disclosure of AI use in recruitment has positive or negative effects on applicant reactions (van Esch et al., 2019; Wesche & Sonderegger, 2021; Acikgoz et al., 2020 compared to Langer, König, & Papathanasiou, 2019; Langer, König & Scheuss, 2019). Accordingly, recruiters or providers of AI services would find little guidance in whether they would benefit from actively informing the job applicant about their AI use. Despite this, in the mentioned research, explorations and measurements of applicants' reactions are generated by informing subjects that AI is, or is not, hypothetically or experimentally used. These implicitly assume that the applicant is informed of AI tools in the cases that they are used in real-life settings. Whether recruiters or providers of AI screening tools believe they benefit from being transparent about their AI use, legal requirements prescribe AI disclosure in the European Union (EU) (Felzmann et al., 2020). However, as the following section will discuss, there is also scholarly critique against the actual effectiveness of such legislation that brings the assumption of an AI-informed applicant into question.

## 2.4. AI Transparency

As the previous section alludes, AI transparency aims to inform applicants about if and how their data will be processed. While research commonly assumes AI transparency, there is reason to question whether applicants are effectively informed of AI use in the actual recruitment process. Accordingly, considering how applicants reason about who (or what) is screening them leads to the third and last area of our research topic, AI transparency.

Although AI screening tools may be a support to humans rather than their replacement (Shrestha et al., 2019), it still influences their decision-making. As such automated decision-making can have a significant effect on both the actor using it and the stakeholder evaluated by it, AI transparency becomes a central concern for both parties involved (Felzmann et al., 2020). The concept of AI transparency lacks a commonly accepted definition (Buiten, 2019) and may take on different meanings in different contexts (Weller, 2019). For our purposes, what matters most is whether individuals applying for jobs online are informed of when and how AI screens their applications. Therefore, our starting point for discussing transparency is the legal forces prescribing this type of disclosure. From a legal standpoint, AI transparency is often discussed as an ideal meant to protect stakeholders that are affected by the critical decisions that AI can make (Felzmann et al., 2019). The European General Data Protection Regulation (GDPR) focuses on protecting the autonomy and privacy of the data subjects whose data is processed (Regulation 2016/679). For our study, this data subject is the job applicant. Legally, AI transparency concerns not only applicants' right to know *when* AI is being used but also *how* it is being used. As defined in the GDPR Art. 5(1)(a), transparency encompasses both a prospective and retrospective element. Prospective transparency means providing information upfront about how an algorithm processes data in general. Retrospective transparency instead refers to an explanation of how a specific algorithmic decision was made, and is provided in hindsight (Felzmann et al., 2019; Paal & Pauly, 2018).

Prospective transparency in theory ensures that data subjects can either consent or object to their data being processed by receiving information about such processing before it happens (Al-Sulaiti et al., 2023). When an organization provides information about its data processing along with the option to accept or reject those terms, it is referred to as notice and consent (cf. Art. 13 of the GDPR). This includes supplying "information about themselves (who), the quantity and quality of processed data (how), the time(-frame) of the processing activities (when), the reason (why), and the purpose of processing (what for)" (Felzmann et al., 2019, p. 3). However, the practical efficiency of notice and consent has been questioned. Although GDPR also requires information to be easily accessible and understandable, several scholars question if such disclosure is enacted in practice (Felzmann et al., 2020). Ben-Shahar & Schneider (2014) critique the effectiveness of public disclosure due to individuals' inability to comprehend and sift through the vast text masses of disclosure, amongst other factors. Similarly, Ananny and Crawford (2018) note that organizations can both intentionally and unintentionally hide AI disclosure in "haystacks" of information.

Retrospective transparency relates more directly to explaining how AI works (Al-Sulaiti et al., 2023), which concerns both the explainability of the algorithm (explainable AI) and the data subject's ability to understand such explanations (AI literacy). Explainable AI describes AI that is able to provide explanations of its decisions (Vishwarupe et al., 2022), which is a prerequisite for retrospective transparency (Felzmann et al., 2020). Deep learning algorithms have been driving the increasing popularity of AI due to their high level of sophistication and performance (Pouyanfar et al., 2018). However, this performance comes at the cost of explainability (Vaassen, 2022). Deep learning algorithms are often referred to as 'black box' due to being opaque and have generated an interest in engineering them to inherently be able to explain their output and processing comprehensibly (Vilone & Longo, 2021). As such complex AI is also applicable within recruitment (Qin et al., 2020), it may cause tensions between GDPR's request for explanations and the ability of the algorithm to explain itself. It is worth noting that legal scholars have also questioned whether the right to an explanation is even included in GDPR (Felzmann et al., 2020).

Explanations of AI decisions, if provided, need to be understood by the job applicant. Another perspective that is equally relevant in studying how AI can be understood is *AI literacy*. Instead of focusing on the algorithm or legal regulations, this concept takes a starting point in the individual and their need to comprehend an increasingly artificially intelligent world (Ali et al., 2019; Dai et al., 2020; Kong et al., 2021; Steinbauer et al., 2021). Ng et al. (2021) describe the concept as fostering four aspects: to know and understand AI, to use and apply AI, to evaluate and create AI, and to consider the ethics of AI. Focusing instead on "casual" audiences, Long & Magerko (2020) exclude the criteria of model creation, defining AI literacy as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (p. 2). This better suits the needs of self-presenting job applicants as they may not have a direct need of programming such technology to impress it (Long & Magerko, 2020). AI literacy suggests that beyond receiving information about if and how AI is used, the job applicant's own knowledge about AI can be important for their ability to understand what such information means and, accordingly, their ability to adjust to a new and automated screening process.

## 2.5. Research gap

As the final part of our literature review, we bring together its contents to clearly define a research gap. While there is extensive research on how and why applicants attempt to impress in traditional hiring processes, little research investigates how self-presentation takes shape with an imagined AI recipient. Literature that focuses on applicants' reactions to AI dominantly focuses on reactions beyond self-presentation and implicitly assumes AI disclosure. At the same time, whether applicants are informed of AI in the screening process can be questioned from a legal perspective. Subsequently, we identify a research gap at the intersection of applicants' self-presentation, AI use in screening, and AI transparency.

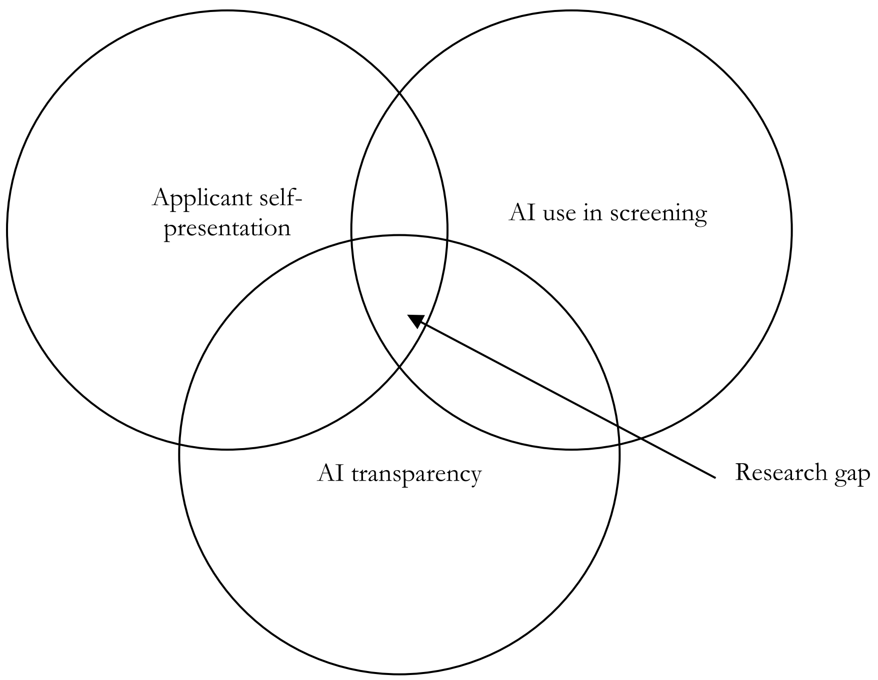


*Figure 1: Illustrated Research Gap*

# 3. Methodology

This section provides an overview of the decisions made when designing and conducting the study. First, we present the choices made on the research strategy (3.1) and research approach (3.2). Next, we present how data was collected (3.3), followed by how it was analyzed (3.4). Finally, we present considerations made for the quality of data (3.5).

## 3.1. Research strategy

Our study was designed to explore how applicants form assumptions about AI use in recruitment and how this informs their subsequent application adjustments. Accordingly, we focus on the applicant's beliefs instead of assuming they are explicitly informed of the usage of AI. This focus is established in the research question considering the applicant's “assessments” of AI. The size of the research gap and the early stage of research on the new phenomena of AI in recruitment also prompts a method of openness (Edmondson & McManus, 2007). When considering the focus on the applicant's perspective, the size of our research gap, and the newness of this phenomenon, a qualitative approach is well suited. In contrast to categorical inquiries that suit a quantitative approach (Bell et al., 2019), when studying how applicants assess AI use and their subsequent adjustments, we must remain open to making observations that have yet to be defined. To ensure the best methodological fit with our open-ended inquiry, we collected qualitative data and used thematic analysis to interpret this data for patterns and meaning (Edmondson & McManus, 2007).

A qualitative approach also implies certain assumptions of the nature of reality; in other words, it informs our ontology. While a qualitative research approach is often associated with constructivism (Lee, 2012), other ontologies also fit with a qualitative design and better align with what we aim to study and the method of analysis we chose (Braun & Clarke, 2006). As our goal is to contextualize how an applicant's subjective assessments of an objective reality could explain the adjustments they make to their applications, we find a contextualist method like critical realism well aligned (Braun & Clarke, 2006; Welch et al., 2020). Critical realism as a paradigm combines a realist and relativist ontology to simultaneously acknowledge that there is an objective truth to discover, about which different individuals will come to different conclusions in different ways (Stutchbury, 2022). Accordingly, we go beyond trying to describe applicants' subjective experiences and instead seek to explain how they came to their conclusions and how this affects their job applications (Bell et al., 2019; Stutchbury, 2022; Welch et al., 2020).

## 3.2. Research approach

Initially, our research approached the gathering and analysis of data inductively to fit our exploratory objectives. This openness to discovering data eventually allowed us to observe unexpected surprises in the responses of applicants, which prompted an abductive approach where a search for new explanatory theory was conducted alongside data analysis (Dubois & Gadde, 2002; Mantere & Ketokivi, 2013). This surprise related to the fact that many applicants were not considering AI in their application processes. With few exceptions, they also made no case-to-case assessments about whether AI would screen their documents that affected their application adjustments. In turn, this prompted a search for theory that could explain such unexpected results. With an abductive approach, we were able to utilize the exploratory benefits of inductive research while simultaneously not ignoring relevant existing research to answer our research question (Bryant & Charmaz, 2007).

## 3.3. Data collection

The following section will present the approach for data collection in terms of semi-structured interviews (3.2.1), selection and sampling (3.2.2), pilot study (3.2.3), and interview design (3.2.4).

### 3.3.1. Semi-structured interviews

In order to ensure consistent methodological fit with a qualitative research strategy and approach, we chose to use interviews for data collection (Edmondson & McManus, 2007; Saunders et al., 2009). Specifically, semi-structured interviews align with our philosophical stance as they allow for probing to understand the meanings behind words and ideas, thereby allowing us to understand the participants' subjective reality in context (Saunders et al., 2009). Our aim was to understand the perspective of the job applicant, and semi-structured interviews are well suited for providing detailed descriptions of how subjects interpret reality (Guest et al., 2011). This type of interviewing is also appropriate when subjects reconstruct events, such as in our case, which largely focused on their latest job applications (Weiss, 1995). The interviews were based on an interview guide with open questions that allowed participants to build on their responses and bring perspectives we may not have initially considered. The follow-up questions depended on the participant's responses to allow for the participant to share what they felt was most relevant and to allow for both depth and detail in responses (Dilley, 2004).

### 3.3.2. Selection and sampling

As our research is exploratory, we chose to use purposive sampling to elicit rich and interesting data from participants that were well-suited to discuss our research question (Bell et al., 2019; Taherdoost, 2016). We desired a sample of job applicants possessing a limited professional network and having both recent and frequent experience with the online application process. Thereby, they would primarily conduct their job search through traditional application processes instead of through network referrals, ensuring a screening stage, and would be able to recall this process in detail. We also wanted a sample applying to job listings in the EU so that the regulations governing AI transparency would be comparable. Specifically, GDPR has had interesting scholarly discussions surrounding the efficiency of AI transparency and applies to all companies based in the EU or processing personal data from data subjects in the EU (Regulation 2016/679). We aimed to use a fairly homogenous sample and accordingly decided to focus on university students pursuing an education in business-related fields at the Stockholm School of Economics (SSE).

Selecting SSE students was well-suited to provide valuable insights into our research topic for two main reasons. First, the types of roles and companies they applied to were comparable, which would not have been the case if we had included students with a variety of academic backgrounds. Second, as SSE is a highly ranked and competitive business school (*European Business School Rankings*. 2022), it stands to reason that the students would display high aspirations and drive with regard to the job application process and could provide detailed insights accordingly. This is important as our study benefits from thorough descriptions of thoughts and understandings. The decision to sample a homogenous group was also made so that we, given the scope of the study, could reach saturation in a limited time frame amidst a limited but feasible diversity of perspectives.

Within this sample, we aimed for diversity in terms of age and background (Swedish or non-Swedish) and equal numbers of men and women to achieve a breadth of perspectives within our homogenous sample in accordance with our exploratory approach. To also ensure that the individuals were highly relevant for our purposes, we applied criterion sampling with the following requirements:

1. Have applied to online job advertisements within the last six months in pursuit of post-graduation employment.
2. Are searching in the European job market.

In total, 24 participants were interviewed in the main study. Participants ranged in age from 22 to 31 years old, with the average age being 26 years old. The gender distribution of the sample was 50 percent female and 50 percent male. Lastly, the sample consisted of 62.5 percent Swedish nationality and 37.5 percent other nationalities, with all participants currently residing in Sweden. A list of the participants can be found in Appendix 1.

The number of interviews was not decided beforehand. After 21 interviews, additional subjects no longer generated new codes. We held three more interviews to ensure we had reached saturation and that the codes present allowed for a thorough analysis of the data (Bell et al., 2019; Hennink et al., 2017). The purpose of the study was to describe individual perspectives and subsequent behavior, not to determine a generalizable truth applicable to a majority. Therefore, when the sample approached such a size that additional subjects no longer added new perspectives, they no longer served a purpose in answering the research question.

### 3.3.3. Pilot study

In addition to the 24 interviews in the main study, three pilot interviews were conducted to test the interview guide before launching the study. These lasted around 30 minutes, and the participants were applying to online job advertisements for positions in Europe and studying at Nordic business schools outside of SSE. This was done to test the ability of the interview guide to answer the research questions with a representative group near our sample and to ultimately increase the research quality (Malmqvist et al., 2019; Van Teijlingen & Hundley, 2001). After the pilot interviews, questions were rephrased to improve their clarity and to minimize the number of responses that fell beyond the scope of the study.

| Interview | Gender | Age | Studying business | Studying at SSE | Applying for jobs online | Looking in the European market |
|---|---|---|---|---|---|---|
| P1 | Female | 26 | Yes | No | Yes | Yes |
| P2 | Male | 25 | Yes | No | Yes | Yes |
| P3 | Female | 22 | Yes | No | Yes | Yes |

*Table 1: Pilot study participants and sample relevance*

#### 3.3.4. Interview guide

There were several considerations made regarding the creation of the interview guide and how the interviewing was conducted. The interview guide consisted of four parts: a) background, b) applicant strategies in job applications, c) applicant perceptions of AI use in recruitment, and d) comparative and concluding questions (see Appendix 2).

The interviews started with simple background questions in part a) to familiarize us with the participant, better contextualize answers to later questions, and understand the participant's experiences with the job application process as a whole. These questions framed where they were in the job search, the types of jobs they searched for, and their overall methods for the application process. In part b), applicant strategies in job applications, we aimed to understand the participants' experiences with submitting a specific job application and the way in which they adjusted their documents. The questions in the guide were structured to minimize generalized accounts and largely focused on the participant's most recent job application for increased reliability and interpretability of the data (Weiss, 1995). In part c), applicant perceptions of AI use in recruitment, we wanted to gain insights into how they imagined the screening process in their most recent application and in application processes in general. The concluding section, part d), focused on how their methods have changed over time and between applications, and how they envision them changing in the future. Every interview session concluded with asking the participant if there was anything else they would like us to know that we overlooked to ensure we were open to observations that had yet to be defined (McGrath et al., 2019). The interview guide was subject to minor alterations in response to unexpected emergent patterns from the first nine interviews to better facilitate later theoretical insights in subsequent interviews (Eisenhardt, 1989).

Before each interview, all participants signed a consent form explaining the purpose of the study and how their data would be processed. Each interview also started with a reassurance of confidentiality and anonymity as well as asked for explicit verbal consent to their interview being recorded. To ensure participants were comfortable and instill confidence early on in the interview, we also clarified that we were not looking for a specific type of answer, anything they shared would be interesting to us, and they could take their time with responding (Rubin & Rubin, 2005). The interviews were between 30 to 60 minutes and were conducted in March 2023. They were conducted face-to-face, either in person or over a digital video call to accommodate the environment the participant was most comfortable with and minimize the impact on their daily routine. This allowed us to pick up on visual cues and facial expressions even when unable to meet in person (Rubin & Rubin, 2005). Although these cues were not directly reflected in our data, they did inform follow-up questions.

Both authors were present at each interview, with one author in a leading role guiding the interview and the second author in an observing role taking notes and asking follow-up questions when appropriate. This allowed for complementary insights and a more consistent interpretation of the data and, therefore, more confidence in the findings (Bechhofer et al., 1984; Eisenhardt, 1989). It also minimized the number of overlooked leads as both authors could ask follow-up questions, providing further clarification and a richer generation of data (Velardo & Elliott, 2021). The interviews were conducted in English, as all participants were native or fluent in the language. All interviews were recorded either with a mobile phone or within Microsoft Teams, depending on the interview setting, and transcribed within one day.

## 3.4. Data analysis

The data analysis was conducted using thematic analysis, a six-step process that started with (1) familiarization of data. The familiarization step consisted of transcribing and repeated reading of the interview transcripts in search of patterns. At this step, surprising patterns in the data became apparent, which prompted an open approach to coding and a reflexive approach to thematic analysis (Braun & Clarke, 2021a). This resulted in five subsequent steps: (2) coding, (3) generating initial themes, (4) reviewing and developing themes, (5) refining, defining, and naming themes, and (6) writing up. A code is a phrase capturing a single-faceted observation used to develop initial themes (Braun & Clarke, 2021b). Themes, in turn, were used as patterns of shared meaning, capturing a multifaceted observation developed from the single-faceted codes (Braun & Clarke, 2012). Importantly, thematic analysis is an iterative process, and refinements occurred between themes and codes throughout the analytic process.

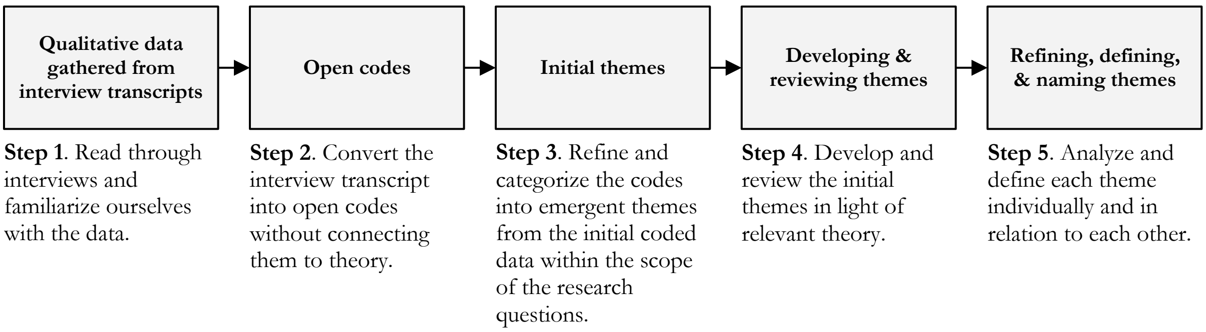


*Figure 2: Data analysis process overview*

After familiarizing ourselves with the data, initial codes were generated using an open coding approach to be theoretically open and to illuminate patterns across interviews (Holton, 2007). From this initial open coding, 238 codes were generated. These initial open codes were then refined to remove overlaps, ensure consensus of their meaning between us as researchers, and filter out codes with both low frequency and low relevance to the research questions. For example, while we initially had a code for "AI as a black box," we chose to merge this code into "uncertain of how AI works" since there was an overlap in meaning between these. We also eliminated codes such as "test invitations received after screening" because it was outside the scope of our research question. This helped us refine the initial codes down to 129 codes. Each interview was initially coded by one author, then after refining the initial codes, a second round of coding was conducted by the other author to compare coding results and discuss differences to ensure a common vision of the codes (Miles & Huberman, 1994). During this process, the software Quirkos was used to support seamless coding and recoding by both authors and to prevent data loss (Gibbs, 2014).

After refining the initial codes, the authors discussed patterns that we had noticed across the interviews as well as looked at how the initial codes could be grouped into types of observations. Additionally, we considered how these groupings pertained to the research questions, as some trends we observed, while interesting, were outside the scope of what we aimed to answer. From this, we established 17 emergent themes.

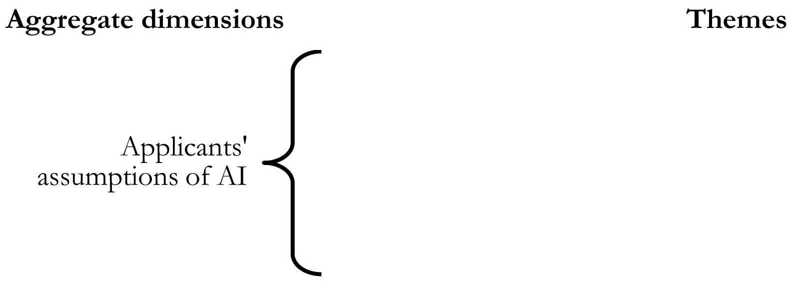


*Figure 3: Thematic framework*

The investigation of the nature of the themes in relation to each other led to five identified aggregate dimensions of the themes: applicants' assumptions of AI, confidence in understanding AI, desire for a role, perceived impact from modifications, and application adjustments. Organizing themes into these areas allowed us to ensure the themes worked in relation to the coded extracts as well as to theory. With these five dimensions and 17 themes in mind, we re-named and defined the themes and grouped the codes into their appropriate theme. This process allowed us to further iterate on our codes, resulting in a final total of 76 codes (Appendix 3).

| Qualitative data gathered from interview transcripts | Code | Theme | Aggregate dimension |
|---|---|---|---|
| *"You kind of implicitly understand that when you apply for the big corporate stuff that this will probably go through a computer because it's so mechanic, but not explicitly, no." - I23* | Type of company | Signals before submission could influence awareness of AI | Applicants' assumptions of AI |
| *"I actually always try to get some feedback. Most of the time, they don't really provide you with much, but yeah, even if I passed like all the incentives I tried to get some feedback still." - I22* | Seeking out rejection feedback | Limited feedback upon request | Applicants' confidence in understanding AI |
| *"It depends on how much I want the role since it's so time-consuming. If I want the role really bad, then I'll spend a lot of time to make a good cover letter. If it's not as desired, if it's implied in some way that you can share documents, then I mean it says a lot on your effort that you put in if you don't send it I guess but if it's something I'm just applying to spontaneously, then I won't include if I don't have to." - I24* | Modifying more for more attractive roles | Balancing quality versus quantity | Applicants' desire for a role |
| *"For someone from SSE who I mean, companies know it's someone having some sort of quality on the education and you could just maybe put less time on your cover letter and include the things that you just see important in the job ad and then have a big pretty big chance to go through in the first processes at least." - I20* | Higher role fit means lower adjustment of documents | Importance of role fit | Applicants' perceived impact from modifications |
| *"[For the CV] I have it designed in Canvas. I think that's also a plus, if you make it look a bit more fun and not just like an engineer or mathematician has written it." - I19* | Visual adaptations | Applicants consider how to make quick impressions for human recruiters | Applicants' application adjustments |

*Figure 4: Example of data analysis process*

## 3.5. Data quality

While reliability and validity are important measures to assess the quality of research, these are closely tied to quantitative research as they relate to measurability (Bell et al., 2019). Additionally, reliability and validity are linked to the assumption of a single, objective reality. Therefore we will use the criteria of trustworthiness and its four sub-criteria, *credibility*, *transferability*, *dependability*, and *confirmability,* as a basis for a data quality assessment as they are better aligned with qualitative research (Guba & Lincoln, 1982; 1994; Lincoln & Guba, 1985).

*Credibility* refers to the internal validity of the research, namely whether the participants find the analysis and interpretations to be believable (Guba & Lincoln, 1982). We used respondent validation to share our findings and confirm with the participants that our account of what they shared in their interview is accurate and resonates with their experiences (Bell et al., 2019). Furthermore, by conducting pilot interviews to verify the interview guide, we were able to check its validity to improve the credibility of the study (Malmqvist et al., 2019; Srinivasan et al., 2017).

*Transferability* refers to the external validity of the research, namely whether the research is generalizable and representative of a larger population (Guba & Lincoln, 1982). Our study examined the experiences and perceptions towards AI-enabled recruitment processes. We are aware of the constantly changing nature of AI technology and acknowledge this could limit the transferability of our findings after further technological advances. We also acknowledge our participants occupy a specific subset of job applicants that could further limit the findings' transferability. However, we are not aiming for wider empirical generalization as this is misaligned with our critical realist approach and instead hope that the depth and insight provided in our findings will assist readers in evaluating the applicability of our results to other situations (Lincoln & Guba, 1985; Welch et al., 2020). We see the concepts we are studying as an empirical area of interest for a larger population and our study's transferability as extending the current research context (Willing, 2013).

*Dependability* is ensured by keeping records from all steps of the research process to demonstrate the research is trustworthy and the findings can be repeated. All interviews were recorded and transcribed, and the data was analyzed by both authors. This record-keeping also holds the authors to a standard of objectivity, or *Confirmability*, although in qualitative research, it is impossible to be truly objective. Therefore, the focus of objectivity is on the confirmability of the data instead of on the objectivity of the researchers (Bell et al., 2019; Guba & Lincoln, 1982). Nevertheless, we minimized personal biases by having both authors present at interviews and by individually coding data before comparing and discussing content interpretation (Bell et al., 2019; Eisenhardt, 1989). We acknowledge that through our own experiences with the job application process, we have intrinsic biases that arise from our interpretations of the usage of AI. Additionally, as the sample is comprised of SSE students, both authors have had previous contact with several of the interview participants of this study which may reduce author objectivity. Our primary goal was to understand the participants' experiences, and by taking a reflexive approach to data interpretation, we believe the bias we do have did not detract from our findings (Willing, 2013).

# 4. Results

In the following section, the results of the study are presented according to five aggregate dimensions: applicants' assumptions of AI (4.1), applicants' confidence in understanding AI (4.2), applicants' desire for a role (4.3), applicants' perceived impact from modifications (4.4), and applicants' application adjustments (4.5). Themes were sorted into these aggregate dimensions to improve the clarity between the results and the upcoming analysis section and were selected to answer the research question of how applicants' assessments of AI in recruitment inform their adjustments to their job applications. For the coming presentation of our results, we refer to application documents or applications as the resume, cover letter, and application forms; we exclude transcripts and references as we found they were not modified and therefore not relevant to the purposes of our study. An overview of the themes and codes can be found in Appendix 3.

## 4.1. Applicants' assumptions of AI

The dimension of applicants' assumptions of AI focuses on the job applicant's assumptions about if AI was used to screen the documents that they submitted for an application. Despite a prominent lack of disclosure from recruiters regarding their screening process, applicants formed their own assumptions of who or what would be processing their application.

### 4.1.1. Lack of AI disclosure

Notably, the vast majority of participants recalled no instances of being informed about the use of AI screening before submitting their applications. Among these participants who did not recall disclosure, there was a high level of uncertainty about how they would be able to find out and participants discussed this in uncertain terms. For the few participants who had experienced disclosure about AI in recruitment, the only example given was after the application was submitted and as part of an AI-evaluated interview. Recalling any instance in which it was disclosed that a human would be processing the application was as rare as the disclosure of AI processing.

> "*I think it was for the H&M one, they said that the AI was used for the interview process, but I don't think it said that AI would be used in the initial screening. Not that I can recall at least. But other than that, I don't recall it being stated in the description of the role. I'm sure that a lot of roles that I applied to have used it, but I don't recall it being like, in the description when applying.*" *- I16*

### 4.1.2. Signals of AI before submission

In the absence of explicit disclosure, several participants made inferences about AI use based on characteristics of the job advertisement and the hiring company. When looking at these case-to-case judgments, two types of signals were discussed: those that influence awareness of AI before the application was submitted, and those that were considered when retrospectively discussing if AI was used. Notably, very few applicants had their application strategy influenced by a case-to-case judgment before the application was submitted. Although these were hints that occurred before submission, the applicants only actively reasoned about them when prompted to do so during the interview. The signals from before submission included the type of company, the size of the company, and the way the applicant applied to the role.

> "*I would maybe assume that a large company… that they use AI to facilitate their recruitment process. And a smaller, more independent company probably doesn't.*" *- I7*

#### 4.1.3. Signals of AI after submission

The other case-to-case judgments participants make were retrospective in nature and were cues that occurred after the submission of an application. These signals included the response times to their application, usage of testing tools, the number of other applicants for the role, and the number of recruiters involved in the process. All of these were discussed by participants in a reflective manner and did not influence their applications since all were cues that occurred after the initial submission.

> "*You've been sent to some sort of landing page where you conduct an intelligence test and those sorts of quizzes and then I think it's much more like the interface speaks for a more AI-oriented approach." - I3*

#### 4.1.4. Generalized assumptions of AI

In contrast to case-to-case judgments, the dominant way for applicants to approach their application strategy in the screening process was to make *generalized assumptions* across all applications. Notably, these assumptions could not be described as binary, that is, in terms of whether an AI *or* a human would process the application. As will be discussed in the following sections, the vast majority of participants acknowledging AI use in the screening process recognized a sequential process in which first an AI *and then* a human screen candidates. General assumptions of AI's role in the screening process were communicated explicitly. Applicants assuming AI use had also actively considered what the screening process would look like before submitting their application.

> *"I think nowadays I always think that AI is involved." - I16*

Assumptions of a human screener came across both explicitly and implicitly. Implicit assumptions were often communicated when participants referred to considerations in their application strategy that fell outside of their understanding of AI's capabilities, such as discussing purely visual modifications to their documents. The assumption of a human was most commonly latent, meaning that these applicants often stated that the screening process overall did not occupy a place in their minds when applying for jobs.

> *"I never really thought about it. And in my head, I thought it was people doing it." - I11*

#### 4.1.5. Personal background influences awareness of AI

A pattern amongst participants expressing assumptions of AI was having a background in technologically-related fields. These backgrounds included prior education, long-term recreational interest in technology, and work and recruitment experience. The first two types of background, prior education and interest in technology, informed participants' awareness of AI in general, with its usage in recruitment processes as a byproduct of that.

> *"…because I went to a university where most people go into the tech industry, like I've always been taught to go in with the assumption that your resume is going to initially be looked at by a robot."* - I4

In comparison, the third type of background, work and recruitment experience, was often connected to their understanding of recruitment processes with AI-enabled recruitment as a byproduct of that.

> *"It just comes from me having worked in recruitment…I guess I'm a bit aware that like some companies, they use a process or like an AI system."* - I10

#### 4.1.6. General discourse influences awareness of AI

Similar to a background in technological fields, several participants also described societal and personal discourse as a source of awareness of the technology. Some referred to news and conversations about ChatGPT as a source of increasing AI awareness, while others referred to reading posts from their network on LinkedIn. When a participant with a general assumption of AI use in the screening process was prompted to reflect on the reason for this, they simply responded:

> *"I don't know. It's just you hear a lot about it."* - I15

Others in contrast mentioned the *lack* of AI as a topic in personal discussions as a reason why they did not consider it when applying for jobs.

Some also reflected on their ignorance of AI in the screening process during the interview itself, stating that they found it confounding that they did not consider AI in the screening process when applying for jobs. Although they had a human in mind when creating their documents, they recognized in hindsight that their documents would likely be met by an algorithm.

> "*Yeah, I don't think much about it. But now talking about it, I realize how weird it is."* - I6

### 4.2. Applicants' confidence in understanding AI

Awareness of AI did however not appear to be sufficient for applicants to actually adjust their application to be screened favorably by an algorithm. In several cases, participants expressed being fully aware of AI screening tools and their prevalence, yet this did not translate into their behavior.

This connects to the next dimension, namely the applicant's confidence in their *understanding* of AI. The concept of understanding in this context refers to how applicants feel that they comprehend how AI functions and what it favors. The related themes include what limited as well as what motivated this confidence in understanding AI.

### 4.2.1. Limited feedback

In understanding how their applications were evaluated, an overarching theme for the participants was a lack of specific feedback upon rejection. When participants would be informed that they did not advance in the recruitment process, which was not a guarantee, the specific reasons behind the rejection were left undisclosed. Interest in actively demanding feedback varied. The lack of feedback was in several cases explicitly described as hindering applicants from understanding the evaluation of their applications.

> *"And in the end, you don't really know what was the reason why something worked out and what was the reason why something didn't work out."* - I17

Feedback on applications was however not completely inaccessible. Several participants looked towards friends and CV workshops to refine their applications. Importantly, by receiving feedback from humans the recommendations were often implicitly directed towards improvements for impressing a human screener.

### 4.2.2. Uncertain requirements

Understanding how to present oneself in an application was not clear-cut for many participants. This uncertainty was occasionally mentioned in terms of what the hiring company wanted in an applicant, but more frequently it concerned an uncertainty of how an AI screening tools worked and thereby what they favored. The latter type of uncertainty was prevalent across many interviews where applicants recognized that an AI screening would affect them differently relative to a human. Some were unsure of whether the AI would differ at all from a human in screening their documents, while some believed that AI would differ, but could not explain exactly how.

> *"I haven't seen how an AI recruiter works, like everyone was talking about AI…I can rationally think okay, it probably matters. But I can't see how because I haven't really explored or seen how that kind of tool works."* - I2

Other participants reflected further and made an explicit statement of how their lack of understanding caused them to not adapt to potential AI screening tools. Describing his documents as prepared for a human, one applicant concurrently assumed AI to be a prevalent screening tool. When prompted to elaborate on optimizing applications for a human and not an AI the participant explained:

> *"I don't know what would be different…I should consider this, but then again I don't know what to consider."* - I17

### 4.2.3. Explicitly informing applicants motivates increased learning

There was a trend of participants discussing how they would act in future job applications. Many participants expressed a desire to research more about AI in recruitment after our interview. Several also expressed that if future applications explicitly stated AI would be used, they would do research to optimize their application.

> *"[If it was disclosed] then you could actually, like read up on this AI recruiting tool, and then I think it would be quite easy to find information on how that sort of values applicants… so yeah, definitely I would, I would look up how to do it." - I23*

This future speculative behavior to increase their understanding also is filtered through how desirable they find the role. If the job meant a lot to them, applicants were willing to learn.

> *"If I really wanted a job, I would really invest time in understanding what the AI wanted. Because I mean, it's a matter of making yourself interested in it. And with AI, it's quite straightforward like they probably have data points that they look for in your cover letter and your CV, so I will just find out where those were and really incorporate it in the cover letter and the CV, so yes, if they told me that they were using it, I would invest time in understanding what they were looking for." - I9*

### 4.2.4. Confident understandings of AI

Several applicants however already had confidence in their understanding and provided detailed accounts of how they understood the workings of AI screening tools. This uncovered both perceived differences and similarities between screening done by AI compared to human recruiters. A common understanding was that AI tools were relatively limited in holistically assessing applications. This referred to the ability to draw conclusions that considered not only parts but the whole of an application communicating more nuances than the sum of these individual parts. Accordingly, several interviews expressed that humans would be more capable of evaluating soft skills and personality traits.

> *"The human might be more lenient and understand more of the general or the holistic view of the paper, the document, where the AI might be selecting only did it say XYZ, and if not maybe not a good candidate potentially." - I12*

In terms of other similarities between the algorithmic and human screener these were expressed in both specific and more general terms. Although *keywords* were most commonly associated with AI, several participants believed that these were equally beneficial to use for a human screener.

> "*I guess AI is more based on keywords, but I still think it's not like super stupid, I think it probably looks at some of the similar keywords that a human does… hiring managers also look for certain things.*" - I22

Notably, several participants still had thoughts about the workings and outputs of AI despite expressing considerable uncertainty about their thoughts. Although they were expressed more as guesses than understanding, they largely aligned with the understanding of more confident participants.

## 4.3. Applicants' desire for a role

Beyond awareness of AI and understanding its use in recruitment what also mattered for participants' AI-related adjustments was their desire for a role. This desire was largely shaped by their overall approach to the application process of prioritizing either quality or quantity when applying, as well as by their time in the job search.

### 4.3.1. Balancing quality versus quantity

When discussing their approach to applications, participants had varying perspectives on how to balance between submitting a high quantity of applications versus maintaining a high quality of individual applications. While some applicants prioritized applying to a wide range of roles with less time spent on each individual role, others prioritized applying to fewer roles and spending more time on each individual role. This overall was a difference between prioritizing high-quality applications or prioritizing a high quantity of applications.

> "*It's a numbers game. Very much. I mean, if you look on LinkedIn, on like the job postings that get presented to you a lot of the time and you see that they have anywhere between 100 and 1500 applicants on the LinkedIn thing, obviously, if the hiring company has that many applicants to choose from, you have to kind of match that if you expect to end up with at least one offer. So my philosophy is to shoot wide and reduce the effort.*" - I8

Further, participants find role attractiveness a strong factor in how likely they are to modify their application for a given role. If they thought the role itself was interesting, they expressed more interest in spending time on their application and making further modifications to personalize their application for that role. This was discussed more with regards to general application modifications than to AI-focused modifications specifically, though there were some participants who also connected modifying their applications for AI specifically with how attractive they found the role.

> "*It very much depends on how interested I am in the role, but obviously if there's some hard skills that they're looking for like HubSpot or a specific program that I worked with before, I always make sure to have it included in that part of the resume. So yes, there's obviously some sort of modification, but it depends on how interested I am in the role.*" - I3

### 4.3.2. Time in search

Participants also discussed how time limitations factor into the decision-making process. Some participants express that they put in less effort on early applications and view them as a practice for later applications, and others express feeling a sense of pressure to submit applications before posted deadlines as a result of perceived rolling applications. There were also participants who discussed the role that time plays in changing their overall approach, such as choosing to spend less time on individual applications after not feeling as if their large time investment was paying off.

> "*It goes back to this thing about the mutual respect of spending time, like if they're not willing to spend time, it's probably not wise of me, just in the interest of time having a cost, it'd be probably wiser spending the rest of that day applying to 10 other jobs than to spend eternity on this… Long ago maybe it would take me a day to put together a nice application. Now it's five minutes to an hour because there's a lot of reusing and just tweak a little bit and then it's fine. Good to go. No one's gonna read it anyway." - I8*

## 4.4. Applicants' perceived impact from modifications

The final aggregate dimension influencing applicants' application adjustments was the applicant's perceived impact from making modifications. This perception was largely shaped by two main themes. First, participants s perceived AI as a human decision aid such that application adjustments would eventually reach a human recipient. Second, the role's fit with the applicant's skills affected how crucial they found making case-by-case modifications.

### 4.4.1. Understanding AI as a human decision aid

Although participants made different types of adjustments for human recruiters and AI screening tools, there is an overall perspective of the hiring process as one that holistically incorporates these components so the adjustments and adaptations are made as part of an overall evaluation of the process. Even when making adjustments to pass through AI screening tools, participants still envision their application as having an eventual human recipient and this moderates the capacity for AI modification.

> "*Even if I write a cover letter for a bot, if I move forward in the process properly, somebody at the end will read my cover letter, a person would, so I will have to write the exact same cover letter I guess. I don't know if I would change something. I guess maybe trying to be more explicit about what they're looking for. I know that us as humans we can read that, I don't know, this sentence is about leadership even though we don't write leadership on the sentence and then usually when I explain something on my cover letter I try not to be that explicit that it says leadership, but if it were a bot then I guess you probably need to put exactly the words they want. That's something I guess I will think differently. To be super explicit." - I11*

This perception of AI as a human decision aid also factored into discussions around honesty in applications. Several participants wanted to avoid uncomfortable and unfavorable interactions with an eventual human recipient in an interview or in the role. They viewed AI as only one step in the overall process and made decisions with the assumption that a human would eventually perceive them.

> "*Oh, yeah, I have a very hard time being dishonest with that. But also, I mean, I feel like that gets you past the first hump and it's just not a game I want to play. It's just gonna turn awkward and be a waste of time.*" - *I8*

### 4.4.2. Importance of role fit

How well the participant perceived that their skills aligned with a given role also played a part in their decision-making. Some expressed not feeling as if they needed to have all skills in the job description to be a qualified candidate and perceive the role as a good fit.

> "*I think you don't always have to have, like, all the requirements. Sometimes you can still be suited for a role, even though you don't have one or two years of experience. So I think that I've kind of been going into the recruitment or like, the job searching process with that mindset… When applying for roles now I haven't been restricted to descriptions where I match all the different requirements. Like the job that I got now, I don't think I matched the requirements, but I applied anyway.*" - *I16*

There were also participants who felt as if the role they were applying for had a good fit with their skillset and accordingly did not feel a need to make modifications to their application.

> *"I mean, I feel like my skill set really matched what they are looking for already. I feel like there are not that many companies that are specifically looking for people that are problem solvers and are quite passionate about a particular industry to the capacity that I am. So I think for me it was quite easy because I felt like I was a good fit for the company. If it was a different application, I would probably spend more time thinking about how to make myself seem like a good fit, but this one was just a good match." - I4*

## 4.5. Applicants' application adjustments

The final aggregate dimension focuses on application adjustments which were closely related to applicants' understandings of AI-enabled recruitment processes. Some adapted their documents for AI, though never in complete isolation of the whole screening process, while others only considered a human recipient. Further, many participants considered their applications as part of an overall approach without necessarily making case-by-case modifications, though their adjustments could still align with those for an imagined human or AI recipient. Additionally, there were a few notable differences in the ways participants conceptualized the adjustments made for a human compared to AI.

#### 4.5.1. Applicants consider how to make quick impressions for human recruiters

When putting together their application, participants made alterations to catch the eye of the recruiter assumed to be reading their application. These alterations are ones that would make little difference for an AI screening tool and participants discussed these as ways to stand out to a person reading their application. These changes included *visual* adaptations such as using bold font on keywords or including a photo, *textual* adaptations such as keeping the CV to one page or considering order for readability, and *personal* adaptations such as the inclusion of motivation and interest in the company or industry. In line with their understanding of AI as limited in holistic evaluation capabilities, these changes all aligned with what the participants expressed a person would be screening for.

> "*I think a good CV should be easy to read, like people will get what kind of person you are just by looking at certain points, maybe like the top half of the page even." - I13*

#### 4.5.2. Applicants consider how to check boxes for AI screening

The considerations participants made for AI were discussed in terms of meeting baseline criteria and skill requirements. They typically used the requirements in the job description as a source for describing their experience in their CV based on their understanding of how AI screening tools work using keywords.

> "*I tried to use the same words that are in the job application that are relevant to my skill set. So like if it's something that I haven't done before, I don't put it in because it's not honest. But if it's like we're looking for a problem solver, then I'll be like I problem solved this thing, or if they're saying looking for somebody that has fintech experience then I would say 'at a fintech' or something." - I4*

The participants also considered this "box checking" as something that impacted the time and detail included in their application. A perceived AI-enhanced screening process led to an increased focus on simplicity and a decreased focus on personalization and unique case-by-case effort.

> "*I feel like it would definitely discourage me from like...maybe trying to add personal touch to things, I think it will become a lot more like a cold scientific process." - I10*

Further, there were a few participants who also mentioned themselves using AI tools in response to the rise of AI use in recruitment, though most of these discussed making modifications to the output from AI before submitting.

> "*It seems like at least ChatGPT does a great job of targeting specifically these keywords, so I figured I wanna use the AI to beat the AI in a sense." - I18*

### 4.5.3. Adjustments are considered as part of an overall approach

When discussing how they formed their applications, participants were most likely to express this in general approaches versus customizations for specific applications. There was a tendency to focus on hard skills in the CV and soft skills in the cover letter.

> "*I don't think that I, as like an employee, I think there is much more to me, or like much more nuances that I can't really put into a CV because if I put it there, that would be excess information for them.*" - *I1*

Participants also varied in the extent they customized their application documents, with the majority of applicants making minimal adjustments to their CV while making comparatively more adjustments to their cover letter.

> "*I had already laid out some basic materials such as my CV and transcripts, but especially the cover letter, I really want to tailor it towards the role.*" - *I6*

When discussing changes to their approach, participants expressed their changes in a linear fashion where they improve their applications over time instead of considering specific companies' application processes. There was a general consensus that most companies evaluate for similar base criteria, so the perceived improvements came from learning more about the application process in general than from tailoring to particular companies' processes.

> "*I feel like applying for a job is really just, I would say technique, like, how to present yourself in a sense that the company is interested in you. I would think that I probably didn't think much about how McKinsey per se would evaluate my application. But I feel like throughout the last three years when I've applied for anything, you kind of work out the methodology on how to structure things and what to highlight. Because I feel like every employee probably looks at grades, they probably look at previous experience, extracurricular activities, and also how you tie it all together in your cover letter.*" - *I9*

## 5. Analysis

Following the results, our analysis chapter presents how these were interpreted to answer the research question: *How do applicants' assessments of AI use in recruitment inform the adjustments they make to their job applications?* A theoretical framework was abductively applied to the results together with legal concepts of AI transparency in order to understand the themes and their relationships. The analysis is thereby structured into two main sections (5.1) Introduction to theoretical framework and (5.2) Conceptual framework.

## 5.1. Introduction to theoretical framework

In order to understand the results with regard to our research question, Vroom's (1964) expectancy theory, also known as Valence-Instrumentality-Expectancy (VIE) theory (Ellingson & McFarland, 2011), was applied. Fundamentally, VIE posits that energy allocated to a certain action requires motivation (Lawler & Suttle, 1973). It specifies that decisions between different actions are made regarding beliefs about (1) those actions and (2) their associated outcomes. The former is referred to as a first-level outcome, and the latter as a second-level outcome. The beliefs about first- and second-level outcomes are categorized into three factors that constitute motivation and thereby instigate behavior: valence, instrumentality, and expectancy. First, valence is the strength of one's preference toward a second-level outcome. Instrumentality is the belief in the likelihood that achieving a good first-level outcome will actually result in a second-level outcome. Finally, expectancy is the belief in the likelihood that one's effort will result in a good first-level outcome (Vroom, 1964).

The theory posits that individuals decide what action to take depending on the combined level of valence, instrumentality, and expectancy. If an individual does not believe that the outcome of an action is desirable, that the action itself is not instrumental in achieving this action, nor believe in their ability to successfully achieve the action, they have little motivation to take such an action. That is, individuals choose the actions they are motivated to take. Refinements of the VIE framework have included an additional factor labeled objective ability which refers to an individual's capacity to achieve a first-level outcome (Lawler & Suttle, 1973). This factor highlights the notion that although an individual may be motivated to choose a certain action, it may be beyond their capacity to do so. As this refers to an objective, measurable ability it is, however, beyond the scope of our qualitative research approach.

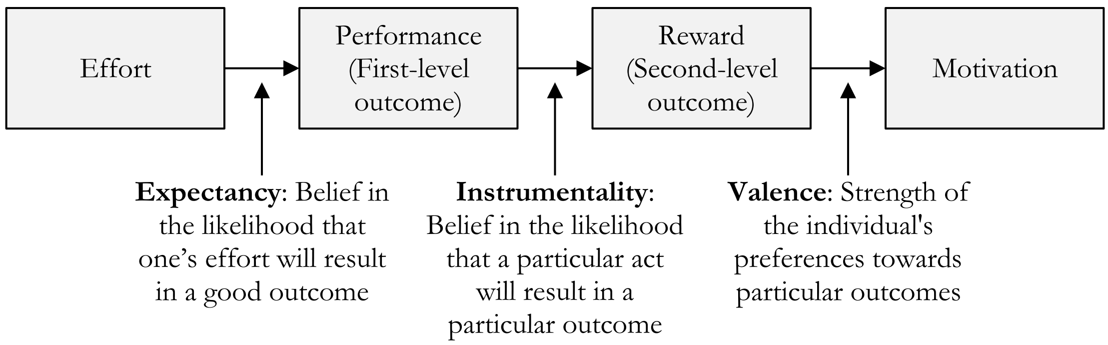


*Figure 5: Vroom's (1964) Expectancy Theory, adapted from Harris et al. (2017)*

The application of VIE theory to a context where applicants may try to impress a recruiter is not new. Authors Ellingson & McFarland (2011) use the VIE framework to explain applicant faking behavior in recruitment. As VIE theory explains behavior through a motivational lens, Ellingson & McFarland argue it is appropriate for understanding faking behavior. The act of faking requires a job applicant to purposefully direct their energy in order to achieve a certain outcome, and deploying energy requires motivation. Although we do not limit our analysis to faking behavior, the same fundamental logic is applicable to more general efforts of self-presentation (Marcus, 2009).

Therefore, we take inspiration from Ellingson & McFarland's (2011) definitions of valence, instrumentality, and expectancy in a recruitment context and define them as follows:

| VIE factor | Factor definition |
|---|---|
| Valence | The belief that the specific role is preferred among other options such that it will bring personal satisfaction. |
| Instrumentality | The belief that making case-by-case adjustments for AI (i.e., first-level outcome) is critical for advancing through screening to the next stage of the process (i.e., second-level outcome). |
| Expectancy | The belief that one is able to make adjustments successfully and thereby submit an application that AI would screen favorably. |

*Table 2: VIE factor definitions adapted from Ellingson & McFarland (2011)*

### 5.1.1. Model fit

VIE theory has several advantages in its ability to address our research question and results. As it is a process theory, it "emphasizes individual perception of the environment and subsequent interactions arising as a consequence of personal expectations" (Isaac et al., 2001, p. 214). Thereby, the framework is able to describe a connection between applicants' assessments of AI use in screening (perception of environment) and how they may accordingly adjust their self-presentation (interaction as a consequence of personal expectations). By taking the perspective of the individual and their beliefs about reality, VIE theory also accommodates a critical realist approach and our perspective on application behavior as self-presentation (Marcus, 2009). Additionally, it can account for both individual and contextual factors and is hence able to address actions that connect to an individual's thoughts, feelings, and environment (Ellingson & McFarland, 2011). In its foundation, VIE theory also posits that behavior is an act of allocating limited energy (Peters, 1977). This is especially relevant for the often time-consuming and time-limited process of job applications, where time serves as a limitation on their overall amount of energy to deploy for an application. Applicants will need to decide how to invest their efforts across applications in light of deadlines as well as the overall limitation of limited hours in a day.

#### 5.1.1.1. Comparisons with legal requirements

Although the focal point of our study is understanding the beliefs of the applicant, the reality of AI transparency is a central comparison in understanding why such beliefs are important. Therefore, VIE theory is combined with the two main components of AI transparency: prospective and retrospective transparency (Felzmann et al., 2020). Although these previously introduced concepts do not constitute a theoretical framework, they provide a useful point of comparison for understanding the importance of an applicant's assessment of AI for their self-presentation alongside VIE theory. Together these constitute the general context through which we understand applicant beliefs and self-presentation.

## 5.2. Conceptual framework

Our conceptual framework is briefly presented in its entirety before elaborating on its components and has two main parts. The first part concerns the applicants' assumption of whether AI is used in the screening process and represents a prerequisite for any application adjustments made with an AI in mind. The latter constitutes the application of the VIE framework to our findings. The first-level and second-level outcomes represent the AI-related application adjustments made by the applicant and any subsequent stage in the recruitment process that these adjustments aim to achieve. Affecting application adjustments is the applicant's motivation to adjust, which in turn depends on the applicants' beliefs about both their adjustments and what the job search process means to them. As a whole, the framework integrates a legal perspective on AI transparency with a motivational perspective on applicant behavior.

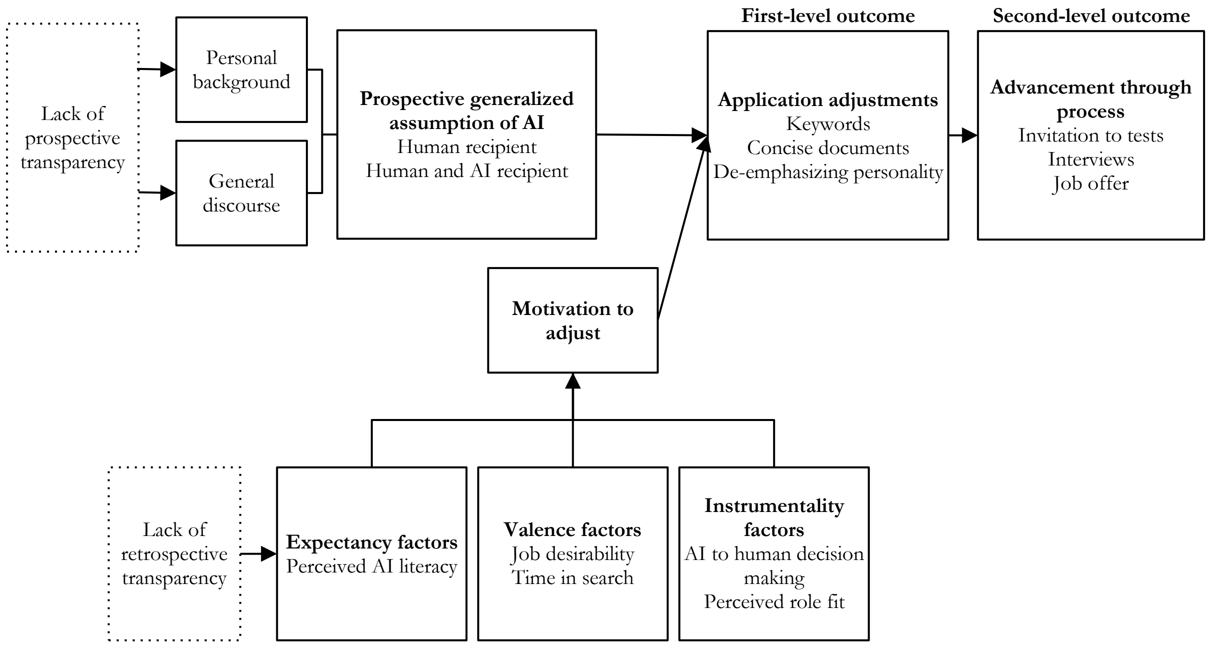


*Figure 6: Conceptualized theoretical framework*

The components of the framework and their relationships will in the following analysis be described in the coming sections, beginning with *applicants' assumptions about AI* (5.2.1), then contextualizing their *motivation to adjust* (5.2.2), and ending with the *application adjustments* made as a result of the two contributory components (5.2.3).

### 5.2.1. Applicants' assumptions of AI

As a starting point in our framework, we first consider the prerequisite for any application adjustments made with regard to AI: being aware of its use in the screening process. The assumption of AI use is conceptualized as a necessary filter that applicants must pass through for motivation to be applicable. Hence, it acts as a prerequisite for VIE's power in explaining why AI-specific adjustments are made.

The nature and importance of applicants' AI assumptions can be understood by contrasting the real tendencies from the results with the legal prescriptions of GDPR (Regulation 2016/679). Although prospective transparency would create assumptions of AI in the cases it was applied, it is clear that no such transparency was experienced. Applicants were uninformed about "the quantity and quality of processed data (how), the time(-frame) of the processing activities (when), the reason (why), and the purpose of processing (what for)" (Felzmann et al., 2019, p. 3), and they did not know *if* AI was even used. Prospective transparency would level the playing field toward equally AI-aware applicants. However, in a context characterized by a *lack of prospective transparency* what instead mattered was the *personal background* of the applicant and *general discourse* that they had experienced. As the interview with the authors itself can also be considered a discourse, this can explain why several participants during it expressed surprise by their ignorance of AI use. In other words, after experiencing discourse about AI, applicants would question their previous assumptions of a human. This highlights that the assumption of AI in the screening process is an active assumption, relative to the assumption of a human.

As illustrated in the framework, both assumptions (*Assumed human* and *Assumed human and AI*) are labeled under the category of *Prospective generalized assumptions of AI*. "Prospective" is chosen to exclude assumptions that were described retrospectively by applicants, as these did not relate to any choices made by the applicants with regards to AI. "Generalized" refers to that applicants made consistent assumptions across applications of either an *assumed human* or *assumed human and AI*. These two subcategories in turn represent the two overarching assumptions applicants approached the application process with. The former is representative of those applicants who, through the lack of AI transparency and AI-related experiences, consistently assumed a human to be the recipient of their application. The latter represents those applicants who assumed an AI recipient but notably understood it as a complementary tool to human assessment. As touched upon earlier, an assumed human recipient is in the framework conceptualized as a result of a lack of awareness. Rather than assuming a human because they actively believed AI would not be screening their applications, a human recipient was an assumption made due to the absence of active consideration of the recruitment process. This distinguished the two types of assumptions as an active assumption and latent assumption. Conceptualizing the assumption of a solely human recipient as an absence of information reflects that AI is a relatively new tool in recruitment (Black & van Esch, 2020) and is not yet the perceived status quo. In conclusion, redirecting assumptions toward AI requires active exposure to it from experience (*personal background* and *general discourse),* as little transparency is given to change applicants' pre-existing assumptions.

### 5.2.2. Motivation to adjust

Assuming the use of AI is not the only prerequisite for applicants to adjust their application for AI screening. As supported by VIE theory, they also need to be motivated to do so. In other words, applicants need *motivation to adjust.*

#### 5.2.2.1. Expectancy factor

We begin with the component *expectancy,* defined as the belief that one is able to make adjustments successfully and thereby submit an application that AI would screen favorably. Given that an applicant already assumes the use of AI in the screening process, their perceived understanding of how to appeal to it becomes an important consideration for adjusting to such technology.

Our starting point in understanding how applicants understand AI is, similar to the previous section, to compare the observed results with the ideal situation from the perspective of GDPR. Applicants were in no recalled cases given feedback specifying how the processes had informed their rejection or advancement in the process. Notably, applicants who did seek out feedback would receive it from the human perspective that in turn implicitly built knowledge on self-presentation towards a human recipient. This lack of AI-specific feedback, or in other words, *lack of retrospective transparency,* was widespread. Retrospective transparency would increase the AI literacy amongst applicants after the cases that it was indeed used, reducing the significance of pre-existing individual differences in perceived knowledge. In the absence of such literacy-enhancing information, many applicants did not adopt strategies to present themselves favorably to AI despite assuming that it is commonly used.

This phenomenon can be explained by considering *perceived AI literacy* as an influence on expectancy. The motivation to adapt an application for AI depends on the applicant's belief in their ability to do so. Notably, expectancy factors are related to the individual's *belief* in their own ability to achieve a first-level outcome- an adjusted application for a given role (Harris et al., 2017). Therefore, when we discuss AI literacy within this framework, it is not the applicant's objective understanding of AI in screening but rather their perceived AI literacy that is relevant. An ability to self-present towards AI could be developed if retrospective transparency offered applicants specific explanations of their performance in the screening process. In its place, the job applicant's perception of their abilities is more important as no participant, although they may have general knowledge of AI, has received specific insight into how AI screening tools in recruitment actually work.

##### 5.2.2.2. Valence factor

The second factor of motivation to adjust alongside expectancy is *valence*, which we define as the belief that the specific role is preferred among other options such that it will bring personal satisfaction. The valence factor has an overall effect on an applicant's motivation to adjust, including adjustments made with regard to AI but not limited to just AI-considered adjustments. The influences on valence, *job desirability* and *time in search*, therefore help explain both the decision to adjust for a specific role and accordingly adjust for AI screening tools.

Job desirability refers to how attractive the applicant finds a particular role. When looking at how participants viewed the job searching process, some treated it as a numbers game, applying to a large number of positions with low specific role desirability. Others prioritized role fit, applying to a more limited selection of positions with high specific role desirability. There is a distinction to be made between wanting *the* job versus wanting *a* job. Considering job desirability as an influence on valence explains the desire to move further in the recruitment process for *the* job as a motivator for time-consuming adjustments, including adjustments for an AI screener. A desire to move further in the recruitment process for *any* job on the other hand had the opposite effect. Notably, less application-specific adjustments did not always imply that an applicant did not attempt to impress AI at all. When applicants with a quantity over quality approach had confidence in their understanding of AI in recruitment (perceived AI literacy), they would consider AI in how they formed their overall approach, such as using a standardized CV to save time or using components from previous cover letters to quickly adapt new applications.

As job applicants' different perspectives on their job search affected their application adjustments with regard to AI, the question then follows from where such differences could originate. Accordingly, we will next look at the second influence on valence: time in search. Time in search refers to how long an applicant has been searching for a position. Our findings show that applicants' approaches to job searching change over the course of their job searching process. Some participants who started off their search with a highly personalized approach and only applied to roles with a perceived high role fit personalize less and apply to a larger volume of roles over time. The longer they search without success, the more motivated they are to find a job. On the other hand, some participants were aware of the impact of time and actively prioritized applying for higher-value roles after sending out a few less-valued applications to minimize the chances of minor errors on processes they value. Overall, time seems to reduce the likelihood of valence factors for motivation as they experience their attempts at personalization fail to achieve the desired results.

High valence cannot overcome low perceived AI literacy, so even with applicants who express a highly customized strategy without understanding how to modify their application to appeal to an AI-screening tool, the modifications they make largely do not consider AI. Since they saw a given position as highly desirable, they wanted to spend time and effort showing this in their application to move further in the recruitment process. As a result, they often chose to customize their applications by writing cover letters from scratch or personalizing their documents to communicate a company-specific interest. This type of customization can be categorized as one that applicants discussed making with a human recipient in mind, as these modifications were ones that participants generally felt AI would struggle to screen.

#### 5.2.2.3. Instrumentality factor

The final factor of motivation to adjust, *instrumentality*, is the belief that making case-by-case adjustments for AI (i.e., first-level outcome) is critical for advancing through screening to the next stage of the process (i.e., second-level outcome). This section focuses on two influences on instrumentality: applicants' *perceived role fit* and their expectations of *AI to human screening*.

The first influence on instrumentality is the perceived role fit for the specific role. For applicants who believed a role has a high fit with their skill set and background, they believed there to be less of a need to make case-by-case adjustments, for AI or otherwise, since they saw their application as inherently a strong fit for the company. In theoretical terms, the perceived instrumentality of AI adjustments fell with the belief that their application already contains what AI would screen for. This cannot be discussed without also considering applicants' understanding of how AI screening tools work. The common understanding of AI as a keyword search means in regard to perceived role fit, the applicant believed they already had the keywords integrated into their application documents. As a result, there was less of a perceived need to make case-by-case modifications for submitting their application.

The second influence on instrumentality is the applicant's common perception of AI-enabled recruitment as AI to human screening, with AI only the first stage before an eventual human recipient. This understanding explains why applicants who are aware of AI recruitment and have confidence in their ability to make modifications might not make extensive AI-targeted changes, even if they have high valence and expectancy factors. In applicants' minds, making modifications with AI in mind will only help get an application in front of a recruiter, so an application still needs to be created with a human recruiter in mind for advancements in the job process. In theoretical terms, applicants believe that a fully AI-optimized application is limited in achieving a second-level outcome (*Advancement in the recruitment process*) because the second-level outcome is perceived to be reaching a human recipient. Additionally, because of this assumption of an eventual human recipient, there was low perceived instrumentality of adding competencies that applicants perceived to be beyond the scope of what they had done or were capable of doing. This is because they recognized that an eventual human recipient would recognize this as untruthful. In turn, such statements highlight the perceived differences between humans and AI that are necessary for applicants to view optimization for a human and AI as different approaches. Specifically, the reluctance to lie relates to the belief that AI cannot detect information that is not representative of the applicant's history and abilities.

#### 5.2.2.4. Intersecting expectancy, valence, and instrumentality

The above sections on the three motivation factors are together able to address an important question that they individually could not. Although several AI-assuming applicants did not perceive themselves as AI literate and thereby had low expectancy, why did they not simply make an effort to learn more? Applicants expressed motivation to learn more about AI in screening in three scenarios. First, they expressed that they would invest time into learning how to impress AI if a job disclosed its use of such technology. Second, applicants expressed that partaking in the thesis interview itself had increased their motivation to, to a greater extent, adjust to AI by seeking out more information on how AI recruitment tools work. Third, they expressed they would invest time in learning how to modify for AI if the job was one they highly desired. What the former two scenarios illustrate is that when AI is signaled as something mention-worthy or worthy to conduct an entire thesis about, the desire to invest efforts into learning about adapting to it seems to grow. This is an expression of instrumentality. That is, the belief that allocation efforts towards understanding AI has an important effect on the likelihood of advancing in the job process. The third scenario illustrates that when a role is something the applicant views as important, the desire to invest efforts into learning about how to increase their odds of advancing also seems to increase. This is an expression of valence. Therefore, the applicant's perceived AI literacy, their expectancy, showed connection to instrumentality and valence.

### 5.2.3. Application adjustments

The final part of our framework deals with the outcomes, namely the first-level outcome of *application adjustments* preceding the second-level outcome of *advancement through the process*. The second-level outcome of advancement through the process is integral for understanding how applicants' motivations are formed, but whether or not they progress to further stages is outside the scope of this study. The outcome we seek to understand is solely the adjustments applicants make to successfully self-present towards an AI screener in light of the assessments about AI and their motivation to advance that we have discussed in the previous sections that explain that an applicant optimizing their application for AI, and AI only, is rare. When AI transparency fails, applicants may not be actively aware of AI. They also may have beliefs about themselves, the AI, and the job search process that impair their motivation to adjust. The application adjustments aiming to impress an AI screener are instead commonly slight adjustments, if any adjustments at all.

Finally, as the results uncovered, there was a selection of adjustments made with regard to AI, given that the applicant assumed an AI screener and was motivated to make them. These could include the use of keywords, keeping application documents concise, and in certain cases de-emphasizing the applicant's personality. All of these adjustments are consequences of the applicant's understanding of how AI screening tools work. Here, a connection must also be made specifically to applicants' understanding of the screening process as AI to human screening. This concept has already been discussed as an influence on instrumentality, and when we compare this understanding to the actual adjustments made, *de-emphasizing personality* distinguished itself as a trade-off between self-presenting towards a human versus an AI. The use of *keywords* and *concise documents,* in contrast, were adjustments that, while made to appeal to AI, were also commonly understood as beneficial for a human screener. The benefit for a human screener was these adjustments quickly convey their experiences and skills based on the understanding that a recruiter is likely spending limited time reading the document and looking for the same criteria they would ask AI to screen for.

# 6. Discussion

In our analysis, we have addressed the research question: *How do applicants' assessments of AI use in recruitment inform the adjustments they make to their job applications?* In the following discussion, we begin by clarifying how this analysis has answered our research question (6.1) and then how our findings relate to existing research (6.2). The section ends with the analytical limitations of the study (6.3).

## 6.1. Answering the research question

In answering our research question, we began by understanding the beliefs of applicants in order to understand their behavior. The former relates to the first part of the research question, "applicants' assessments of AI use in recruitment." The latter relates to the last part of the research question, "the adjustments they make to their job applications." By understanding applicants' beliefs from a legal and motivational perspective, we were able to answer *why* they did or did not make adjustments for AI in the way that they did. In other words, *how* application adjustments were made was explored through the applicant's perspective. In short, we found that applicants operate in uncertainty, and in the absence of AI transparency, their experiences determine their beliefs that take a paramount role in whether they assume AI use in the screening process. Further, given that AI use is assumed, the applicant's motivation to adjust informs both whether and how they adjust. Applicants' confidence in their AI literacy, desire to advance in the job process, and beliefs about an eventual human recipient all have an important impact on how much an applicant adjusts their application for AI. What our findings state is that there are several prerequisites for AI-related adjustments in job applications founded on the assessments of the applicant.

Accordingly, given that applicants even make any effort to self-present towards an AI, these efforts are not too different from those towards a human.

## 6.2. Elaboration of findings

It is important to note that our framework only provides an overview of our findings as they relate to our empirical data. Our analysis reveals the impact of motivation and AI assumptions on application adjustments. The next section expands on our findings and insights by comparing our findings to existing literature.

### 6.2.1. In absence of AI transparency

Our findings of the dominantly uniformed applicant expand on scholars' previous critique of the effectiveness of GDPR in achieving AI transparency (Ananny & Crawford, 2018; Ben-Shahar & Schneider, 2014; Felzmann et al., 2020). Relative to this legal perspective, our analysis offered a highly contextual, but relevant, expansion of the topic by moving beyond the question of whether legislated AI transparency achieves its goals to instead understand what can happen in its absence. While we make no claims of generalizability, the lack of disclosure our study uncovered brings into question the previous implicit and general assumption that an applicant who is reacting to AI knows that it is being used (Acikgoz et al., 2020; Langer et al., 2019; Langer et al., 2019; Langer et al., 2020; van Esch et al., 2019; Wesche & Sonderegger, 2021).

### 6.2.2. Understanding to adjust

With perceived AI literacy as an important influence on motivation, our analysis has highlighted applicants' understanding how to self-present as an important prerequisite for self-presentation efforts. This echoes the suggestions made by Marcus (2009) on self-presentation in a proposed framework of how motivation and skills affect self-presentation in selection processes. Similarly, and more specifically, our analysis also aligns with findings of Langer et al. (2020) that overall impression management could be limited when applicants are faced with automated interviews that they did not understand the workings of. Notably, Langer et al.'s study had a quantitative research design and data was gathered through an artificial experiment. In other words, subjects' beliefs about future advancement in the recruitment process after the interview were not on the table. By applying VIE theory to data from real life experience, we could account for applicants' thoughts about the entire job application process. Thereby, we were able to uncover more beliefs than just perceived AI literacy that were relevant for applicants' self-presentation efforts, such as the importance of believing that AI would eventually be followed by a human assessment in later stages. Although our study focuses on a different stage of recruitment and selection than Langer et al., this widening of the context is a useful reminder that qualitative research has a particular strength in exploring the novel domain of applicant responses to AI in recruitment.

### 6.2.3. Time in search

In line with Schmidt et al. (2022), we found that the duration of an applicant's job search process impacted the valence for receiving an offer for a particular role. While their study looked at the positive role time plays in an applicant's willingness to fake, we acknowledge that an applicant's time in search had less of a clear-cut one-directional impact on valence in an applicant's motivation to make application adjustments. For some applicants, the duration seemed to decrease their valence for a given role as they started caring more about finding *a* role and less about finding *the* role. On the other hand, other applicants chose to apply for more valued roles later in the process and their time in search was then related more with higher valence as time went on. Notably, Schmidt et al. find that the duration of an applicant's job search process is correlated with a higher valence factor and therefore higher motivation to fake or embellish their self-reported skills and experience. Within the time frame of our study, we did not find this same connection to an applicant's motivation to make AI-specific application adjustments, but we acknowledge that the results from Schmidt et al. suggest that if our participants still have not found a job by some point in the future, their perspective on the value of making modifications could change.

#### 6.2.4. Role fit

In our findings, we note the importance of role fit for the instrumentality factor, finding that applicants who already have a perceived strong fit with the role do not see case-by-case adjustments as critical for their application to pass through AI screening. This can be compared to McFarland and Ryan's (2000) findings on faking in personality tests where an individual's true score impacts their opportunity to fake; someone who already would have high scores has less opportunity to fake compared to someone with lower true scores. We found that applicants with the skills or experiences a company would be screening for would have fewer adjustments they could make to their applications, regardless of their perceptions of whether AI is used, further contextualizing the interviews with applicants who were aware of AI use and assumed it was prevalently used but did not make adjustments themselves.

#### 6.2.5. Interaction between motivation factors

Prior research on the three factors of motivation has shown that they play a significant role in determining motivation both individually as well as in combination with each other (Bott et al., 2010; Ellingson & McFarland, 2011; Shiflett & Cohen, 1982). As our analysis discussed, we found a connection between expectancy and the two remaining factors of instrumentality and valence. The relationship specifically illustrated that the latter two fed into the former. Bott et al. (2010) found a positive relationship between instrumentality and expectancy when comparing them to applicants' conscientiousness. Although we differ in methodology, we arrive at similar findings where we see that there is some relationship between expectancy and instrumentality, however, make no claims to the strength of this relationship. Evaluations of this nature would be better suited for future quantitative studies on the topic. Further, we also saw possibilities for the interaction between expectancy and valence.

### 6.3. Analytical limitations

As mentioned, our analysis was able to address the *why* of applicants' application adjustments which was the core of the research question. In several cases, the analysis was also deepened to address why certain beliefs occurred. For example, why many applicants made no adjustments for an AI screener could be explained by the fact they were not assuming its use in absence of retrospective transparency. Further, why some applicants did not assume its use could be connected to their lack of AI-related experience. However, the analysis did fall short in achieving similar deeper explanations of two main statements. First, the results showed that applicants dominantly made generalized assumptions of AI use in the screening process, but the analysis was unable to account for *why* such assumptions were general. Case-by-case assessments, such as assuming bigger companies use AI screening tools, is a clear example of a heuristic (Gigerenzer & Gaissmaier, 2011). Initially, such "rules of thumb" were thought to be applicable to our data as they by definition are concerned with how people make assumptions with incomplete information (Rynes et al., 1991; Spence, 1973). However, why such heuristics mainly played a part in retrospective reflection and had very limited effect on actual behavior we were unable to account for. Second, why some applicants, despite assuming AI, refrained from AI-related application adjustments could be explained by their lack of confidence in their AI literacy. However, why applicants varied in confidence could again not be addressed. Although it would seem natural that confidence in AI literacy connects to experience with AI, our results combined with the theoretical framework could not bring a deeper understanding of this.

Related to the comparisons of our results with legal concepts of prospective transparency and retrospective transparency, an important limitation must be noted. We recognize that the lack of AI transparency in our results can both be the source of inefficient GDPR or that there was no AI to be transparent about. Although the actual use of AI would make no difference for our analysis of applicants' application adjustments (which is based on their beliefs about reality), the analysis is limited in addressing the actual effectiveness of GDPR. However, we have good reason to suspect that with the increasing use of AI in recruitment, participants have at some point submitted applications to companies using AI in screening. The types of companies the participants applied to varied, with some applying to extra-large organizations like Google, McKinsey, and H&M and most applying to medium to large organizations. A recent survey from the Society of Human Resources Management found that 42% of extra-large organizations and 24-26% of medium to large organizations are using automation or AI for HR activities, the most common of which is recruitment and selection (SHRM, 2022). Among the 24 recipients, there were collectively hundreds of recent application processes referenced. Although it would seem highly unlikely that there were no cases of AI screening, it does not lie within the strength of this study to make such definite claims of the inefficiencies of GDPR.

# 7. Conclusion

The purpose of this study was to explore how applicants think and act in an increasingly AI-assisted recruitment process. At the intersection of applicants' self-presentation, AI in screening, and AI transparency, we found a research gap in *how applicants' assessments of AI use in recruitment inform the adjustments they make to their job applications.* Our analysis used both VIE theory and legal transparency concepts as a context for understanding the applicants' assessments of AI and subsequent application adjustments. The analysis concluded that in the absence of AI transparency, applicants' beliefs took a paramount role in whether they assumed AI use in the screening process. Given that AI use was assumed, the applicant's motivation to adjust informed both whether and how they adjusted. Due to limited AI transparency and motivation to adjust, the final application adjustments made were modest, if existent. The viewpoints our participants shared provide a valuable perspective to the discussion on how applicants respond to AI in recruitment and can serve as the base for further empiric inquiry. To conclude this thesis, this section will address the theoretical contributions (7.1), practical implications (7.2), methodological limitations (7.3), and finally suggestions for future research (7.4).

## 7.1. Theoretical contribution

Our findings have two main contributions for the field of recruitment and impression management. The first relates to addressing our research gap, and the second to our application of the VIE framework to understand this gap. The study has made an initial contribution at the intersection of applicant self-presentation, AI use in screening, and AI transparency. It has highlighted that the latter two areas of research can be relevant contextual considerations in modern-day self-presentation. The unspoken assumption that a self-presenting applicant exclusively has a human recipient in mind can, with our findings, be called into question in terms of how reflective this is of the realistic application scenario. Second, our findings have also raised the question of the realism of assuming that an applicant is informed of who or what is screening them. Fundamentally, both of these considerations, AI use in screening and AI transparency, constitute a contribution as our study found that they can have an influence on the way applicants apply for jobs. To conclude, in the context of an increasingly automated screening process in recruitment, our study has highlighted the value of recognizing AI as a possible undisclosed recipient. The generality of VIE theory (Vroom, 1964) has also shown its promise in understanding relatively uncharted territory and has suggested that motivation is a useful lens through which to understand how applicants' understanding of AI relates to their application strategies.

## 7.2. Practical implications

Our study brings insights useful for both AI developers and recruiters considering the use or active disclosure of AI in their screening process. Although applicants may not be explicitly informed about the use of AI, this does not necessarily imply that they are not adapting their documents to an automated screener. The general assumptions of AI (or lack thereof) have relevance for recruiters as adjustments for AI versus a human may differ and thereby affect the applicant's profile presented to a recruiter. However, applicants mostly limited their AI-related application adjustments to also please the human screener. With that being said, there are two main adjustments that could be of special relevance to recruiters. First, applicants' de-emphasizing of their personalities could impede recruiters' ability to assess desirable personality traits in job applications (Cole et al., 2009). Second, our findings point towards that the increasing presence of AI may have a limited impact on how accurately applicants perceive that they present themselves. Applicants' recognition of the eventual human recipient can mitigate recruiters' potential concerns about candidates gaming the AI system.

## 7.3. Methodological limitations

While our goal for this study was not empirical generalizability, it still needs to be highlighted that there are some limitations that inform the bounds of our research, and highlighting these limitations can serve as inspiration for future research.

### 7.3.1. Implications of narrow sample

Although our research method was not chosen with the objective of achieving high generalizability, our choice of sample implies two main boundary conditions. First, our sample exclusively focused on soon-to-be graduates. These all were or had found themselves in a position of potential unemployment should they not succeed in at least one job process. We theorize that this may have changed the nature of their motivation relative to groups with the motive of switching their job. As VIE theory is built on the notion that efforts are dependent on motivation (Vroom, 1964), we recognize that the sample could display overall more motivation, as the perceived payoff of succeeding in the application process may increase with higher stakes, or lower motivation, as the individual application divides their total available energy on more applications, to make adjustments that appeal to the recipient, regardless of if that is a human or AI.

Second, our sample consisted of students that were all able to include a prestigious university on their job applications. As expressed in our results section, several participants noted that they perceived themselves as a good fit for the role already, thereby needing fewer modifications or adjustments for a role. This could potentially make the sample less prone to further invest efforts into adjusting applications to appeal to AI (and also a human) considering the impact of instrumentality on motivation (Ellingson & McFarland, 2011).

### 7.3.2. The embellishing participant

The participants' incentives to provide data truthfully reflecting their actions and thoughts can also be brought into question. As self-presentation in job applications may include actions of purposefully presenting information that the applicants themselves do not consider truthful, such data may have a higher sensitivity for the participant. Therefore, we recognize the risk that participants may have edited their responses to frame themselves in what they perceive to be a better light. This act in itself can be considered a form of impression management (Schlenker, 1980). We therefore also recognize the risk that applicants who presented information that they thought to be inaccurate in their application could be exactly the ones who avoid disclosing this during an interview with the same objective of making a good impression. Although there may be several contextual factors that affect the likelihood that such behavior transcends situations, there is research on impression management that ties the act of presenting favorable, but less accurate, versions of themselves to personality (Arkin & Lakin, 2001; Boyce, 2005; Hogue et al., 2013). Such research would argue that this behavior has an element of consistency across scenarios. Concluding, the effect of this type of participant behavior may have reduced the paper's ability to understand the type of self-presentation that applicants perceive as misleading and how this could relate to AI in the screening process.

### 7.3.3. Researcher bias

Prior knowledge, experience, and attitudes of a researcher can greatly influence their perception and interpretation of what they find (Bell et al., 2019). Accordingly, as both researchers are also students at SSE and have our own experiences with the job application process, our point of view was carefully considered and informed a reflexive approach (Willing, 2013). This reflexive approach not only guided how we carried out our research and analysis, but also the decision to study the research gap where this study sits. There is a reason why we found this question interesting, and our experiences informed our decision to look further into this area. During our research, our findings challenged some of our assumptions and we made an effort to exercise reflexivity in staying aware of our biases and letting our participants' experiences speak for themselves. Accordingly, not only did our perspective shape our research, but our research also shaped our perspectives moving forward. By using semi-structured interviews, remaining open to unexpected responses, having both authors present at interviews, and continually discussing our interpretations of content, we worked to minimize the influence of bias on our findings. Even with this, we acknowledge that it is impossible to completely eliminate researcher bias and make no claims as such.

## 7.4. Future research

As this study aimed to take a neutral approach to the objective morality or accuracy of applicant actions, a conceptualization of self-presentation with the perspective of motivation through VIE was used to explain their behavior. As discussed, there are other perspectives that could also be used to further explain and contextualize applicant behavior in response to AI recruitment tools in future research. It is valuable to conduct further research on this area to incorporate the perspectives of applicants' personalities, capabilities, and perceptions of situational norms to evaluate how those relate to our findings regarding the role of motivation.

While this study uncovered many interesting findings among the relatively homogenous sample, it also uncovered potential areas of future interest relating to the role that perceived role fit plays in an applicant's decision to adjust. Future research could focus on comparing two or more populations with more or less role fit or other sampling measures to try and uncover how much this truly factors into motivation.

As this is a master's thesis, our study did have a time limitation. Regardless of this, our results did find that time in search played a role in determining applicants' responses to AI in recruitment. Therefore we see potential in future research that takes on a longitudinal design to further probe at how these factors might change over time to further uncover nuance in this factor.

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# 9. Appendix

## Appendix 1: Participant sample

| Participant | Gender | Background | Age | Date | Length | Type |
|---|---|---|---|---|---|---|
| 1 | Female | Swedish | 24 | 2023-03-01 | 28:24 | In person |
| 2 | Female | Swedish | 26 | 2023-03-01 | 41:37 | In person |
| 3 | Female | Swedish | 24 | 2023-03-02 | 45:03 | Microsoft Teams |
| 4 | Female | Non-Swedish | 24 | 2023-03-02 | 31:01 | Microsoft Teams |
| 5 | Male | Non-Swedish | 23 | 2023-03-02 | 32:48 | In person |
| 6 | Male | Non-Swedish | 25 | 2023-03-02 | 41:32 | In person |
| 7 | Female | Swedish | 31 | 2023-03-03 | 48:48 | Microsoft Teams |
| 8 | Male | Swedish | 27 | 2023-03-07 | 61:32 | In person |
| 9 | Female | Swedish | 28 | 2023-03-07 | 48:09 | In person |
| 10 | Male | Swedish | 23 | 2023-03-08 | 37:17 | Microsoft Teams |
| 11 | Male | Non-Swedish | 30 | 2023-03-08 | 44:46 | Microsoft Teams |
| 12 | Male | Non-Swedish | 29 | 2023-03-10 | 35:01 | Microsoft Teams |
| 13 | Female | Non-Swedish | 26 | 2023-03-10 | 42:30 | Microsoft Teams |
| 14 | Male | Non-Swedish | 23 | 2023-03-14 | 43:49 | Microsoft Teams |
| 15 | Female | Swedish | 25 | 2023-03-14 | 26:33 | In person |
| 16 | Female | Swedish | 25 | 2023-03-16 | 49:22 | Microsoft Teams |
| 17 | Male | Non-Swedish | 25 | 2023-03-17 | 40:54 | Microsoft Teams |
| 18 | Male | Swedish | 29 | 2023-03-17 | 28:09 | Microsoft Teams |
| 19 | Male | Swedish | 25 | 2023-03-19 | 36:54 | Microsoft Teams |
| 20 | Female | Swedish | 28 | 2023-03-24 | 36:26 | Microsoft Teams |
| 21 | Female | Non-Swedish | 26 | 2023-03-25 | 43:04 | Microsoft Teams |
| 22 | Male | Swedish | 25 | 2023-03-25 | 40:12 | Microsoft Teams |
| 23 | Male | Swedish | 26 | 2023-03-27 | 47:01 | Microsoft Teams |
| 24 | Female | Swedish | 26 | 2023-03-27 | 48:20 | Microsoft Teams |

## Appendix 2: Interview guide

| Topic | Question |
|---|---|
| *Background information* | ➢ Are you currently applying for jobs or have you already gotten a post-graduation job?<br>➢ Tell a bit about what type of jobs are (or were) you applying for?<br>➢ How long have you been looking for a job for after graduation?<br>➢ How would you describe your overall approach to finding a job? How did you develop this? |
| *General applicant strategies in job applications* | ➢ Walk me through the steps of submitting your last job application from the point at which you found out about the opening until you submitted your documents for the job opening.<br>○ What documents did you submit?<br>○ Walk us through how you edited your (CV/cover letter/other document). Why?<br>➢ How much time did you spend on this application?<br>➢ What did you think [company] looked for in that application?<br>➢ Was the CV/resume/documents you sent the company an accurate representation of you? Why, why not? |
| *Applicant perceptions of screening methods and AI use in recruitment* | ➢ After you sent in the application, how do you think they evaluated if you met the criteria for what they looked for in the application?<br>○ How do you think they did to tell suitable applicants apart from less suitable?<br>○ Did this inform any decisions you made in your application?<br>➢ How do you think AI tools work in recruitment?<br>➢ Did you consider if it's AI or a recruiter that would evaluate your application?<br>○ Do you think that an AI would differ from a human in how it evaluates your application? In what way?<br>○ Do you think that AI would affect your odds of advancing through the initial screening process?<br>➢ Have you ever applied for a job where you thought that AI/a person was screening your CV instead? |
| *Comparative and concluding questions* | ➢ How did this application/these applications compare to other job applications you've had?<br>○ Have you adjusted your application strategy accordingly?<br>➢ Do you think modifications you've made have changed the accuracy of your representation of self in your CV/cover letter?<br>➢ How would you approach new job applications now that we've talked about this? Are there things you would do differently?<br>➢ Would you act differently if a job listing explicitly stated it used AI to process your application?<br>➢ Is there anything more you'd like to add that we haven't asked you? |

## Appendix 3: Description of codes

| **Applicant's assumptions of AI** | | |
|---|---|---|
| **Theme** | **Code** | **Description** |
| Lack of AI disclosure | No AI disclosure, believing in finding out | The applicant has not seen AI usage disclosed but thinks they could find out in the future or if they wanted to |
| | No AI disclosure, believing no way to find out | The applicant has not seen AI usage disclosed and thinks this is on purpose and not possible to find |
| | Seen AI disclosure | The applicant has experienced explicit AI disclosure in a previous recruitment process |
| Signals before submission could influence awareness of AI | Way of applying | Text box questions or application tools suggest AI to the applicant |
| | Size of the company | The size of the company influences how applicants think they will be screened |
| | Type of company | The type of company influences how applicants think they will be screened |
| Signals after submission retroactively influence assumptions of AI | Number of applications | Assuming a large amount of applicants is more likely to require AI |
| | Number of recruiters for the role | Assuming few recruiters for a large number of applicants is more likely to suggest AI |
| | Response time | Assuming a quick response time is more likely to suggest AI |
| | Invitation to tests | Applicants connect the use of screening tests to AI |
| Generalized assumptions of AI | Non-specific assumptions made of AI use | The applicant makes assumptions about AI as an overall proportion of companies using it, not based on signals |
| | Implicit assumption of human recipient | The applicant refers to aspects of their strategy that are implicitly tied to a human reader |
| | Explicit assumption of human recipient | The applicant explicitly refers to a human reading their application |
| | Not considered screening recipient | The applicant expresses they have not considered who screens their application before |
| Personal background influences awareness of AI | Tech interested | The applicant expresses an interest in tech and AI |
| | Tech industry background | The applicant has prior experience through working or studying in tech |
| | Prior work experience | The applicant has increased awareness of recruitment processes through previous work experience |
| General discourse influences awareness of AI | AI common in conversation | The applicant mentions hearing about AI in everyday conversation or news |
| | ChatGPT | The applicant associates AI with ChatGPT and expresses familiarity with the tool |
| | Thesis interview as discourse | The applicant expresses increased awareness after discussion in thesis interview about AI |

| **Applicants' confidence in understanding AI** | | |
|---|---|---|
| **Theme** | **Code** | **Description** |
| Limited feedback upon request | Lack of feedback | The applicant does not generally receive feedback on rejected applications |
| | Seeking out rejection feedback | The applicant seeks out feedback routinely in recruitment processes after rejection |
| | No interest in receiving feedback on rejections | The applicant does not ask for feedback from applications or remember receiving feedback |
| | Increased desire for feedback from AI | The applicant would request feedback if they knew they were filtered out by AI |
| | Applicant got feedback from others before applying | The applicant gets feedback on their applications from peers or mentors before submitting |
| Uncertain requirements | Difficulties determining what the company wanted | The applicant is unsure what qualities the company is assessing applicants on |
| | Low understanding of the screening process | The applicant has low certainty in who they think is scanning their application |
| | Unsure of how AI and a human would screen differently | The applicant has low certainty in how they think AI would screen compared to a person |
| | Unsure of how AI screening functions | The applicant has low certainty in how they think AI would screen application documents |
| | Uncertainty of AI function results in reduced adaptation | The applicant expresses their low certainty in how they think AI works impacts how likely they are to adjust their application accordingly |
| | Honesty because unsure of what they are screened for | Not considering anything other than being honest because they do not know what the company would be looking for |
| Explicitly informing applicants motivates increased learning | Increased desire to research AI before future applications | The applicant acknowledges increased awareness from discussing AI in the interview that could impact future applications |
| | Informed of AI motivating learning | The applicant expresses that if informed of AI use in a recruitment process, would try to learn about AI tools to adapt their application |
| | Informed AI use would impact applicant honesty | The applicant expresses that if informed of AI use in a recruitment process, would consider alterations that would reduce the honesty of their application to appeal to AI |
| Understanding AI relative to a human | AI limited in holistic assessment | Assuming AI cannot holistically assess a document and can only evaluate for specific criteria |
| | Human evaluation appropriate for soft skills | Believing the personal touch of a human would be better suited to evaluate personality fit |
| | Human supervising AI | Believing that a person sets the parameters and determines how the AI will screen |
| | AI evaluates more consistently than humans | Relative to AI, humans can make more mistakes and are influenced by external factors |
| | AI screening dependent on how it's set up | Believing that screening will depend on the information given to the algorithm |
| | Assuming AI equals keyword search | Directly associating AI screening with keywords |
| | AI focuses on skills and experience | Understanding AI screening as focused on hard skills and quantifiable experience |

| | | |
|---|---|---|
| | Keywords important for humans | Understanding human screening as based on keywords also |

| **Applicants' desire for a role** | | |
|---|---|---|
| **Theme** | **Code** | **Description** |
| Balancing act between quality and quantity | Quality over quantity | The applicant prioritizes spending more time on fewer applications with higher interest alignment |
| | Quantity over quality | The applicant prioritizes sending out as many applications as possible with minimized time investment |
| Time in search | Strategy influenced by time of application | The applicant's strategy changes from when they started to look for jobs as the date for needing a job gets closer |
| | Feeling pressure to submit application quickly | The applicant prioritizes speed in applying and does not want to miss out on a job that could be quickly filled |

| **Applicants' perceived impact from modifications** | | |
|---|---|---|
| **Theme** | **Code** | **Description** |
| Understanding AI as a human decision aid | AI then human screening | The assumption that an AI screens first and then a human |
| | Both human and AI adapted | Applicant recognizes that their CV need to appeal to both humans and AI as they will both scan it |
| | Honesty because of eventual human recipient | The applicant mentions honesty as important in applications for future interview stages |
| | Honesty because of future job match | Not wanting to be dishonest to get a job you're not capable of doing |
| Importance of role fit | Modifying more for attractive roles | Explicitly referring to how interesting the role is when discussing how many modifications they would make |
| | Higher role fit means lower adjustment of documents | Finding it easier to apply if they are already a good fit for the company |
| | Honesty because of good role fit | The applicant does not feel the need to be anything but honest since their skills align well with the role |
| | Honesty because skills viewed as preferred not required | Believing there is no need to embellish or lie in an application because it will not affect their likelihood of moving forward if missing a skill |

| **Applicants' application adjustments** | | |
|---|---|---|
| **Theme** | **Code** | **Description** |
| Applicants consider how to make quick impressions for human recruiters | Visual adaptations | The applicant mentions their documents being visually designed, such as including a photo, using color, or font choices |
| | Emphasizing order in cover letter | The applicant gives thought to the order of paragraphs in their cover letter |

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|---|---|---|
| | Ease of reading | The applicant focuses on readability and flow because of an assumed human recipient |
| | Focus on personal factors | The applicant mentions a human recipient as better for motivating personal interest in the company |
| Applicants consider how to check boxes for AI screening | Keywords | The applicant uses keywords specifically with AI screening tools in mind |
| | Focus on simplicity | Applicant thinks that AI would focus on simplicity and reduce their efforts accordingly |
| | Less personalization | The applicant perceives AI as less capable of screening for soft skills or motivation, so AI tools encourage less personal documents |
| | Lower effort | Knowledge or assumption of AI reduces effort in the application |
| | Using AI tools | The applicant mentions using AI tools to put together and test their application before submitting to meet AI requirements |
| Adjustments are considered as part of an overall approach | Hard skills on CV | The applicant focuses on hard skills like education, experience, or competencies on their CV |
| | Hard skills on cover letter | Focusing on hard skills such as education, experience, or competencies on their cover letter |
| | Soft skills on cover letter | Focusing on soft skills such as personality or interpersonal skills on their cover letter |
| | Keywords in CV | Including keywords for a job in their CV |
| | Keywords in cover letter | Including keywords for a job in their cover letter |
| | Passion in cover letter | Conveying passion for the industry or role in the cover letter |
| | No adjustment of CV | Making no change to the CV for a specific job listing |
| | Minimal adjustment of CV | Making very little change to the CV for a specific job listing |
| | Moderate adjustment of CV | Making multiple changes to the CV for a specific job listing, but not making the CV from scratch |
| | Standardizing cover letters | Having one or several cover letters that are minorly adjusted for individual job applications |
| | Highly customizing cover letters | Writing the majority of the cover letter from scratch or emphasizing customizing the cover letter for each company or role |
| | Improving applications over time | The applicant describes their application documents as gradually developing and early applications help improve later applications |

# Appendix 4: Analysis of empirical results

X means the code occurred during the respective interview.

| **Applicant's assumptions of AI** | | **Interviewee** | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Theme** | **Code** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| | No AI disclosure, believing in finding out | | | X | X | X | X | X | | | | X | X | | X | X | | | X | X | X | | X | X | X |
| | No AI disclosure, believing no way to find out | X | X | | | | | | | | X | | | | | | | X | | | | | | | |
| Lack of AI disclosure | Seen AI disclosure | | | | | | | | X | X | | | | | | | X | | | | | | | | |
| | Way of applying | | | | | X | | | | | | | | | | | | | | | | X | | X | |
| | Size of the company | X | X | | | X | | X | X | | X | | | X | X | | X | X | X | | | X | | X | X |
| Signals before submission could influence awareness of AI | Type of company | X | | | X | X | | X | | | | | | X | X | | X | | | | | | | X | |
| | Number of applications | | X | | | | X | X | X | X | | | | | X | | X | | X | | X | X | X | X | |
| | Number of recruiters for the role | X | | | | X | | | X | | X | | | X | | X | | | | | | | | | |
| | Response time | | X | X | X | X | X | X | | X | | | X | X | | X | | X | X | X | | | | | |
| Signals after submission retroactively influence assumptions of AI | Invitation to tests | | | X | | | | | X | X | | X | | | | | | | | | | | | | |
| | Non-specific assumptions made of AI use | | | | X | | | | X | | X | | X | | X | X | X | X | X | | | X | | | X |
| | Implicit assumption of human recipient | X | | X | | X | X | X | | | X | | X | X | | | X | | | X | X | | | | |
| | Explicit assumption of human recipient | | X | X | | X | X | | X | X | | X | X | | | | | | | X | X | | X | X | |
| Generalized assumptions of AI | Not considered screening recipient | X | X | | | X | X | X | X | | | | | X | | X | | | | X | X | | X | | |
| | Tech interested | | | | | | | | | | | | | | X | | | | X | | | | | | X |
| | Tech industry background | | | | X | | | | | | | | | | | | | | | | | X | | | |
| Personal background influences awareness of AI | Prior work experience | | | X | | X | | | | | X | | | | | X | | | | X | | X | | | |
| | AI common in conversation | | X | X | X | | | | | X | | | | | | X | | | | X | | X | X | | |
| | ChatGPT | | | X | | X | X | | X | | | | | | | | | | | | | | | | X |
| General discourse influences awareness of AI | Thesis interview as discourse | | X | | | | | X | | X | X | X | | X | | | | | | | X | | | X | X |
| **Applicants' confidence in understanding AI** | | **Interviewee** | | | | | | | | | | | | | | | | | | | | | | | |
| **Theme** | **Code** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| | Lack of feedback | | X | | | | | | | X | | X | | X | | | | X | | X | | | X | | X |
| | Seeking out rejection feedback | | | | | | | | | X | | | | | | | | | | | | | | | |
| | No interest in receiving feedback on rejections | | | | | | | | | | | | | | | X | | X | | | | | | | |
| | Increased desire for feedback from AI | | | | | | | | | X | | | | X | | | X | | | | | | | | |
| Limited feedback upon request | Applicant got feedback from others before applying | | X | X | | | | | | X | | | | | | X | X | X | X | | X | | X | X | X |
| | Difficulties determining what the company wanted | X | | | X | X | X | | | | | | | | | | | | | | | | | X | |
| | Low understanding of the screening process | | X | X | | | | | | X | | | | | | | | | | | X | | X | X | |
| Uncertain requirements | Unsure of how AI and a human would screen differently | X | X | | | | | X | | | | | | | | X | | | | | | | | X | |

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| | Unsure of how AI screening functions | X | X | | | | X | | | X | | | | X | X | X | X | X | | X | | | X | X | |
| | Uncertainty of AI function results in reduced adaptation | | | | | | | | | X | | | | | | | X | X | | X | | | | | |
| | Honesty because unsure of what they are screened for | X | X | | | | | | | | X | X | | | | | | | | | | | | | |
| | Increased desire to research AI before future applications | | X | | | | | | | X | | | | X | | | | | | | | | | X | X |
| | Informed of AI motivating learning | | | | | | | | | | | | | X | | | | X | | | | | | X | X |
| Explicitly informing applicants motivates increased learning | Informed AI use would impact applicant honesty | X | | | | X | | | X | | | | | | | | X | | | | X | | | | |
| | AI limited in holistic assessment | | X | X | X | | X | | | | | | X | | | X | | X | X | X | | X | | | X |
| | Human evaluation appropriate for soft skills | | X | X | | | | | X | | | | X | | | | X | | | | | | | X | X |
| | Human supervising AI | | | | | | | | | X | | X | X | X | | | | X | | | | X | | | |
| | AI less biased than humans | | | | | X | | X | X | X | | | | X | | X | X | | | X | X | X | | | |
| | AI evaluates more consistently than humans | | | | | | | | | | | | X | | | | | | | | | | | | |
| | Understanding AI as potentially biased | | | | | | | X | X | | X | X | | | | X | | | | | | X | | X | |
| | AI screening dependent on how it's set up | X | | | | | | | X | X | X | X | | X | | X | | | | | | | | | X |
| | Assuming AI equals keyword search | X | | | | | | X | X | | | | X | | X | | | X | X | | | X | X | | X |
| | AI focuses on skills and experience | | X | | | | | | X | | X | | | | | | | | | | | | | X | |
| Understanding AI relative to a human | Keywords important for humans | | | X | | | | | X | | X | | | | | | | | | | | | | | |
| **Applicants' desire for a role** | | **Interviewee** | | | | | | | | | | | | | | | | | | | | | | | |
| **Theme** | **Code** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| | Quality over quantity | | X | | | | | X | X | | | | | | | | | | | | X | | | | X |
| Balancing act between quality and quantity | Quantity over quality | | | X | | X | | | X | | X | | | | | | | X | | | | | | | |
| | Strategy influenced by time of application | X | X | | | X | X | X | X | | | X | | | | | X | | | | | X | | | |
| Time in search | Feeling pressure to submit application quickly | | | | | | | | | | X | | | | | | | X | | | | | | | |
| **Applicants' perceived impact from modifications** | | **Interviewee** | | | | | | | | | | | | | | | | | | | | | | | |
| **Theme** | **Code** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| | AI then human screening | | X | | X | | X | | X | X | X | X | X | | X | | X | X | X | | | X | X | | |
| | Both human and AI adapted | | | | X | | | | | | | | X | | X | | | | | | | X | | | |
| | Honesty because of eventual human recipient | | | | | X | | | X | | | | | | X | | | | X | | | | X | X | |
| Understanding AI as a human decision aid | Honesty because of future job match | | X | | X | | | X | | | X | | | X | | | | | | | | | | | |
| | Modifying more for attractive roles | | | X | | | | | | | | | | X | X | | | | | | X | | X | X | X |
| | Higher role fit means lower adjustment of documents | | | | X | | | | | | | | | | | | | | | | X | | X | | |
| | Honesty because of good role fit | | | | X | | | | | | | | | | X | | | | | | | | X | | |
| Importance of role fit | Honesty because skills viewed as preferred not required | X | | | X | | | | | | | | | | X | | X | | | | | | | | |
| **Applicants' application adjustments** | | **Interviewee** | | | | | | | | | | | | | | | | | | | | | | | |
| **Theme** | **Code** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
| | Visual adaptations | | | | | X | X | | X | | X | X | X | X | X | | X | X | X | X | X | | | | X |

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| Applicants consider how to make quick impressions for human recruiters | Emphasizing order in cover letter | | | | | | X | X | | X | X | X | | | X | | | X | | X | | | | | |
| | Ease of reading | | | X | | X | X | | | | X | | | X | X | | | | | X | X | | | X | |
| | Focus on personal factors | | | | | | | | | | | | | | | | X | X | | | | | | X | |
| Applicants consider how to check boxes for AI screening | Keywords | | | | X | | | | | | X | | X | X | | | X | | X | | | X | | | X |
| | Focus on simplicity | | | | | | | X | | | | X | | X | | X | | | | | | | | | |
| | Less personalization | | X | | | | | | | | X | | | X | | | X | | X | | | | | X | |
| | Lower effort | | | | | | | | X | | X | X | | | | | | | | | | | | | |
| | Using AI tools | X | | | | | X | | X | | X | | X | | X | | | | X | | | | | | |
| Adjustments are considered as part of an overall approach | Hard skills on CV | X | | X | | X | | X | X | X | | | X | | | X | X | | X | | X | X | | | |
| | Hard skills on cover letter | | | | | | | | | | | | | | | | X | | | | | | X | | |
| | Soft skills on cover letter | | | X | | | | | X | | | X | | X | X | | | X | | | | | | | |
| | Keywords in CV | | | | | | | X | X | | | | X | | X | | X | | | | | | X | | |
| | Keywords in cover letter | | | | X | X | | | | X | | | X | | | | X | | | | | | | | |
| | Passion in cover letter | | | X | | X | | X | | X | | | X | | X | X | | X | | | | | | | X |
| | No adjustment of CV | X | | | | X | | X | | | | | | | | | | | | | | | | X | |
| | Minimal adjustment of CV | | | | X | | X | | | | X | | X | X | | X | | | | | X | X | X | | X |
| | Moderate adjustment of CV | | | | | | | | | X | | | | | X | | X | | X | X | | | | | |
| | Standardizing cover letters | | | X | X | | | | X | X | X | | X | X | | X | X | X | | X | X | X | X | X | X |
| | Highly customizing cover letters | X | X | X | X | X | | X | | X | | | | X | X | X | | | | | | | X | | X |
| | Improving applications over time | | | | | | X | | | X | | | | | X | | | | | | | | | | |