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“The perception of fairness in AI-enabled algorithm-driven personnel preselection”

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Abstract

Filling vacancies becomes increasingly challenging for some companies. Personnel preselection can either be done by human recruiters or by AI-enabled algorithms. Deploying such algorithms can save a lot of resources, especially time and costs, and might increase employers' attractiveness as well. Moreover, many tools to deploy AI-enabled algorithms already exist. So far, they are rarely used in Austria. Still, in the first place, applicants must accept the selection process to be successful. Therefore, selection systems must be perceived as fair.

The concept of fairness is challenging to grasp. Many different models are trying to measure fairness perception. This research uses the model of applicants' reactions to employment selection systems (Gilliland, 1993). Along with ten procedural justice rules, the overall fairness of a selection process can be directly derived. This thesis tries to answer the research question: *How is perceived fairness changed when implementing AI-enabled algorithms in personnel preselection?*

The method used in this research is a quantitative online survey. The sample comprises 101 students and young professionals aged 18 to 35. They were asked about two scenarios; one involves AI in personnel preselection, and the second one involves a human recruiter. Subsequently, the direct comparison of the two modes of decision-making was also surveyed. The respondents' answers given in the survey are used to verify the hypotheses. Along with these findings, the posed research question is addressed.

The given research question cannot be answered clearly. Therefore, neither AI nor human recruiters are perceived as fairer than the other one. Still, the results show AI is perceived as fairer regarding the mode of procedure. At the same time, human recruiters are preferred regarding human aspects, such as interpersonal exchange. Moreover, there are some aspects for which the decision-making mode does not impact fairness perception, such as 'selection information'. This research concludes that applying AI and human recruiters might be the right mix to achieve the greatest fairness perception by applicants.

Zusammenfassung

Die Besetzung freier Stellen wird für einige Unternehmen zunehmend schwieriger. Die Vorauswahl von Personal kann entweder durch menschliche Personalvermittler:innen oder durch KI-gestützte Algorithmen erfolgen. Durch den Einsatz solcher Algorithmen können viele Ressourcen, insbesondere Zeit und Kosten, eingespart werden. Außerdem kann dadurch die Attraktivität eines Unternehmens gesteigert werden. Darüber hinaus gibt es bereits viele Programme, die KI-gestützt sind. Bislang werden sie in Österreich allerdings nur selten eingesetzt. Damit ein Auswahlverfahren auch erfolgreich ist, müssen es die Bewerber:innen allerdings zunächst akzeptieren. Dafür müssen sie ein Auswahlsystem fair empfinden.

Das Konzept von Fairness ist jedoch schwierig zu erfassen. Viele verschiedene Modelle versuchen, die Wahrnehmung von Fairness zu messen: In dieser Arbeit wird das Modell der Reaktionen von Bewerber:innen auf Personalauswahlsysteme verwendet (Gilliland, 1993). Zusammen mit zehn Regeln der Verfahrensgerechtigkeit kann die gesamte Fairness eines Auswahlverfahrens direkt abgeleitet werden. In dieser Arbeit wird versucht, die folgende Forschungsfrage zu beantworten: *Wie verändert sich die wahrgenommene Fairness beim Einsatz von KI-gestützten Algorithmen in der Personalvorauswahl?*

Die angewandte Forschungsmethode ist eine quantitative Online-Befragung. Die Stichprobe umfasst 101 Student:innen und junge Berufstätige im Alter von 18 bis 35 Jahren. Sie wurden zu zwei Szenarien befragt: In einem Fall geht es um eine KI in der Personalvorauswahl, im zweiten um eine:n menschliche:n Personalvermittler:in. Anschließend wurde auch der direkte Vergleich der beiden erfragt. Die Antworten der Befragten werden zur Überprüfung der Hypothesen herangezogen. Damit wird die Forschungsfrage behandelt.

Die vorliegende Arbeit zeigt, dass die gestellte Forschungsfrage nicht eindeutig beantwortet werden kann. Weder KI noch menschliche Personalvermittler:innen werden als fairer wahrgenommen. Dennoch zeigen die Ergebnisse, dass KI in Bezug auf die Art des Verfahrens als fairer wahrgenommen wird. Gleichzeitig werden Personalvermittler:innen hinsichtlich menschlicher Aspekte, wie zwischenmenschlichem Austausch, bevorzugt. Darüber hinaus gibt es einige Aspekte, bei denen der Entscheidungsmodus keinen Einfluss auf die Wahrnehmung der Fairness hat, beispielsweise ‚Information zum Auswahlprozess‘. Eventuell könnte der gemeinsame Einsatz von KI und menschlichen Personalvermittler:innen ein Weg sein, um die größte Wahrnehmung von Fairness bei Bewerber:innen zu erreichen.

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1. Introduction

1.1 Problem definition

For some companies, finding the right people for certain positions is and will become more difficult (Elias-Linde, 2013). Elias-Linde (2013) mentions vacancies regarding IT professionals and Engineers, for example. She speaks about well-known strategies for personnel shortage, such as personnel retention and employer attractiveness, next to solutions starting with employee reproduction (Elias-Linde, 2013).

Proper recruitment pays into employer attractiveness. This appears as a crucial interface whether a company finds the right applicants to proceed. Especially personnel preselection must be mentioned here, as it is often the first touchpoint of potential future employees after a company's personnel marketing activities (Wickel-Kirsch et al., 2008). Preselection takes place right after having received incoming applications and before entering the final selection procedure (Wickel-Kirsch et al., 2008). Therefore, personnel preselection is crucial for the later recruiting success and the final decision of whom to hire.

These days, preselection can either be done by human recruiters or by algorithms. In personnel preselection, this is about the mode of decision-making primarily. Furthermore, it is about who or what applicants are facing during the preselection process, for instance, during a video interview. Algorithms used in personnel preselection are often AI-enabled, which lets them learn and draw their own conclusions (Jäger & Teetz, 2021).

Although there is already a variety of AI-supporting personnel selections developed, it is only used by a minority of companies (Weitzel et al., 2020). Logically, selection systems only work out when they are accepted by applicants. Otherwise, they do not want to be hired or will not apply anymore at these certain companies (Lederer et al., 2021). To be accepted, a selection procedure needs to be perceived as fair. Of course, this also applies significantly to the deployment of AI.

Grasping fairness is not an easy task. There are many models trying to measure the overall fairness of selection typically done by human recruiters or not explicitly distinguishing between decision-makers. This thesis uses the model of applicants' reactions to employment selection systems developed by Gilliland (1993) that considers several factors of fairness in a selection process.

Perceived fairness must prevail for a successful personnel preselection process. Therefore, it is important to know how fairness perception changes regarding the deployed mode of decision-making. This master thesis addresses fairness perception in personnel preselection carried out by a human recruiter or by AI.

1.2 Objectives and research question

As already mentioned in *section 1.1 Problem definition*, the objective of this thesis is to find out whether the perceived fairness of applicants is higher when preselection is done by human recruiters or if an algorithm is deployed.

In further detail, this master thesis' main objective is to answer the following research question along 13 hypotheses, three main hypotheses, and ten subcategorized ones, given in *section 4. State of research:*

How is perceived fairness changed when implementing AI-enabled algorithms in personnel preselection?

Answering this question is of utter importance as perceived fairness during a selection process can already have a great influence on various factors concerning not only applicants but also organizations (Gilliland, 1993). Among these are increases in motivation, self-esteem, self-efficacy, endorsement of organizational outputs, job acceptance decisions, later job satisfaction, and job performance, etc. (Ryan & Ployhart, 2000). Moreover, the fairness perception of applicants not only pays off on the reputation of the company but ultimately also on the future applicant pool in the case of recommendation or non-recommendation (Hausknecht et al., 2004). The importance of applicants' fairness perception is discussed in further depth within chapters 3 and 4.

Moreover, increasing perceived fairness will lead to more overall fairness in selection procedures and equality. All this adds up to the overall goals of society (Hausknecht et al., 2004).

1.3 Research method

Here, the research method is only briefly outlined, whereas, in section 5, Research method gives an in-depth description.

In order to fulfill this thesis' objectives, a quantitative online survey is conducted. This survey assesses different perceptions of fairness regarding aspects posed along the set hypotheses. After completion of the questionnaire on Sosci Survey, it is available online on the same platform for participation for about one month. It is distributed via a link on social media platforms. The final sample is aimed to consist of 100 to 150 participants aged between 18 and 35. This way, the sample is most likely to cover students and young professionals who might have applied for a job recently or are not in their jobs for a long time. The next step is to filter the data in the first place and then analyze them. In the end, the results are compared and contextualized. Then the hypotheses are tested. Ultimately, the research question will be answered. The research method

1.4 Structure of the thesis

Mainly this thesis can be divided into two parts, a theoretical and an empirical one. First, the theoretical part deals with a short section of introduction to give a short outline of the forthcoming master thesis, consisting of the problem definition, objectives and the research question, the research method, and the structure of the thesis.

Furthermore, sections 2 and 3 are dedicated to the two main theoretical issues. The first one is digitization and, therefore, transformation in human resources (HR), and the second is fairness in the preselection. Personnel preselection starts out with necessary definitions. Afterward, algorithms in preselection form the next subchapter. Finally, debates by analogy offer a short digression to cases of other research fields that deal with the same main question concerning the perceived fairness of artificial intelligence (AI). The section on fairness in preselection also starts out with some definitions and continues with Gilliland's model of applicants' reactions to employment selection systems. Related approaches and models complete this section. An in-depth analysis of previous studies conducted is carried out in section 4, State of research. Along this, research gaps are identified, and hypotheses are phrased during the next subsections. The 13 hypotheses, three main hypotheses, and ten sub-categorized ones created lead to the second part of this master thesis.

Section 5, which deals with the research method, rings in the empirical part. The method of a quantitative online survey, the chosen sample, and the operationalization and procedure are described. Afterward, section 6 consists of the empirical research and builds the most important part of the thesis. Here, results are analyzed and interpreted. Moreover, the set hypotheses are tested. Section 7 closes the conducted research by giving a conclusion and an outlook for further research.

2. Digitization: transformation in HR

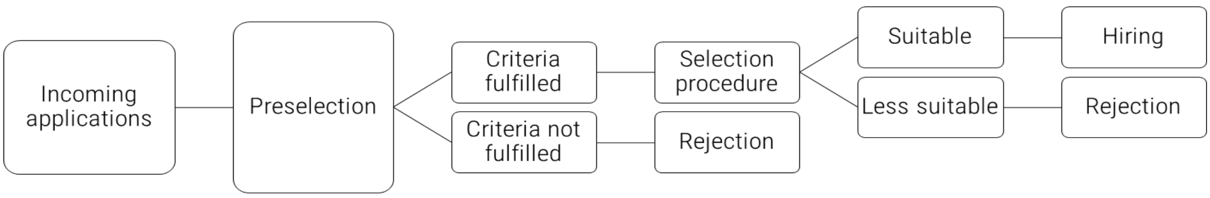
Our world has always been changing. Some researchers use the term VUCA to describe this phenomenon – an acronym for volatile, uncertain, complex, and ambiguous (Mack et al., 2016; Sharma & Sharma, 2019). Today's high global interconnectedness increases the pace of change (Mack et al., 2016). Inevitably, this leads to continuous adjustments in many different areas and does not omit adaptations in human resource management either (Sharma & Sharma, 2019).

Wickel-Kirsch et al. (2008) speak of changing responsibilities of personnel departments that are now deploying economic considerations and managing human resources when they were mostly focusing on administration and payroll. The researchers locate one of many reasons for this in the changing labor markets (Wickel-Kirsch et al., 2008). Employees are becoming more and more independent of one company and are more likely to have several employers throughout their lives (Wickel-Kirsch et al., 2008).

Still, this cannot be considered the only reason. Moreover, rapid developments in digital solutions in many different areas make a transformation of HR processes necessary to keep up (Sharma & Sharma, 2019). According to Sharma and Sharma (2019), automated processes need to be implemented wherever possible and are mentioned as exemplary in the field of recruiting. The study by Weitzel et al. (2020) has proven that 8 out of 10 surveyed enterprises believe that the digital transformation of their human resource department is vital for survival. Additionally, the covid-19 pandemic has sped up digital transformation in many organizations (Twilio, 2020). Nonetheless, another study has shown that examined HR managers see their organizations' digital setup as generally well-positioned but are still hesitant regarding the future (Softgarden, 2021). Weitzel et al. (2020) came to the result that only 4 out of 10 enterprises believe that their employees are well prepared for their digital transformation. It seems there is still a way to go here.

2.1 Personnel preselection

Before diving deeper into the digitization of recruiting, some definitions are necessary. This way, this thesis' frame and terms used can be defined clearly. According to Wickel-Kirsch et al. (2008), personnel recruitment is the term for the complete process of recruiting personnel. More accurately, this process consists of four core sections after demand planning has taken place. These are personnel marketing, recruitment, selection, and hiring (Wickel-Kirsch et al., 2008). So, personnel recruitment can be regarded as an umbrella term for the whole process but also as a single part. In contrast, personnel selection is simply the determination of candidates (Wickel-Kirsch et al., 2008).



(Illustration 1: Simplified application process. Modified depiction based on Wickel-Kirsch et al., 2008, p.4)

Illustration 1 shows the simplified process an applicant for a job has to go through to be finally hired and only covers two of the aforementioned core sections, namely selection and hiring. The procedure depicted starts out with incoming applications and continues with the preselection and the check of certain criteria. According to Wickel-Kirsch et al. (2008), preselection describes screening and sorting out applicants earlier in the cycle. Wickel-Kirsch et al. (2008) mention cover letters, resumes, school reports, training certificates, and work references as subjects of preselection.

Instruments used for applicant preselection can vary a lot. Goth (2009) mentions several of them, like reference information from previous employers, telephone interviews, test procedures, and self-description questionnaires, to give applicants the opportunity to give a suitable image of themselves. For all these instruments, Goth (2009) suggests structured guidelines to ensure fair preselection processes. Especially for telephone interviews, it is mentioned that it is a cost-effective and time-saving way of checking whether the company's expectations and the candidate's expected performance and abilities match (Goth, 2009). Further researchers, such as Weitzel et al. (2020), mention screenings of applicants, which might be performed by digital selection systems, such as AI. Section 2.2.1 Definition and fields of application elaborate on this.

If the aforementioned criteria are not fulfilled, the first rejection takes place, but if fulfilled, there is another selection procedure that finally leads to hiring or a rejection. This thesis' focus lies on preselection that can be done by a human recruiter or by an algorithm these days, as indicated in illustration 1. Algorithms in preselection will be discussed in the upcoming section 2.2.

Furthermore, there are two kinds of preselection. It is important to distinguish between preselection based on applications received and preselection from platforms such as LinkedIn or Xing. Tippins et al., 2021 use the term *'passive job candidates'* (p.4) for the latter. Those candidates are contacted by the organization because their profile seems to fit an available vacancy (Tippins et al., 2021). In this case, the candidate does not previously apply for the job in a conventional way. This thesis focuses primarily on the first kind.

2.2 Algorithms in preselection

2.2.1 Definition and fields of application

An algorithm can be generally defined as "*(…) a computational formula that autonomously makes decisions based on statistical models or decision rules without explicit human intervention.*" (Lee, 2018; p.3).

There are two types of algorithms (Jäger & Teetz, 2021). There are algorithms that are related to AI as well as linear algorithms (Jäger & Teetz, 2021). The term AI is used when referring to algorithms that can work and solve problems autonomously (Jäger & Teetz, 2021). AI-enabled algorithms differ from linear algorithms in so far as the latter always apply a given set of rules, while algorithms empowered to use AI are able to learn and make their own conclusions (Jäger & Teetz, 2021). Due to this, AI can even help to predict events in the future (Murphy, 2012; Tippins et al., 2021). Within this master thesis, the focus lies on AI-enabled algorithms. Therefore, whenever one of the two terms, AI or AI-enabled algorithms, is used, they refer to the same concept.

In this context, the term *machine learning* is found as well and can be regarded as the most important capability of AI (Jäger & Teetz, 2021; Lochner & Preuß, 2018). Machine learning can be seen as a part of AI, which specifically refers to learning and reasoning from data analysis and applying it to other situations (Petry & Jäger, 2021). Moreover, the researchers introduce understanding, concluding, learning, and interacting as the four significant aspects of AI (Petry and Jäger, 2021). The main purpose of AI is to provide support in those areas where humans reach their limits in decision-making (Morse et al., 2021; Pezzo & Beckstead, 2020). In recruiting, these can be, for instance, biases when it comes to candidate selection or other human limitations (Morse et al., 2021; Pezzo & Beckstead, 2020). In this context, researchers use terms like *Recruiting 4.0* or *AI-based recruiting* as well (Jäger & Teetz, 2021).

Algorithms that apply AI can be implemented in various domains if sufficient data is available to have it trained (Jäger & Teetz, 2021). Jäger and Teetz (2021) and Wittram-Schwardt and Bogs (2021) mention several scenarios across personnel recruitment that range from job requirements and advertisement, over application and CV parsing to finally, preselection and evaluation of applicants or as a supportive feature as in chatbots. It is conceivable that digital selection systems might check, either partially or fully automatically, the extent to which the applicant profile and the job profile match and then make a preselection (Weitzel et al., 2020). A German study conducted in 2022 has shown that almost 50% of 388 participants could well imagine the deployment of AI in preselection (Dekra, 2022). This way, algorithms are thought to speed up the preselection process, simplify it, and make it less discriminatory for vulnerable groups (Weitzel et al., 2020). Still, algorithms are not immune to discrimination, and their way of working might raise issues regarding data protection, for instance (Jäger & Teetz, 2021). Moreover, new ethical challenges but also societal and further legal questions are brought up that need to be clarified (Greenwood et al., 2020; Jäger & Teetz, 2021).

2.2.2 Functionality

It has already been examined what AI-enabled algorithms are capable of and areas in which they can support recruiting, especially selection procedures. What still needs to be clarified is how these algorithms work.

They can work with structured data that is already categorized and unstructured data, like text documents, indexes, images, or voice (Wittram-Schwardt & Bogs, 2021). AI is able to find correlations and is developing through machine learning, as was already mentioned throughout the previous paragraphs (Wittram-Schwardt & Bogs, 2021).

Their interaction appears almost human, as AI can see, hear, and speak (Wittram-Schwardt & Bogs, 2021).

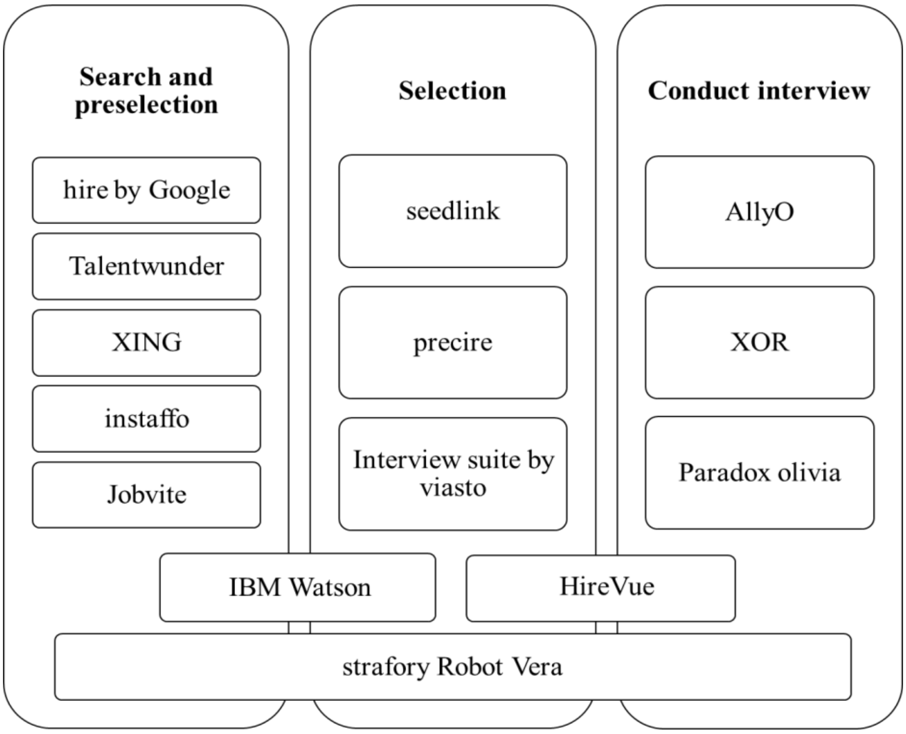
How does AI exactly work? It is common to combine so-called artificial neural networks (ANN) with other methods, such as fuzzy logic or else (Jäger & Teetz, 2021). To give a short explanation: Fuzzy logic supports expressing perception-based states under imperfect information, as in what might be the fastest vs. the shortest way to go somewhere (Zadeh, 2009). ANN functions very similarly to the human brain (Jäger & Teetz, 2021). After an artificial neuron's computation, there is an output value passed on to further neurons of the ANN (Jäger & Teetz, 2021). Here, the term cognitive computing (CC) must be mentioned. It describes how AI learns and concludes through experience and interactions and is able to do things that were not explicitly programmed before (Kelly, 2015).

Researchers currently differentiate three performance levels of AI (Pöchhacker-Tröscher et al., 2017; Lichtenthaler, 2021). These are Artificial Narrow Intelligence which has the lowest performance level, Artificial General Intelligence follows, and at the highest level, Artificial Superintelligence (Pöchhacker-Tröscher et al., 2017; Lichtenthaler, 2021). The following table will shortly summarize the main characteristics of each.

Type	**Abbreviation**	**Capabilities**	**Fields of application**	**Development stage**
Artificial Narrow Intelligence	ANI	current state of the art; use of algorithms, machine learning, and other techniques in combination; usually in the form of previously learned applications.	applications in applicant portals, recognition of applicant documents of any media type	weak AI
Artificial General Intelligence	AGI	same intellectual capabilities as humans; able to think logically, strategically, and creatively	imitation of a personnel expert for candidate selection	strong AI
Artificial Superintelligence	ASI	superior to humans	proactively identifying fake claims; capturing the fit for the job	development goal

(Table 1: The performance levels of AI. Own depiction is taken from Pöchhacker-Tröscher et al., 2017; p.13; Lichtenthaler, 2021; p.44).

There are several AI-based recruiting tools that are already deployed. Wittram-Schwardt and Bogs (2021) divide them into three categories, whereas three applications can be subordinated to more than one category (see illustration 2). The categories are search and preselection, selection, and conducting an interview (Wittram-Schwardt & Bogs, 2021). For the kind of preselection depicted here, job portals are necessary to serve as a database, e.g., XING, or an AI's own job portal, e.g., instaffo, Jobvite (Wittram-Schwardt & Bogs, 2021). Seedlink, precire, and Interview suite support in selection processes via analysis of videos and sound (Wittram-Schwardt & Bogs, 2021).



(Illustration 2: Categorized AI-based recruiting tools. Own illustration based on Wittram-Schwardt & Bogs, 2021, p.163)

Even more multifaceted are IBM's Watson and Hire Vue's tool HireVue which combine search and preselection with selection (Watson) and selection with conducting interviews (HireVue). Here is a brief outline of HireVue's process taken from Wittram-Schwardt and Bogs (2021): once a recruiter has selected a suitable candidate, HireVue emails that person an interview link. HireVue then conducts an automated interview. Finally, recruiters receive the candidate's answers and analysis from HireVue.

The most developed AI-based recruiting tool is Strafory Ltd.'s Robot Vera. Robot Vera uses a job description to search for suitable candidates from a database and conducts preselection interviews by phone (Wittram-Schwardt & Bogs, 2021). Recruiters then receive Vera's preselection of candidates and can choose with whom they want to proceed (Wittram-Schwardt & Bogs, 2021).

Some researchers consider the implementation of AI in recruiting still in its infancy (Weitzel et al., 2020; Jäger & Teetz, 2021M; Lichtenthaler, 2021). Researchers locate a need for modernization (Jäger & Teetz, 2021). A study examining the top 1000 enterprises in Germany regarding their revenue has shown that only 5% had implemented AI in HR in 2020 (Weitzel et al., 2020). Generally, the majority of those enterprises are open to AI implementation (Weitzel et al., 2020). Weitzel et al. (2020) see two main reasons for the non-implementation of AI: First, the lack of data to even train an AI. Second, lack of trust in decisions made by an AI. The second applies to about one-third of the companies analyzed within their study (Weitzel et al., 2020).

2.2.3 Advantages and Drawbacks

All in all, many benefits and enrichments but also some downsides or aspects that need to be treated with caution can be identified along the deployment of algorithms in the preselection. In the following paragraphs, these issues will be analyzed.

First, the advantages of the deployment of algorithms in preselection shall be addressed. As already mentioned earlier, in the first place, AI is meant to make the preselection process faster, simpler, and fairer (Weitzel et al., 2020; Tippins et al., 2021; Lochner, 2021; Wittram-Schwardt & Bogs, 2021). This is partly confirmed by a study. The Innovation Group (2022) identified benefits deriving from the implementation of AI in Italian companies. The most supported advantages found were better speed and efficiency as well as better decision-making processes (The Innovation Group, 2022). Arguments in favor of AI in the Middlefield are fewer errors, fewer costs, and an improvement in customer experience (The Innovation Group, 2022). Some experts even claim that discrimination can be ruled out completely with correct programming (Wittram-Schwardt & Bogs, 2021; Tippins et al., 2021).

Moreover, especially employers that need to assess large volumes of applicants can benefit from AI (Tippins et al., 2021; Jäger & Teetz, 2021; Wittram-Schwardt & Bogs, 2021). According to Obeidat (2012), two more advantages are given: adaptive testing, in other words, testing procedures tailored to a candidate’s specific capabilities, is enabled, and results can be directly implemented in a candidate management system which makes further selection easier to handle. This again increases organizational attraction (Wittram-Schwardt & Bogs, 2021).

On the other hand, the deployment of algorithms in personnel preselection needs to be treated with caution (Fellner, 2019; Tippins et al., 2021). Therefore, the disadvantages should now be taken into consideration. First and foremost, the usage of AI in personnel selection poses a problem regarding data protection and data security (Fellner, 2019; Wittram-Schwardt & Bogs, 2021; Tippins et al., 2021). The AI can only use and be trained by data that is given to it voluntarily and with the data owner’s approval (Fellner, 2019). This leads to the fact that AI can only be applied in a very limited version (Fellner, 2019). Another disadvantage is that AI mostly works on the basis of pattern recognition and, therefore, might reproduce inequalities and biases

(Fellner, 2019). To avoid these, clear learning criteria are important. Nonetheless, personnel selection does not offer them in contrast to, e.g., autonomous driving, as the rules to differ between right and wrong cannot be set easily and clearly (Fellner, 2019).

Amazon's preselection AI can be cited here as a prime example. The AI was able to compare incoming applications with data from the last ten years and establish correlations so that the 'best applicants’ could be hired (Wilke, 2018). Unfortunately, the initial programming was not accurate, and the AI often concluded that 'technophile men' were probably the best employees for Amazon because they were the most frequently hired in the historical data (Wilke, 2018; Morse, 2021). This resulted in a major disadvantage and discrimination for any applicants who did not fall into this group, such as women (Wittram-Schwardt & Bogs, 2021; Morse, 2021).

Additionally, Tippins et al. (2021) mention AI applications that do face scanning. This application of AI is highly controversial. In a study by the National Institute of Standards and Technology (NIST), it was proven that faces of African American or Asian origin were wrongly detected 10 to 100 times more frequently (Singer & Metz, 2019; Tippins et al., 2021). As Totty (2020) writes in an article for the Wall Street Journal, the study Gender Shades showed that several facial-recognition systems recognized darker-skinned women 35 times more likely in a wrong way than light-skinned men. In these cases mentioned, seemable AI is reaching its limits and, therefore, is heavily criticized.

Moreover, organizations applying AI in personnel selection must hire trained staff to ensure professional and legally correct handling (Fellner, 2019; Lochner, 2021; Wittram-Schwardt & Bogs, 2021). Furthermore, the quality of an algorithm-driven selection process must be paid attention to (Fellner, 2019; Lochner, 2021; Tippins et al., 2021). According to Fellner (2019) and Lochner (2021), the quality of an algorithm-driven selection process needs to remain as high as within an analog one to do so. Further aspects need to be considered, like technical issues, supportive measures, and the danger of cheating. To counteract manipulations, attendance parts, the usage of cameras, or tracking measures are already a reality (Fellner, 2019). Regarding a selection process’ quality, the question arises whether it is at all possible to verify with certainty that AI only includes factors relevant to evaluation (Fellner, 2019).

Additionally, the lack of human contact and the ability to show appreciation and interpersonal sensitivity towards an applicant is criticized in relation to the deployment of AI (Fellner, 2019; Wittram-Schwardt & Bogs, 2021). The implementation of AI and algorithms comes along with liabilities and risks that need to be considered with care and dealt with by the proactive engagement of experts (Tippins et al., 2021).

2.3 Debates by analogy

As the last section has shown, the deployment of AI in personnel preselection raises many concerns. However, these concerns are not limited to this field and can be transferred to many other application areas. Three different areas will be discussed shortly in the following section.

The first is about the German Armed Forces Drone Debate conducted in 2020 (BMVg, 2020). Till then, the German Armed Forces were not allowed to use armed, unmanned drones at war as this was seen as unethical behavior (BMVg, 2020). Controversial discussions have been held for several years (BMVg, 2020; Koch, 2015). The usage of drones is particularly challenging under international law (Schöberl, 2015). There are several arguments that were put forward to allow the use of armed, unmanned drones, like the argument for more protection of soldiers but also civilians (Koch, 2015). Another argument questions whether peace increases through the implementation of technology (Koch, 2015). Probably the biggest counter-argument deals with the autonomation of weapon systems and points at the fear that humans could lose the upper hand and no longer be able to intervene as these systems might develop further (Koch, 2015). Questions similar to personnel preselection might arise: Is the implementation of armed, unmanned drones perceived as fairer compared to weapons so far controlled by humans who might act more error-prone?

The second analogy addresses fully autonomous vehicles. In contrast to the human nature of driving, those offer double transparency (Xu & Ding, 2019). 'Double' means no opaque human decisions and no secrecy to third parties (Xu & Ding, 2019). Xu and Ding (2019) dedicated their research about fully autonomous vehicles to drivers' willingness to sacrifice. This variable is defined *"(...) as the maximum number of humans a person is willing to harm to save himself/herself."* (Xu & Ding, 2019; p.26). Via the implementation of fully autonomous vehicles, these driving decision rules need to be clearly communicated to make sure the autonomous vehicle will perform in the driver's sense (Xu & Ding, 2019). This way, the attitudes of people are known, which have never been before, although they have always been existing (Xu & Ding, 2019). Here as well, similar questions to personnel preselection might offer themselves: Is perceived fairness higher when a self-driving car closely follows the driver's will and, if required, kills someone else to save the driver? Or is it fairer to leave such scenarios to chance and not disclose attitudes regarding willingness to sacrifice as previously?

The third case of analogy is about AI in surgery. In this context, too, the question of fairness arises in many respects. AI in surgery can have a direct impact on patient safety and system integrity (Rudzicz & Saqur, 2020). If the AI is (unconsciously) trained with a bias and therefore makes decisions that can have far-reaching consequences in the field of surgery (Rudzicz & Saqur, 2020). For example, AI can be used to assess pre-operative risks or to estimate which patient should be treated first

(Rudzicz & Saqur, 2020). Errors can have far-reaching consequences if patients belong to underrepresented groups that were not considered during programming and are, therefore, incorrectly assessed by the AI (Rudzicz & Saqur, 2020). According to Rudzicz and Saqur (2020), AI is still less error-prone than human surgeons. Is the use of AI in surgery perceived more fairly than the deployment of human surgeons? Such and other questions are pressing in this context.

3. Fairness in preselection

As the previous section has already foreshadowed, the issue of fairness perception is crucial in many contexts. For an algorithm-driven selection process to work at all, it must do one thing above all: it must be accepted (Fellner, 2019). Acceptance also requires perceived fairness. This is why perceived fairness is particularly important in times of staff shortages, such as today (Fellner, 2019). According to Fellner (2019), it is essential to find the fine line between meaningful, applicant-friendly, and appreciative personnel selection. Therefore, this section is dedicated to fairness, especially perceived fairness and the theoretical models surrounding it.

3.1 Definitions

Before going into depth, some definitions of terms that are often used similarly are given. This way, all terms can be clearly distinguished, and this thesis' topic is understood unequivocally.

Leventhal (1980) defines perceived fairness as follows:

> "(…) an individual's perception of fairness is based on justice rules. (…) a justice rule is defined as an individual's belief that a distribution of outcomes, or procedure for distributing outcomes, is fair and appropriate when it satisfies certain criteria." (Leventhal, 1980; p.4).

He explains procedural fairness in further detail using perceived fairness as a basis.

> "Every group, organization, or society has procedures that regulate the distribution of rewards and resources. There is a network of regulatory procedures that guides the allocative process. (…) The concept of procedural fairness refers to an individual's perception of the fairness of procedural components of the social system that regulate the allocative process." (Leventhal, 1980; p.15)

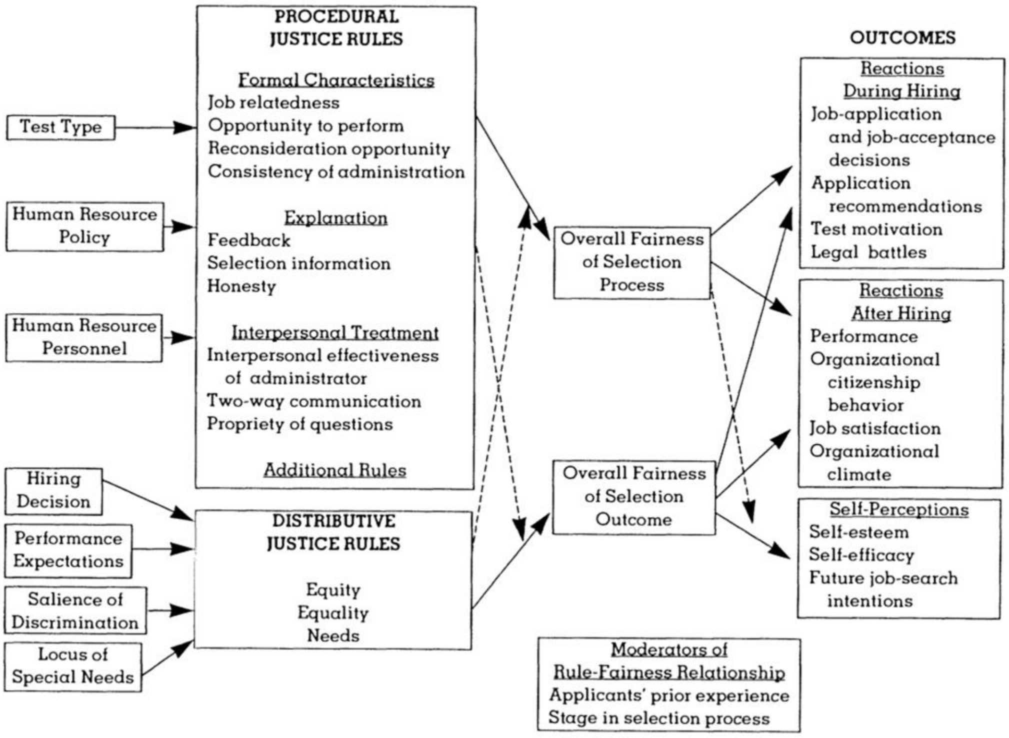
As Leventhal's (1980) definition shows, the distinction between the two terms 'justice' and 'fairness' is often vague. This is due to a lot of research done about individual perceptions of fairness (Goldman & Cropanzano, 2014). In this context, imprecision has spread in the differentiation of the two terms (Goldman & Cropanzano, 2014). Goldman and Cropanzano (2014) dedicate their research to this issue and plead for a clear distinction. They clarify that 'justice' should be used for adherence to rules and standards, while 'fairness' should be saved for the evaluative perception of them (Goldman & Cropanzano, 2014). Therefore, this thesis uses both terms according to these definitions. Whenever other research is mentioned throughout this thesis, the terms that were originally utilized are used.

Furthermore, Vermunt and Törnblom (2007) focus on the concept of justice. They explain that *“An allocation process consists of a distribution (an outcome) and a procedure (...)”* (Vermunt & Törnblom, 2007; p.8). Selection is such a process. Therefore, the terms distributive justice and procedural justice shall be explained. Folger and Cropanzano (1998; p. xxi) define distributive justice as “(...) the perceived fairness of the outcomes or allocations that an individual receives. ”Distributive justice originates from equity theory (Alneyadi et al., 2019). Still, Vermunt and Törnblom (2007) mention further factors that influence distributive justice. These might be further types of rules like equality or need but also the valence of the outcome, the type of relationship between the parties involved, or else (Vermunt & Törnblom, 2007).

Procedural justice is defined as *“(...) the assessment of impartiality with regards to decisions (...). This concept contemplates the approach employed to arrive at these decisions.”* (Alneyadi et al., 2019; p.648). Alneyadi et al. (2019) further state that procedural justice points to the perceived fairness of those decisions (Alneyadi et al., 2019). Procedural justice *“(...) connect(s) outcomes and procedures (...)”* (Vermunt & Törnblom, 2007; p.5). Some authors further distinguish interactional justice (Alneyadi et al., 2019). In this thesis, this third form of justice is not considered as it does not play a role in Gilliland’s model of applicants’ reactions to employment selection systems which will be dealt with in the upcoming section 3.2.

3.2 Gilliland’s model of applicants’ reactions to employment selection systems

In this section, Stephen W. Gilliland’s so-called model of applicants’ reactions to employment selection systems will be introduced. In some research, this model is described as the most dominant theoretical framework (Gilliland & Steiner, 2012). The researcher’s intention with this model was to bring all previous research to a common thread as well as to create a solid link between the theory of organizational justice and reactions to personnel selection (Gilliland, 1993). Moreover, it is about further development and new implementation of some organizational justice issues (Gilliland, 1993).



(Illustration 3: Model of Applicants' Reactions to Employment Selection Systems. From Gilliland, 1993; p.700)

The model, see illustration 3, consists of several stages. For an easier explanation, the model will be analyzed along those four parts or columns. The first one is situational and personal conditions such as test type, human resource policy, or human resource personnel (Gilliland, 1993). These influence the extent to which the procedural justice rules are satisfied or violated in applicants' perceptions (Gilliland, 1993). The first part has an effect on the second part, which consists of procedural and distributive justice rules (Gilliland, 1993).

The third part consists of the combination of the fulfillment or unfulfillment of those rules and results in an overall evaluation of the fairness of the selection system (Gilliland, 1993). Moreover, Gilliland (1993) adds so-called *"moderators of rule-fairness relationship"* to this part. Those are applicants' prior experience and their stage in the selection process (Gilliland, 1993). Furthermore, Gilliland (1993) considers the interrelation of procedural justice rules on the overall fairness of the selection outcome and distributive justice rules on the overall fairness of the selection process. According to Gilliland (1993), those are said to moderate each other. See the two dashed arrows on the left in illustration 4. The fourth and last part analyzes the relationship between overall fairness perception and personal and organizational outcomes (Gilliland, 1993). Those cover several aspects concerning accepted but also neglected applicants (Gilliland, 1993).

In the following paragraphs, the aforementioned two kinds of justice rules, procedural and distributive, will be analyzed in greater detail. Finally, the main conclusion of the model will be addressed.

3.2.1 Procedural justice rules

As established by Leventhal (1980), procedural justice depends on the satisfaction or violation of 10 procedural justice rules. Gilliland's model (1993) builds on these procedural justice rules and further research concerning justice theories but also applicant reactions models. These ten procedural justice rules can be categorized into three components that were established by Greenberg (1990): formal characteristics, explanation, and interpersonal treatment see Table 2 (Gilliland, 1993). Gilliland (1993) also includes further possible rules that have not entered previous research. In the following section, these ten rules will be explained in further detail to make clear what each of them is.

Procedural rule	Formal characteristics	Explanation	Interpersonal treatment
	• Job relatedness • Opportunity to perform • Reconsideration opportunity • Consistency	• Feedback • Selection information • Honesty	• Interpersonal effectiveness • Two-way communication • Propriety of questions

(Table 2: Three components of the ten procedural justice rules. Own illustration based on Gilliland, 1993; p.702)

Column 1: Formal characteristics

- 'Job relatedness': this very first rule is about the test type that is applied (Gilliland, 1993). It is necessary to differentiate content validity sense, the relation of test content to job content, and criterion-related validity sense, the relation of test performance to job performance (Smither & Pearlman, 1991 as cited in Gilliland, 1993). The higher those two relations, the higher the perceived fairness originating from 'job relatedness' (Gilliland, 1993).

- 'Opportunity to perform': here, it is about the option to provide some input before a decision is made (Gilliland, 1993). Some researchers speak of applicants gaining back a bit of control over the selection process and the possibility to show their skills (Schuler, 1993; Arvey & Sackett, 1993, as cited in Gilliland, 1993). Gilliland (1993) concludes that interviews provide the best 'opportunity to perform' among selection methods. Procedural fairness is higher when applicants have this possibility (Gilliland, 1993).

- ‘Reconsideration opportunity’: This rule concerns the option to adjust or redo the evaluation process (Gilliland, 1993). Gilliland (1993) even speaks of a sort of ‘second chance’ for applicants to prove their real capabilities or prior distorted outcomes. Given an opportunity for reconsideration, the higher procedural fairness perception (Gilliland, 1993).

- ‘Consistency of administration’: this rule comprises two components of consistency, namely over time and across people (Gilliland, 1993). In more detail, this concerns the ‘consistency of administration’ in terms of content, scoring, and interpretation to give all applicants equal chances (Gilliland, 1993). This is why Gilliland (1993) locates higher consistency for structured interviews than for unstructured ones. Applicants’ previous experiences are crucial for their perception of consistency as they can only evaluate consistency along those (Gilliland, 1993). A clear violation of consistency exists in case applicants are hired because of their networks and not their skills (Gilliland, 1993).

Column 2: Explanation

- ‘Feedback’: this rule is satisfied if ‘feedback’ is timely and informative (Gilliland, 1993). If ‘feedback’ of this nature is provided, procedural fairness is perceived as higher (Gilliland, 1993). Moreover, delays in ‘feedback’ lead to the withdrawal of applications and a loss of interest for the employer (Gilliland, 1993). Still, providing ‘feedback’ is easy, valued regardless of the outcome, and low-cost for companies and should therefore be provided in a useful form and fast (Gilliland, 1993).

- ‘Selection information’: the sixth rule addresses the offer of justification for hiring or rejecting (Gilliland, 1993). Fairness perception is also dependent on the kind of ‘selection information’: the information’s validity, the scoring itself, and the way scores are considered (Gilliland, 1993). Furthermore, ‘selection information’ prior to its conductance has an influence on fairness perception, as well as applicants, know what to expect (Gilliland, 1993).

- ‘Honesty’: this rule is about ‘honesty’ in communication (Gilliland, 1993). Fairness perception is dependent on the correctness and credibility of recruiters (Gilliland, 1993). Research has shown that this can have a vast impact on applicants’ reactions and impressions concerning the selection process but also the whole organization and, therefore, acceptance decisions (Liden & Parsons, 1986; Schmitt & Coyle, 1976, as cited in Gilliland, 1993).

Column 3: Interpersonal treatment

- 'Interpersonal effectiveness of administrator': this rule takes care of how applicants are handled by recruiters and whether there is appreciation involved (Gilliland, 1993). Gilliland (1993) underlines that the 'interpersonal effectiveness of administrators' especially shapes applicants' overall view of the company, their assumptions about their fit to it, and their likelihood of accepting a potential final job offer (Schmitt & Coyle, 1976 as cited in Gilliland, 1993).

- 'Two-way communication': here, it is about applicants not only being the ones who must answer questions but also them having the possibility to provide interpersonal interaction (Gilliland, 1993). Satisfying this rule, they are able to ask questions themselves (Gilliland, 1993). Gilliland (1993) found that computerized processes that did not provide the opportunity for 'two-way communication' failed in fairness perception, especially for more prestigious jobs. Just certain phases within a selection process that only provide one-sided communication might still satisfy this rule (Gilliland, 1993).

- 'Propriety of questions': the final procedural justice rule addresses the kind of questions an applicant is asked during a selection process (Gilliland, 1993). Some questions might be simply improper, irrelevant to the job, or built on prejudice and therefore inadequate (Gilliland, 1993).

All in all, these ten procedural rules plus two additional rules are components that form the overall fairness perception of selection processes (Gilliland, 1993). As indicated before, test type, human resource policy, and human resource personnel influence the satisfaction or violation of the rules presented and lead to applicants' fairness perceptions (Gilliland, 1993). Gilliland's (1993) research regarding procedural rules resulted in several findings: As Leventhal (1980) suggests, not all procedural justice rules contribute to fairness perception to the same extent. Gilliland (1993) finds that this depends on each individual situation. Moreover, the extent of satisfaction or violation of procedural justice rules also depends on applicants' previous experiences and the point in time at which fairness perceptions are examined (Gilliland, 1993). Finally, the outcome of the hiring decision is an important factor, too (Gilliland, 1993).

3.2.2 Distributive justice rules

In the following, the aforementioned distributive justice rules will be discussed. The decision to hire or reject an applicant is the most outstanding outcome in the selection process (Greenberg, 1993). Gilliland (1993) describes distributive justice of selection systems as the *"(...) determination of what one deserves (...) made on the basis of (...) distributive rules*" (Gilliland, 1993; p.715). These distributive justice rules are 'equity,' ‘equality’, and ‘special needs’, while the first one represents the most dominant one (Gilliland, 1993). Within the following paragraphs, these three rules will be introduced in further detail.

- ‘Equity’: ideally, every applicant receives the outcome coherent with their inputs relative to a referent comparison (Gilliland, 1993). These inputs might be self-perceptions of ability or qualifications for the job (Gilliland, 1993). Still, the rule of ‘equity’ might seem difficult to handle as comparison might not always be easy (Gilliland, 1993). This is why the application of self-referents seems most suitable: applicants contrast current with past or ideal input-output ratios (Gilliland, 1993). These are based on applicants’ expectations that are formed along with qualifications, past success, and the likelihood of being hired (Gilliland, 1993). Finally, ‘equity’ is measured by comparing the actual outcome (being rejected or hired) to prior expectations (Gilliland, 1993). Gilliland (1993) notes that rejections are considered fairer in cases when applicants did not expect to hire.

- ‘Equality’: this distributive rule is satisfied if applicants *“(...) have an equal chance of receiving the outcome, regardless of differentiating characteristics such as knowledge or ability.”* (Gilliland, 1993; p.718). Therefore, only random hiring would further satisfy the ‘equality’ rule (Gilliland, 1993). The research found that this concerns job-irrelevant characteristics more than job-relevant characteristics (Gilliland, 1993). Certain situations might bring ‘equality’ to the fore, although ‘equity’ is mostly dominant (Gilliland, 1993). Especially to applicants prior exposed to discrimination, the satisfaction of the ‘equality’ rule is more important (Gilliland, 1993).

- ‘Special needs’: the final distributive justice rule is satisfied if rewards are distributed according to the ‘special needs’ of applicants (Gilliland, 1993). So-called preferential treatments will be perceived as fair if applied to disadvantaged subgroups or disabled individuals (Gilliland, 1993). For them, Gilliland (1993) suggests that selection processes could be adapted. Finally, it is important to note that the first two distributive justice rules, ‘equity’ and ‘equality’, will perhaps overshadow the ‘special needs’ rule in most cases (Gilliland, 1993).

To sum up, the three distributive justice rules create a problem, as they exist as they are and are differently applicable to certain situations. A violation of one of them leads to the satisfaction of another and the other way around (Gilliland, 1993). Therefore, it is impossible to satisfy all of them within a selection process (Gilliland, 1993). Gilliland (1993) suggests two solutions for this problem: first, by increasing the salience of those distributive justice rules that are satisfied, and second, by only focusing on parts of selection procedures and not on the whole process to avoid perceptions of unfairness. This is also the reason why this thesis is only focusing on procedural justice rules in its empirical part. This way, a research scenario is created that considers only justice rules that are independent of others (Konradt et al., 2013). Due to this, the covariance of different justice rules becomes an option and is no necessity (Konradt et al., 2013). Lastly, related consequences potentially differ as well as the independence of all justice rules taken into consideration is ensured (Konradt et al., 2013).

3.2.3 Significance and critical analysis of the model

In conclusion, fairness perceptions are important as they shape not only individual applicants' behavior but also form organizational outcomes (Gilliland, 1993). Gilliland (1993) mentions three main reasons: applicants' fairness perceptions might influence their recommendation or advice against the organization or the products or services it sells to others. Secondly, applicants who consider the selection process unfair might file lawsuits against organizations and might be successful. Lastly, ethical aspects might be reason enough why organizations should care about applicants' fairness perceptions.

Theoretical models often appear rigid and represent the mere pretension of completeness. This is often accompanied by criticism, which will be addressed in the following. Gilliland's model of applicants' reactions to employment selection systems (1993) is criticized for not being tested enough (Ryan & Ployhart, 2000). Ryan and Ployhart (2000) make a few exceptions but claim that the majority of Gilliland's propositions have never been tested thoroughly.

Further critical examination of Gilliland's model (1993) speaks about the fact that not all procedural justice rules have been tested in the same intensity, i.e., 'job relatedness', 'opportunity to perform', and 'consistency of administration' have been studied most (Gilliland & Steiner, 2012). Regarding distributive justice rules, the situation is similar as 'equity' has been studied mainly (Gilliland & Steiner, 2012).

Moreover, Ryan & Ployhart (2000) look at the model's behavioral and organizational outcomes predicted by Gilliland (1993). As an example, the researchers criticize the non-existence of tested applicant reactions after being hired (Ryan & Ployhart, 2000). Later in their analysis, Ryan and Ployhart (2000) argue that there is not enough proof that applicants' negative fairness perceptions actually have negative impacts on organizations. Finally, five rules are provided that should easily help organizations and the following also applicants but were not presented within the model explicitly (Ryan & Ployhart, 2000):

1. Organizations should be aware that test-taking motivation might influence applicants' performance.
2. Organizations should provide explanations, especially in case of a rejection, that inform sensitively.

3. Organizations should watch their applicants' fairness perceptions on a regular basis.
4. Organizations should investigate whether desirable applicants also behave in their sense or reject job offers due to fairness perceptions of selection processes.
5. Organizations should be aware that selection processes are always about evaluating applicants and, therefore, always represent reactions to being evaluated.

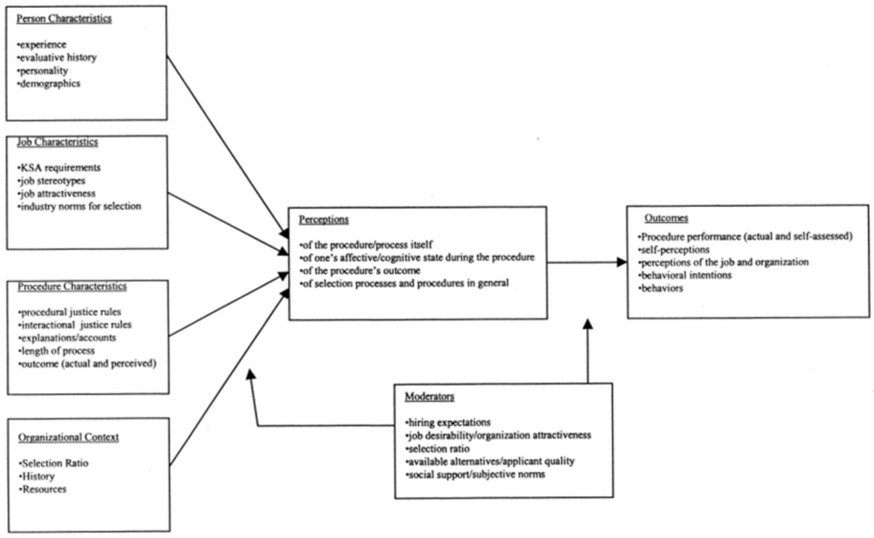
3.3 Related approaches and models

In the following section, related approaches and similar models to Gilliland's model (1993) are introduced. Some of them are less well-established or offer another approach, while others build on Gilliland's work.

The Social validity theory by Schuler (1993) is about applicants' perception of their own treatment being dignified and respectful (Truxillo et al., 2017). Four dimensions are considered: informativeness, participation, transparency, and feedback (Truxillo et al., 2017). In a similar way as Gilliland (1993), those categories represent characteristics like applicants having enough information about the selection process, being able to show their capabilities, knowing exactly about the process they are facing, and receiving suitable feedback about their fit (Truxillo et al., 2017). This model has received further attention in European research, while Gilliland's model (1993) is more popular in the US (Anderson et al., 2010).

Arvey and Sackett's (1993) model is not only about applicants' fairness perceptions but also about organizational decision-makers' perceptions (Truxillo et al., 2017). Moreover, it covers several sources of antecedents of fairness (Truxillo et al., 2017). According to Arvey and Sackett's model (1993), the nature of selection tests and organizational context shapes fairness perceptions (Truxillo et al., 2017). Also, this model serves as an important basis for many younger models (Truxillo et al., 2017).

The so-called Heuristic model by Ryan and Ployhart (2000) combines key antecedents, outcomes, suggested moderators, and future research, see illustration 4 (Ryan & Ployhart, 2000). This model's basis is built on two prior models: Gilliland's model (1993) and Brutus and Ryan's model (1998). The latter is a model about the determinants of perceived job-relatedness (Brutus & Ryan, 1998). Ryan and Ployhart's (2000) model adds a new perspective to its two preceding models by categorizing different types of applicant perceptions into perceptions: of the procedure, of the affective and cognitive state during the procedure, of the procedure's outcome, of the selection processes, and of the procedures in general.

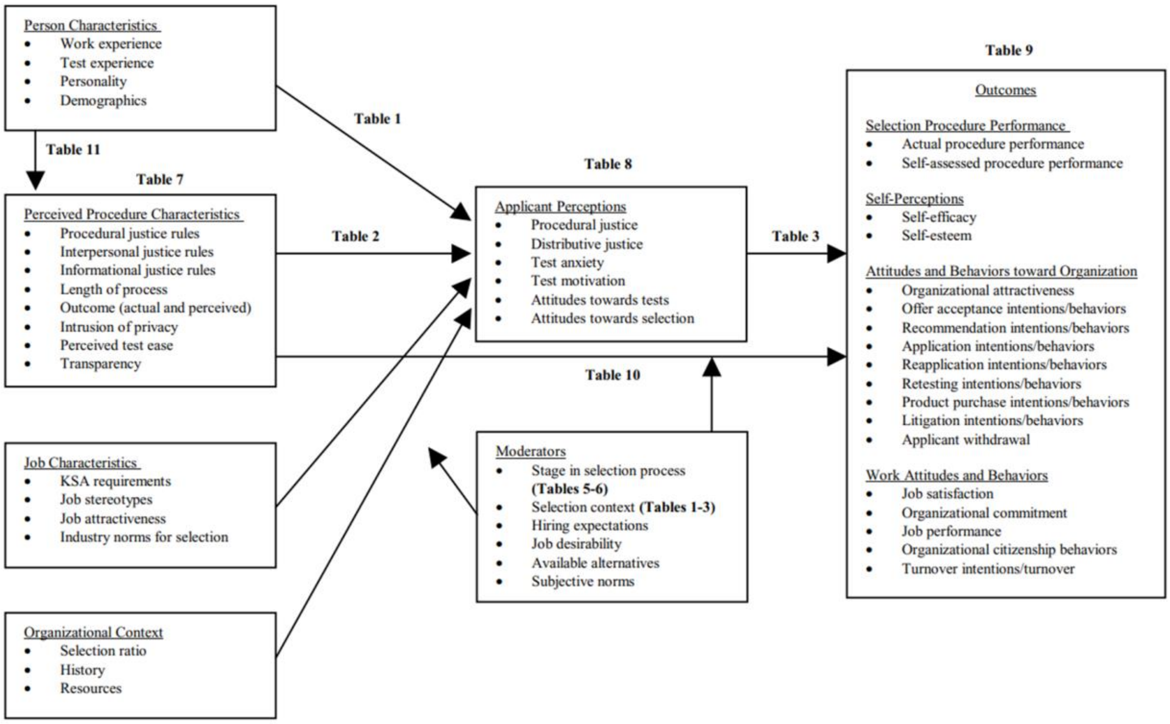


(Illustration 4: Heuristic model. From Ryan & Ployhart, 2000; p.599)

Within the Fairness theory of Folger and Cropanzano (2001), accountability for the actions or inactions of others is addressed. For this purpose, three counterfactuals are described to form applicants' reactions: could, would, and should (Truxillo et al., 2017). Applicants answer questions starting with these three words just introduced and answer via excuses or justifications to reduce those counterfactuals (Truxillo et al., 2017).

Ployhart and Harold's (2004) Applicant Attribution-Reaction theory claims that applicants' reactions are automatically shaped by attributions about the selection process (Truxillo et al., 2017). These might concern perceptions of fairness, motivation, and test perceptions (Truxillo et al., 2017). The basis of this theory is once again built on Gilliland's research (1993), as those attributions made are created by comparison to one's expectations (Truxillo et al., 2017). These, again, are formed by justice rules (Truxillo et al., 2017).

The updated Theoretical Model of Applicant Reactions to Selection (Hausknecht et al., 2004) is based on two models that were discussed previously, Gilliand's model of applicants' reactions to employment selection systems (1993) and Ryan and Ployhart's heuristic model (2000) (Hausknecht et al., 2004). The main point of this model is that many outcomes depend on applicants' perceptions. Also see illustration 5 (Hausknecht et al., 2004). These outcomes might be the performance of selection procedures, self-perceptions, and applicants' attitudes and behaviors (Hausknecht et al., 2004). Moreover, within the model of Hausknecht et al. (2004), four classes of variables that serve as determinants of applicant perceptions and several moderators of their relationships are offered.



(Illustration 5: Updated Theoretical Model of Applicant Reactions to Selection. From Hausknecht et al., 2004; p.642)

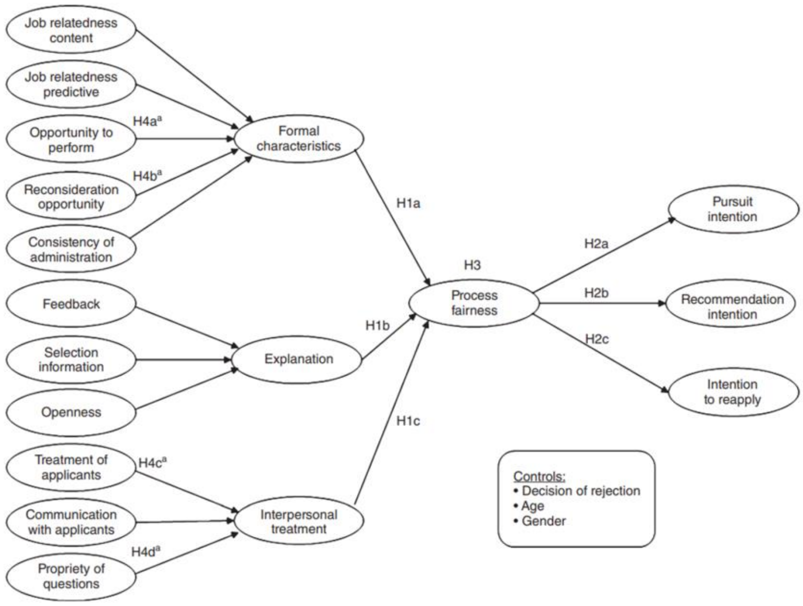
4. State of research

After having had a look at different models and approaches, the current state of research will be discussed. This section starts out with an overview of previous studies. Then, research gaps are identified along which hypotheses are formed.

4.1 Overview of previous studies

The first study that shall be mentioned here is the model of Konradt et al. (2013). Their research model builds on Gilliland's model of applicants' reactions to selection procedures (1993) but takes various web-based selection procedures into consideration instead.

With this model, the researchers have several aims in mind. To find out how the second-order justice factors of the three categories- formal characteristics, explanation, and interpersonal treatment - relate to fairness perception of processes, see illustration 6 (Konradt et al., 2013). Moreover, Konradt et al. (2013) examine the connection between process fairness and several reactions of applicants resulting in research on moderating effects of fairness perception between justice rules and the resulting behavior. Finally, the most salient procedural justice rule concerning the web-based context is identified (Konradt et al., 2013).

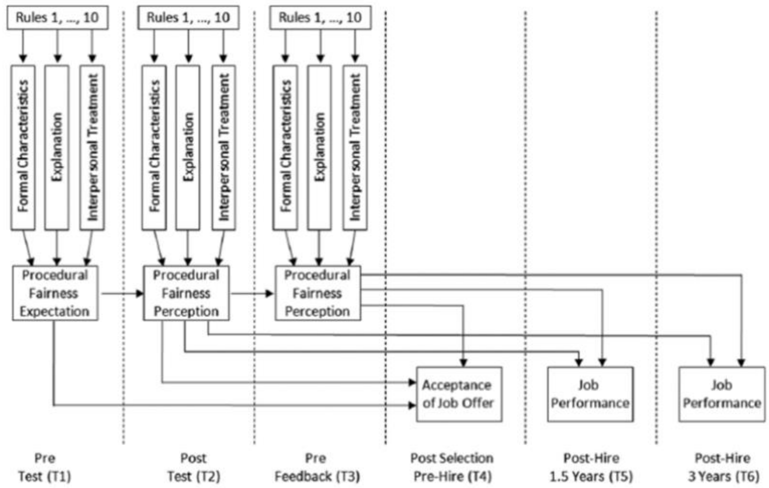


(Illustration 6: Research model. From Konradt et al., 2013; p.157)

Within their research, Konradt et al. (2013) found that interpersonal treatment and formal characteristics have a positive impact on process fairness, while the latter contributes positively to recommendations of and reapplications at organizations. Furthermore, they found that the treatment of applicants, 'opportunity to perform', 'propriety of questions', and 'reconsideration opportunity' provide process fairness (Konradt et al., 2013).

Finally, the study of Konradt et al. (2013) provides three contributions: firstly, it supports Gilliland's model of applicants' reactions to employment selection systems (1993) in a web-based context. Secondly, the study shows the connection between applicants' fairness perception and their outcomes as well as their behavior (Konradt et al., 2013). Lastly, another finding of this study is that the treatment of applicants plays a dominant role in fairness perception (Konradt et al., 2013).

Another study conducted by Konradt in cooperation with different colleagues in the field was published in 2017. It is a longitudinal study covering three years, or six waves, and therefore *"(...) antecedents and behavioral effects of applicant procedural fairness perceptions before, during, and after a personnel selection procedure (...)"* (Konradt et al., 2017; p.113). For this purpose, Konradt et al. (2017) created a hypothesized model that illustrates the relationship between expected and perceived procedural fairness and its outcomes over the six waves already introduced, see illustration 7.



(Illustration 7: Hypothesized model. From Konradt et al., 2017; p.118)

Results show that pre-feedback fairness perceptions contribute positively to job acceptance and mid-term job performance but not to long-term performance (Konradt et al., 2017). Strong correlations of procedural fairness expectation and procedural fairness perception were found for: firstly, formal characteristics and interpersonal treatment explanation at pre- and post-test stages and secondly, for formal characteristics and explanation at the pre-feedback stage (Konradt et al., 2017). Therefore, the research of Konradt et al. (2017) provides explanations of which factors result in different behavioral outcomes of applicants' fairness perceptions at different points in time of the recruiting process, namely before and after hiring.

Lee (2018) considers in her research the (possibly) different perceptions of fairness regarding decisions taken by algorithms and humans. The researcher tested two kinds of tasks: mechanical and human (Lee, 2018). The analysis shows that for mechanical tasks, decisions by algorithms and humans lead to equal fairness and trustworthiness perception, but for different reasons (Lee, 2018). While humans were perceived that way due to their authority, algorithms were perceived as equally fair and trustworthy due to their efficiency and objectivity (Lee, 2018). Moreover, algorithms were generally seen as more critical than human decision-makers (Lee, 2018).

For the human tasks tested, human decisions were preferred to algorithms (Lee, 2018). The reasons for algorithms being seen as less fair were the perceived lack of human characteristics like intuition, subjectivity, and social recognition (Lee, 2018). Lee (2018) examined applicants who felt '*dehumanized*' by algorithms taking decisions upon them. Lee (2018) concludes that her work is an important contribution to understanding applicants' basic attitudes toward different decision-makers and infers that fairness perceptions also depend on the specific selection process that is conducted.

Dahm and Dregger (2019) devoted their research to user perception of AI-driven tools in personnel recruiting, development, and marketing. Furthermore, they wanted to find out which factors support their deployment and which hinder it (Dahm & Dregger, 2019). For this purpose, young professionals, who were studying part-time, were asked to assess three recruiting scenarios in which AI solutions are already applied (Dahm & Dregger, 2019). Dahm and Dregger (2019) use the Technology Acceptance Model (TAM) based on Ajzen (1985) in their research.

They came to the solution that their sample is generally open to the deployment of AI and is not afraid to be replaced by it in their own jobs (Dahm & Dregger, 2019). In recruiting, the most accepted AI applications are chatbots and preselection, whereas, e.g., telephone interviews were more rejected (Dahm & Dregger, 2019). Moreover, respondents argued that the further the selection process proceeds, the more human recruiters should be involved (Dahm & Dregger, 2019). In addition, users differ between different types of AI and appreciate AI, which augments the work of human recruiters the most (Dahm & Dregger, 2019).

Weitzel et al. (2020) conducted two studies: an empirical enterprise study, “Recruiting Trends 2020” that consulted Germany’s top 1.000 enterprises (measured by sales greater than 150m.) and the top 300 enterprises in the German IT sector (measured by sales greater than 30m.). The second is an empirical applicant study called “Bewerbungspraxis 2020” that examined 3.500 applicants.

Along with many other results, the analysis of these two studies has shown that 4 out of 10 top enterprises and 75% of top IT companies believe that a digitized recruiting process leads to more fairness in staffing (Weitzel et al., 2020). On the other hand, only 2% of surveyed applicants agree with this (Weitzel et al., 2020). Weitzel et al. (2020) found that the automation of personnel preselection has not progressed far. In 2020, only 6.1% of the top 1.000 enterprises and 9.4% of the top IT companies implemented such tools. Whilst the publication of advertising and job advertisements is already automated for 36.8% of the top 1.000 enterprises and 45.5% of the top IT companies. However, Weitzel et al. (2020) predict a catch-up by 2030.

Lederer et al. (2021) dedicated their research to the implementation of AI modules in relation to recruiting processes. They conducted an acceptance study consulting students soon to be applying for their first job to find out about their expectations and their limitations regarding the deployment of AI in recruiting processes (Lederer et al., 2021). The research shows that there are reasons for and against the implementation of algorithms (Lederer et al., 2021).

Arguments that speak in favor of the implementation of AI aim at less discrimination in connection with AI, higher practicability for enterprises, shorter waiting periods for applicants due to faster processing, and, therefore, more satisfaction on both sides (Lederer et al., 2021). On the other hand, AI is highly criticized when evaluating feelings and emotions, and its usage is not preannounced (Lederer et al., 2021). Overall, the researchers come to the result that AI is most widely accepted in earlier stages of personnel recruiting, such as preselection, and does not substitute human actions in total (Lederer et al., 2021).

Morse et al. (2021) address fairness perception in their research from an information technology perspective. Due to current developments in deploying machine learning models to make decisions within organizations, a new challenge has risen: those decisions ought to be fair and inclusive (Morse et al., 2021). To the avoidance of unfair perception of algorithmic decisions, five algorithmic criteria proposed by computer science are explored in this research paper (Morse et al., 2021).

The researchers argue that organizations must be aware that managing fairness in connection with AI is complex but of utter importance (Morse et al., 2021). The fairness criteria used in Morse et al.'s work (2021) are fairness through unawareness, demographic parity, accuracy parity, equality of opportunity, and equalized odds. Those are thought to include fairness in the architecture of algorithms further (Morse et al., 2021). Research analyzing whether those criteria also lead to increased fairness perception is still scarce but crucial (Morse et al., 2021). Therefore, Morse et al. (2021) use distributive and procedural fairness from organizational justice theory to take a closer look.

The researchers come to the conclusion that regarding distributive fairness, fairer outcomes are connected to a more technical effort which in turn leads to higher costs (Morse et al., 2021). Every algorithmic criterion has a different potential to ensure distributive fairness (Morse et al., 2021). Purely statistical solutions seem more likely to cause concerns (Morse et al., 2021). Morse et al. elaborate a framework to make clear how these five algorithmic criteria are reflected in procedural fairness perception (Morse et al., 2021). The researchers call for increased caution and that adaptations may be necessary in some cases (Morse et al., 2021). The main issue is how the decisions of algorithms are perceived. Therefore it is important that algorithms always consider the suitable criteria (Morse et al., 2021). In practice, therefore, it is a matter of finding the right technical solutions and implementing them in order to increase people's trust in such systems (Morse et al., 2021).

4.2 Research gaps

After a detailed discussion of previous research findings, a research gap can be identified.

Research addressing fairness perception in the context of selection processes has already been conducted excessively. Some researchers even examined the fairness perception of web-based selection (Konradt et al., 2013). Still, fairness perception in personnel preselection in relation to AI is under-researched. In addition, direct comparisons between human-made selection decisions and AI-driven selection decisions are scarce. Thus, the following research question continues to arise.

How is perceived fairness changed when implementing algorithms in personnel preselection?

Therefore, the following chapters should provide answers on how far changes in fairness perception, if any, might be present in relation to AI-driven preselection. Moreover, a comparison to human-driven preselection shall be provided.

4.3 Hypotheses

In the following section, three main hypotheses are presented. Additionally, ten subcategorized hypotheses are introduced. All of them build on Gilliland's model of applicants' reactions to employment selection systems (1993) and look at procedural justice rules. There are several reasons for this that have already been mentioned in chapter 3.2.2. One of the main reasons is the interdependence of distributive justice rules (Konradt et al., 2013).

For the hypotheses' formation, the current state of research presented in section 4.1, Overview of previous studies, was naturally taken into account.

<u>H1</u> Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the 'formal characteristics' component of procedural justice rules.

> <u>H1a</u> The procedural justice rule 'job relatedness' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.
> <u>H1b</u> The procedural justice rule 'opportunity to perform' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.
> <u>H1c</u> The procedural justice rule 'reconsideration opportunity' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.
> <u>H1d</u> The procedural justice rule 'consistency of administration' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

<u>H2</u> Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the 'explanation' component of procedural justice rules.

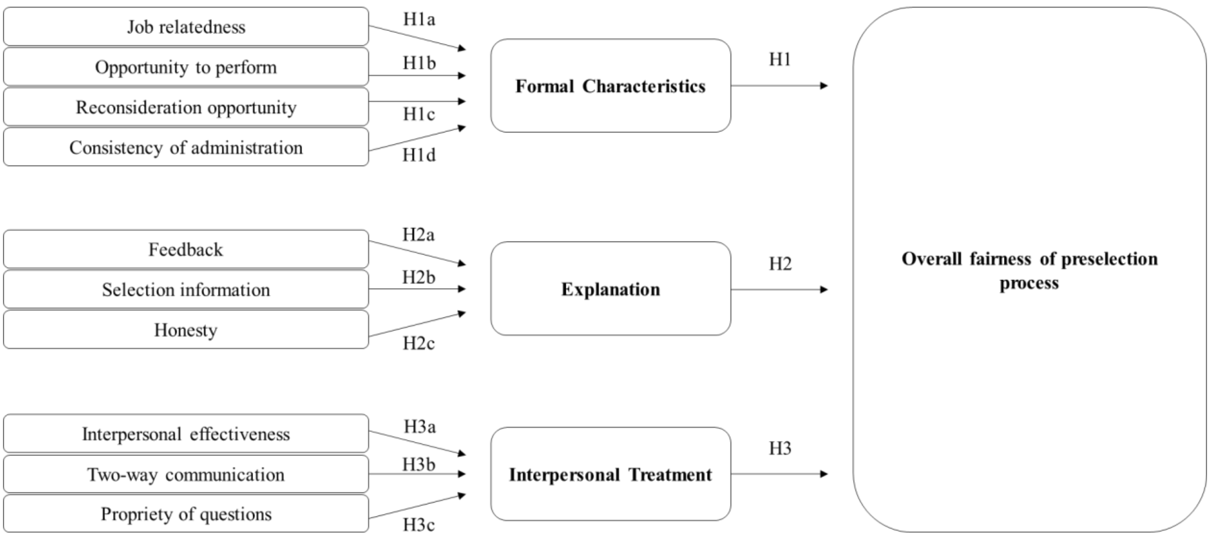
> <u>H2a</u> The procedural justice rule 'feedback' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.
> <u>H2b</u> The procedural justice rule 'selection information' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

H2c The procedural justice rule 'honesty' is satisfied less when deploying an algorithm instead of a human recruiter in personnel preselection.

H3 Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the 'interpersonal treatment' component of procedural justice rules.

H3a The procedural justice rule 'interpersonal effectiveness' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.
H3b The procedural justice rule 'two-way communication' is satisfied less when deploying an algorithm instead of a human recruiter in personnel preselection.
H3c The procedural justice rule 'propriety of questions' is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

Illustration 8 gives a quick overview of the hypotheses' categorization and affiliation. Therefore, it shows how the ten sub-hypotheses and the three main hypotheses interlock.



(Illustration 8: Overview of the hypotheses. Own illustration based on Konradt et al., 2013; p.157)

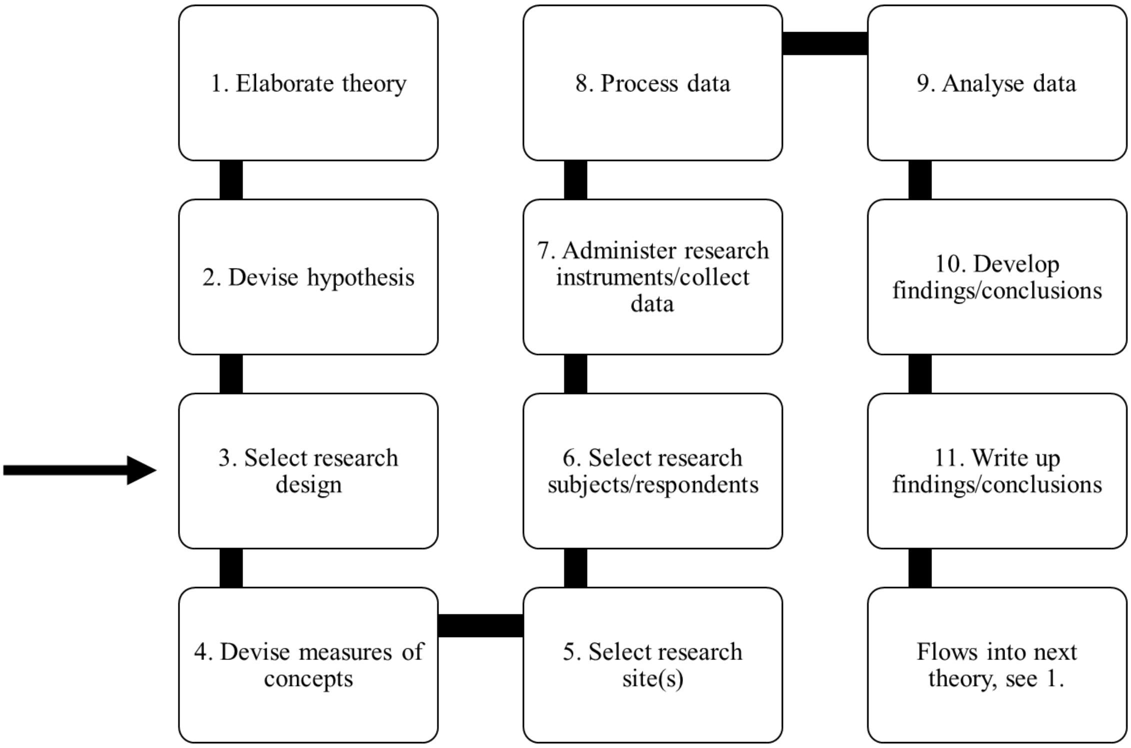
In the following chapters, 5. Research method, and 6. Empirical research of this thesis, the hypotheses are tested from a scientific point of view. According to these findings, they are verified or falsified.

5. Research method

Chapters 5 and 6 form the empirical part of this thesis. In the following section, the research design, a quantitative online survey, will be described. Further onwards, the sample will be analyzed and calculated. The last part of chapter 5 is about the operationalization and the procedure of the applied research design.

5.1 Method description: quantitative online survey

In the first step, quantitative research shall be explained in further detail. In illustration 9, its main steps are outlined (Bell et al., 2019). Furthermore, it is important to note that this sequence is not exhaustive and can also vary throughout different research contexts (Bell et al., 2019). After successfully forming hypotheses within chapter 4, see step 2, those are going to be tested in support of the selected research design being a quantitative online survey, see step 3 in the illustration (Bell et al., 2019).



(Illustration 9: The process of quantitative research. Own depiction is taken from Bell et al., 2019; p.165)

The research method applied, a quantitative online survey, can be further categorized as a ‘self-completion’ or ‘self-administered’ questionnaire (Bell et al., 2019). Self-completion questionnaires can be conducted via several modes of administration via handouts, postal letters, or online as it is done for the present research (Kuckartz et al., 2009; Bell et al., 2019).

Online self-completion questionnaires have certain advantages. They are cheaper to administer as no costs of traveling are involved, and respondents can answer them easily and fast at their own pace (Bell et al., 2019). This makes online self-completion questionnaires very convenient for respondents (Bell et al., 2019). Moreover, data is collected online and is, therefore, easier and faster to administer (Bell et al., 2019).

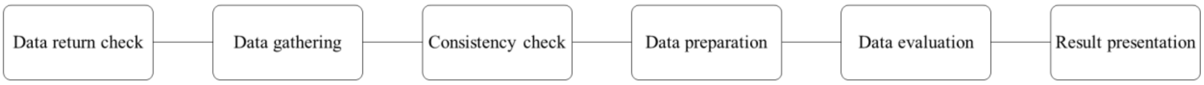
Bell et al. (2019) also note that interviewer effects are not present as such surveys are usually self-completed. The presence of an interviewer might influence answers, might therefore lead to answers that are socially more desirable, or might have an impact on the order of questions posed and answers given (Kuckartz et al., 2009; Bell et al., 2019).

Still, self-completion questionnaires entail some disadvantages too. Questions asked throughout such a survey must be posed in a simpler way in order to have respondents follow easily. This is due to no interviewer guiding them (Kuckartz et al., 2009; Bell et al., 2019). Therefore, most such questionnaires consist of closed questions more frequently than open questions (Bell et al., 2019). This makes it more difficult to explore completely new research fields as respondents cannot elaborate on their answers given, or if response fields enable them, respondents might not want to fill in long extensive answers (Bell et al., 2019). To avoid the so-called 'respondent fatigue', self-completion questionnaires must be shorter and easier to follow than other research methods, as respondents might discontinue or skip certain questions (Bell et al., 2019). Moreover, respondents might have a look through all questions before answering them, which might influence their answers too (Bell et al., 2019). Another disadvantage lies in the anonymity of respondents as researchers can never really know who completes their questionnaire, whereas some groups of respondents cannot be reached by self-completion questionnaires online, i.e., they might not have online access, might be illiterate or might not understand the questions in terms of language (Bell et al., 2019). Finally, response rates are lower as they appear less binding for respondents, which might increase biases (Bell et al., 2019). The application of a lottery can remedy this situation (Bell et al., 2019).

Furthermore, it is important to design a quantitative self-completion questionnaire in a way that does not take respondents longer than 15 minutes maximum to complete while its layout must look attractive and clearly arranged (Kuckartz et al., 2009; Bell et al., 2019). In order to avoid mistakes, a pretest before sending the questionnaire to subjects is suggested (Kuckartz et al., 2009).

For designing an online questionnaire, several response formats are possible (Kuckartz et al., 2009): Drop-down lists, radio buttons (standardized answer pool with one choice option), matrix answers (several questions are combined in one table), checkboxes, free text fields, and checked free text fields (like usual free text fields but with predefined syntax, for example, a date). Moreover, response formats can be binary, numerical, verbal, bipolar numerical, or in a frequency format (Bell et al., 2019). Implementing mandatory fields, filter questions, and a progress bar are powerful tools that help to measure more accurately and appear more legitimate (Kuckartz et al., 2009). Another question type is vignette questions that let respondents think themselves into scenarios and ask about their perceptions (Bell et al., 2019).

Moreover, Braunecker (2016) specifies the data analysis process in greater detail. See illustration 10, which is displayed in steps 8 to 11 in Bell et al.'s (2019) depiction. See illustration 9.



(Illustration 10: Data analysis process. Own depiction adapted from Braunecker, 2016; p.177)

As the first step of a proper data analysis process, Braunecker (2016) mentions a data return check. In this step, researchers should verify whether the data is suitable and complete and whether the sample exhausted is representative (Braunecker, 2016). Eventually, the structure of the obtained sample might vary a lot from reality, or the sample might not be exhaustive enough (Braunecker, 2016). In this case, follow-up surveys might become necessary, or weight factors might be defined (Braunecker, 2016). Braunecker's (2016) second step, data gathering, means bringing all data together into a system, e.g., MS Excel, SPSS, or else. This would evolve greater effort if data were not already collected digitally. The consistency check takes place before any data analysis (Braunecker, 2016). It is about ensuring that the data evaluation can start out without any problems regarding inconsistency, falsifications, or errors (Braunecker, 2016). Within the data preparation, variables, and values are usually described with the support of software for analysis and embellished to receive a more attractive output (Braunecker, 2016).

The last two steps of Braunecker's (2016) data analysis process are finally about the data evaluation and the result presentation. If quantitative data has been gathered, percentages, mean values, frequencies, standard deviations, and further statistical measures are calculated (Braunecker, 2016). If research is taken a little further, correlations and statistical significance tests are conducted to find out about connections between certain sample results and the population (Braunecker, 2016). The very last step consists of the result presentation, which deals with processing, interpreting, and generalizing the results (Braunecker, 2016). Here, the key findings are summarized and elaborated (Braunecker, 2016). Braunecker (2016) notes that, here, small samples can only serve as indicators of possible ratios but do not allow for conclusions on the basic population.

5.2 Sample

Within this chapter, steps 5, the selection of the research site, and 6, the selection of the respondents, of illustration 9 will be addressed. After the sample has been calculated and set, the construction and the implementation of the online questionnaire will be explained.

The selected sample consists of students and young professionals between the age of 18 and 35. This is because these people usually are at a point in their lives at which they have already gone through an application process, are currently going through one, or soon will. Therefore, it is thought that they can put themselves easier in such a situation and make estimations.

The sample is limited to students and young professionals in Austria. Throughout the academic year 2020/2021, 388.000 students were counted at Austrian universities (Statistik Austria, 2021). With this total number, Statistik Austria (2021) counts students from public universities, private universities, universities of applied sciences, teacher training colleges, and theological colleges. Moreover, students who are currently studying at several educational institutions or pursuing several degrees were adjusted to avoid being counted double (Statistik Austria, 2021). Furthermore, this number includes regular students, such as diploma, bachelor, master, teacher, and doctoral degree programs, as well as continuing education course participants (Statistik Austria, 2021).

The second group of the sample is the so-called young professionals. There is no clear definition of the term as such. Büdenbender and Strutz (2011) define this group as having finished a degree and only a few years of professional experience. Therefore, for this thesis sample, graduates below the age of 35 are counted. The number of young professionals in Austria is hard to define: Statistik Austria (2019) counts 307.000 Austrians (aged 20 to 34) who have already graduated.

Due to a lack of valid data, only a rough approximation of the actual affordable sample size can be made: 388,000 students and 307,000 young professionals make 695,000 people. This allows for determining the ideal sample size approximately. In order to receive a valid and representative sample size, factors like the level of confidence and the margin of error need to be taken into account (Survey Monkey, n.d.).

$$\text{Sample size} = \frac{\frac{z^2 * p\,(1-p)}{e^2}}{1+\left(\frac{z^2 * p\,(1-p)}{e^2 N}\right)}$$

$N \triangleq number\ of\ students\ in\ AT$

$e \triangleq margin\ of\ error$

$z \triangleq z\ value \triangleq\ standard\ deviation\ of\ mean\ value$

For setting this sample’s size, the level of confidence was aimed at 95%, while the margin of error was taken into account at 5% (Survey Monkey, n.d.). Therefore, the sample size was calculated at 384 respondents (Survey Monkey, n.d.). If this online questionnaire had reached a sample size of this amount of respondents, it would be a representative one. Still, simple random sampling gives an equal chance to individuals to participate and, therefore, also depends on the willingness of subjects to take part (Dillman et al., 2014).

Then, a questionnaire which can be classified into several question blocks will be provided. Along with the questionnaire, the 13 hypotheses generated will be tested. The questionnaire was available for participants online via Sosci from December 8th, 2022, till January 5th, 2023. Further information about the hypotheses is given in chapter 3, research questions.

On the first page of the questionnaire, participants get to know the thesis topic and learn that this survey especially addresses students and young professionals. Furthermore, they are informed about the time it will most likely take them to complete all questions. Lastly, they are reminded that they participate voluntarily and their data will be dealt with strictly confidential.

The questionnaire is structured along two scenarios, A and B, that address a similar situation like the following:

> You are currently looking for a job at a company of your choice. It is your first application at the chosen company. You have already handed in your CV and a motivation letter. Moreover, you had to answer questions from an **AI (Artificial Intelligence)** enabled robot during a video recording.
>
> Now it is the company's turn for its preselection of applicants like you. You know that the company will do this via deploying **AI** and not a human recruiter. The algorithm will review your CV, motivation letter, and your online interview to determine whether you are suitable for the next round.

Scenario A implies an AI, while scenario B addresses a similar situation but a video interview conducted by a human recruiter instead of the AI. In scenario B it is also a human recruiter who makes the decision whether the applicant is suitable for the next round.

After each scenario, respondents have to rate 4 statements from "strongly agree" to "strongly disagree" or with "don't know" to evaluate their understanding of the described situation. Afterwards, respondents are asked to rate 11 statements in relation to the previously described scenario on a scale from "strongly agree" to "strongly disagree".

A third block draws comparisons between the two deployed recruiting methods, namely AI and human recruiters. Respondents are asked 6 questions along which they have to decide whether they expect the indicated statements to be true for AI or a human recruiter or both equally. An example might be: "I expect that AI/ both equally/ human recruiters make/s their decisions with less biases."

The last part of the questionnaire asks for personal data like respondents' age, highest education completed, occupation, field of study or work, and the country of their current residency.

5.3 Operationalization and procedure

The survey has been online from December 8th, 2022, till January 5th, 2023. This makes exactly four weeks of data collection. It aimed to take respondents about seven minutes to complete. Still, analysis shows that, on average, respondents took about 8 minutes to finish the survey. Outliers are not considered.

A link leading to the online survey on SoSci survey was shared on several social media platforms to reach the desired target group, students and young professionals. The link was shared on WhatsApp, Instagram, and Facebook. Additionally to being shared in stories, it was also posted in dedicated student groups. Therefore, the sample was collected using random sampling.

The greatest difficulty during data gathering was reaching respondents aiming to finish the survey, as only fully finished responses were used for the final sample. Moreover, the final sample decreased after filtering out respondents who did not belong to the desired target group. It was further minimized due to four control questions that needed to be answered a certain way for the response to enter the final sample.

After collecting data for four weeks, the final data were downloaded. For analysis, they were uploaded to MS Excel. At first, the final sample was filtered regarding different aspects such as full completion, students and young professionals, age, education, current residence, and the four control questions.

Firstly, the percentages of drop-outs due to the filter criteria are shown. Afterward, the distributions of frequencies for each question in the survey were evaluated and presented individually. Some responses were summarized in a bar chart for reasons of space and clarity. Prior to this, the distribution of the final sample was analyzed in terms of gender and field of study/work, each shown in a pie chart separately.

Overall, the majority of relative and absolute frequencies were evaluated. The function of pivot tables was primarily used for this purpose. A direct evaluation of the numerical values behind the expressions of the answers was not carried out, as this would not provide any added value. To simplify the evaluation, the same tendencies, such as "strongly disagree" and "disagree", were often combined. This made it easier to analyze tendencies of agreement, disagreement, or neutrality towards a single aspect. Columns and pie charts were used exclusively for illustration purposes.

In the result interpretation, the results of different blocks of questions were compared and analyzed. Moreover, potential explanations for these developments were interpreted. Therefore, further graphs were used for an overview.

In the end, the hypotheses were tested along with the final results. This way, the research question is possibly best answered (Saris & Gallhofer, 2014; Scheufele & Engelmann, 2009). Finally, it is important to note that the final sample is not representative. See section 5.2 Sample.

6. Empirical research

The survey was shared online from December 8th, 2022, till January 5th, 2023. The link was clicked 417 times. The completion rate is at roughly 40%, which means that 168 participants have reached the last page of the survey. Illustration 11 gives a detailed overview of the filtering of the data described below to arrive at the final valid cases.

6.1 Result analysis

6.1.1 Filtering the final sample

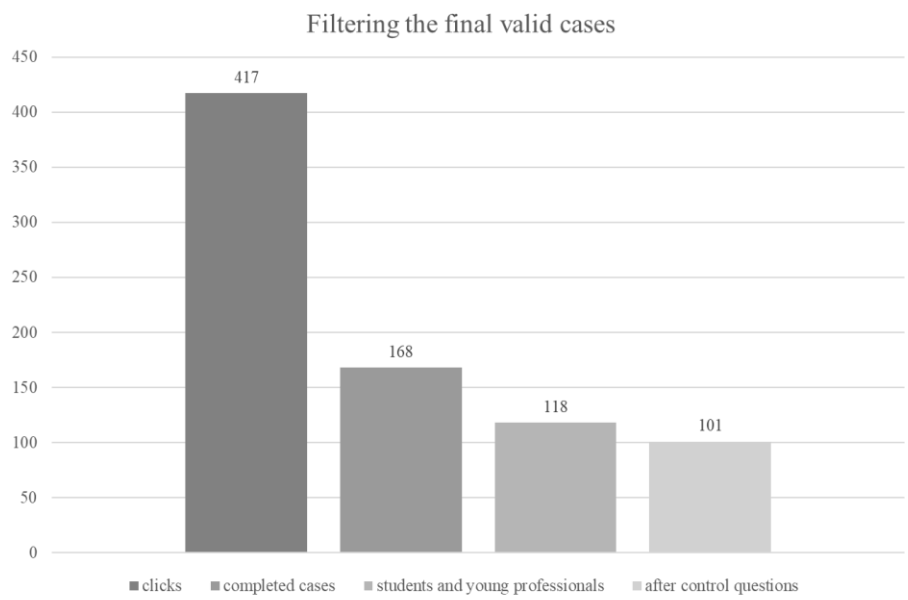
Filtering by two groups, namely students and young professionals, of this sample results in those cases valid for this research. Initially, all valid respondents were filtered into a possible age range of 18 to 35 years. Furthermore, all participants who did not name Austria as their current residence but another country were excluded from the sample. So no respondent taken into further account drops out of this age range or is not currently living in Austria.

Furthermore, the number of students counted as valid is defined as those who chose “university student” when asked about employment. This results in 46 valid respondents for the group of students. The second group taken into consideration are young professionals. For this sample, they were defined as those who chose the option “Vocational university/university of applied sciences/university degree” for the question about their formal education. Of course, those in both groups were filtered out into the second group. This leads to 72 valid respondents for the group of young professionals. In total, the filtered sample counts 118 valid cases.

Moreover, the online survey included four control questions to check whether participants understood the scenarios they were confronted with. The first question was implemented to check respondents’ comprehension of scenario A addressing an AI involved in personnel preselection. Therefore, participants who did not answer the question “The described situation is about AI involved in personnel preselection.” with either “agree” or “strongly agree” were excluded from the sample. The second control question was placed immediately afterward and indicated a totally different scenario than scenario A. Therefore, it should be negated by respondents. This is why participants who did not answer, “The described situation is about me deciding over applicants’ suitability for a job.” with one of the options “strongly disagree” or “disagree” were not counted in the final sample either.

The third control question is similar to the first one but checks comprehension of scenario B. This means that participants who did not choose the options “agree” or “strongly agree” for the statement “The described situation is about human recruiters involved in personnel preselection.” were not taken into further account. The last control question is the same as control question 2 but placed right after control question 3. Therefore, it was asked in the context of scenario B. Respondents who did not answer this question with “strongly disagree” or “disagree” were excluded from the sample again.

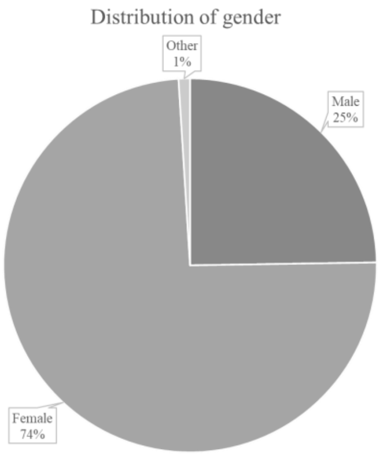
Due to these control questions, the sample of 118 valid cases was reduced to only 101 respondents, which represents the actual sample size to proceed. This means that roughly 24% of all clicks or, differently put, roughly 60% of all respondents finishing the survey are counted into the final sample.



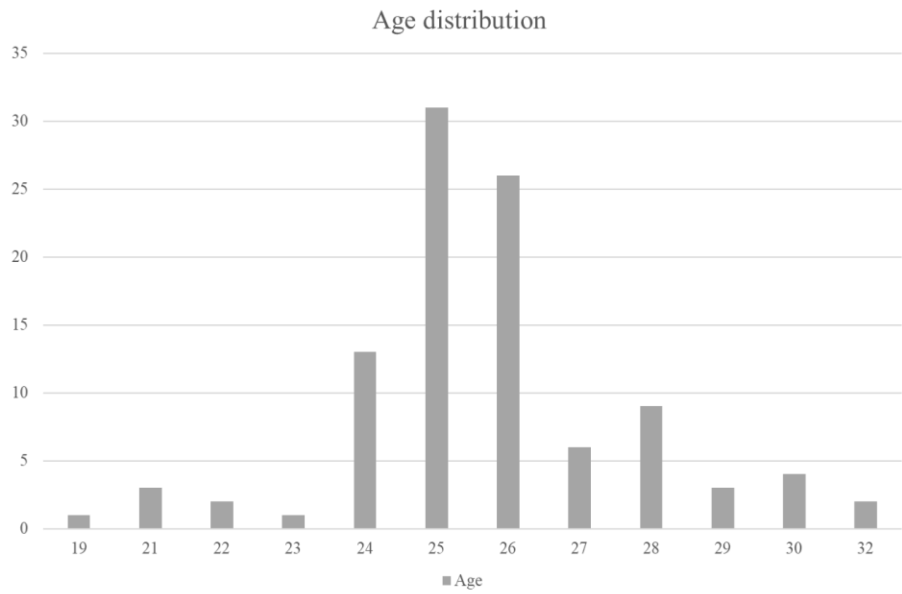
(Illustration 11: Filtering the final valid cases. Own depiction)

6.1.2 Socio-demographic aspects

The following two graphics show the final sample’s gender distribution and age distribution in detail. Illustration 12 clearly visualizes that almost three-quarters of the final sample’s respondents are female. Moreover, illustration 13 shows that the majority of participants are aged between 24 and 28, with culminates at 25 and 26.

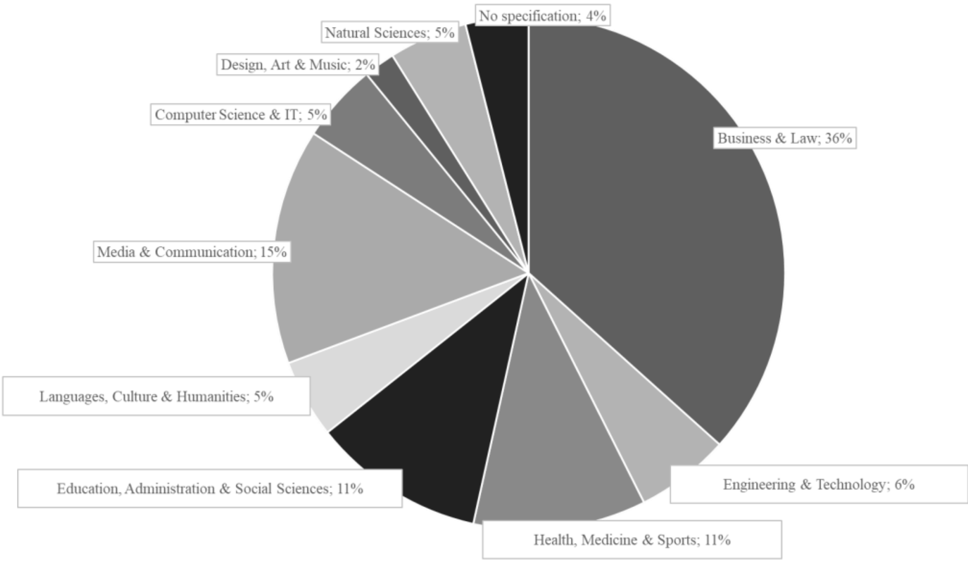


(Illustration 12: Distribution of gender. Own depiction)



(Illustration 13: Distribution of age. Own depiction)

Illustration 14 indicates the distribution of fields of study or work of respondents. The biggest part is “Business & Law” with 36%, followed by “Media & Communication” with 15%. “Education, Administration & Social Sciences” and “Health, Medicine & Sports” are somewhat significant, each with 11%. All other fields are only represented in very small numbers.



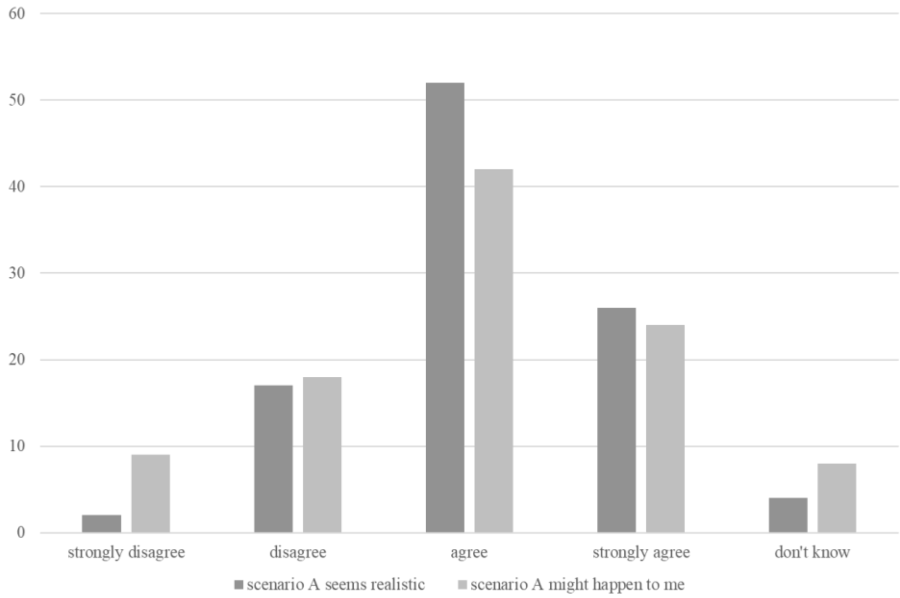
(Illustration 14: Distribution of fields of study/work. Own depiction)

6.1.3 Analysis of scenario A

In the following paragraphs, all further questions directly relevant to the research topic are addressed. This analysis is conducted in the same sequence as arranged in the actual survey.

After introducing scenario A to respondents, the first two of the four statements have already been used for filtering the final sample. Therefore, only two statements are left to be analyzed: “The described situation seems realistic.” and “The described situation might possibly happen to me.”.

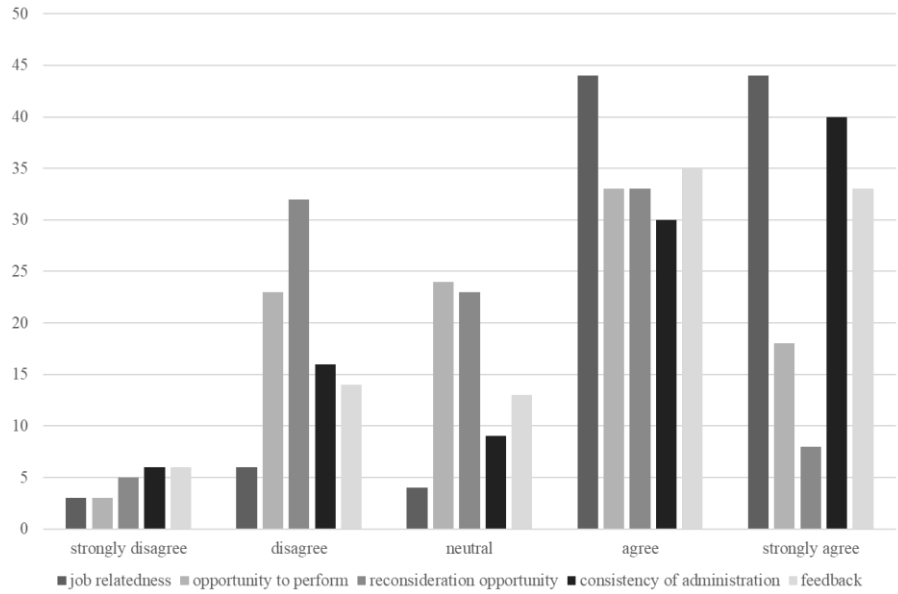
Illustration 16 shows the frequency distribution of answers provided by participants. Both statements show a similar trend in the distribution of votes. In total, the first statement about the scenario’s realisticity received the vast majority of 78 votes for the expressions of agreement and 19 for disagreement. The second statement about the likelihood of occurrence was rated with less agreement, with 66 responses and 27 votes for disagreement. Still, “The described situation might possibly happen to me.” accounts for four times more votes for “strongly disagree” and twice as many votes for “don’t know” in comparison to the first statement.



(Illustration 15: Distribution of responses, scenario A, A1.1, and A1.2. Own depiction)

Illustration 16 shows the distribution of responses regarding scenario A, i.e., AI involved in personnel preselection. For clarity, only five out of the eleven statements were summarized in one depiction. The other six statements are shown in illustration 17 and will be discussed immediately afterward.

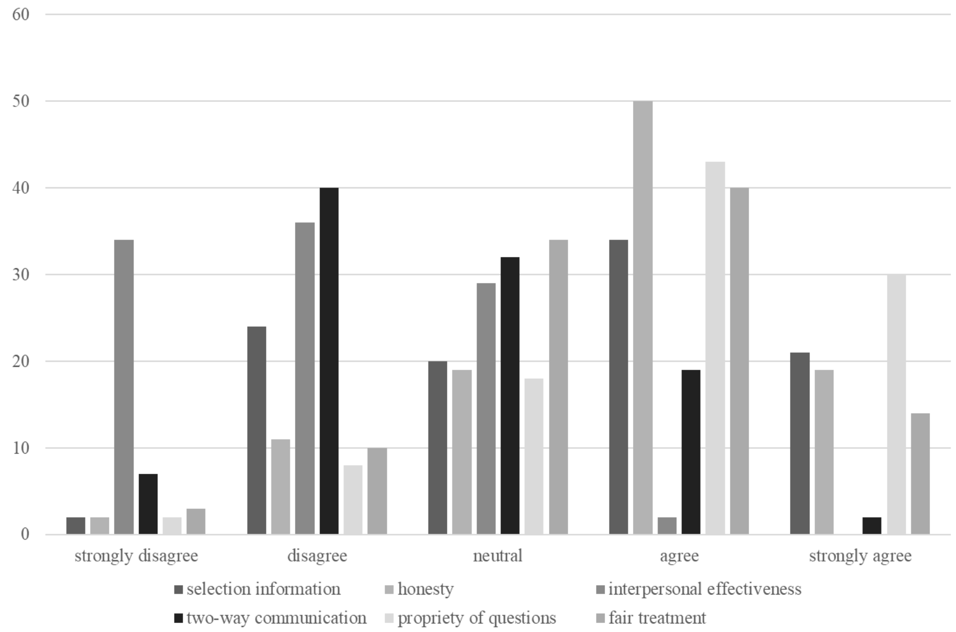
Illustration 16 is about the statements about ‘job relatedness’, ‘opportunity to perform’, ‘reconsideration opportunity’, ‘consistency of administration’, and ‘feedback’. ‘Job relatedness’ was mostly rated with dimensions of agreement with a total of 88 votes. The statement about ‘opportunity to perform’ was assessed more diversely. Options of disagreement make up 26, 24 votes express neutrality, and 51 respondents voted for the agreement. The third statement, ‘reconsideration opportunity’, does not receive clear approval or dislike. “Disagree” and “agree” balance each other with 32 and 33 votes, while 23 respondents chose “neutral”. This is the contrary with ‘consistency of administration’ as this statement receives big approval with a total of 70 counts for both expressions for agreement. Moreover, only 22 respondents took a disagreeing option here. The last statement, ‘feedback’, depicted in illustration 17, draws a similar picture: 68 votes for agreement, 13 neutral counts, and 20 votes for disagreement.



(Illustration 16: Distribution of responses, scenario A, A2.1 to A2.5. Own depiction)

As indicated before, illustration 17 deals with the remaining statements. These are ‘selection information’, ‘honesty’, ‘interpersonal effectiveness’, ‘two-way communication’, ‘propriety of questions’, and fair treatment.

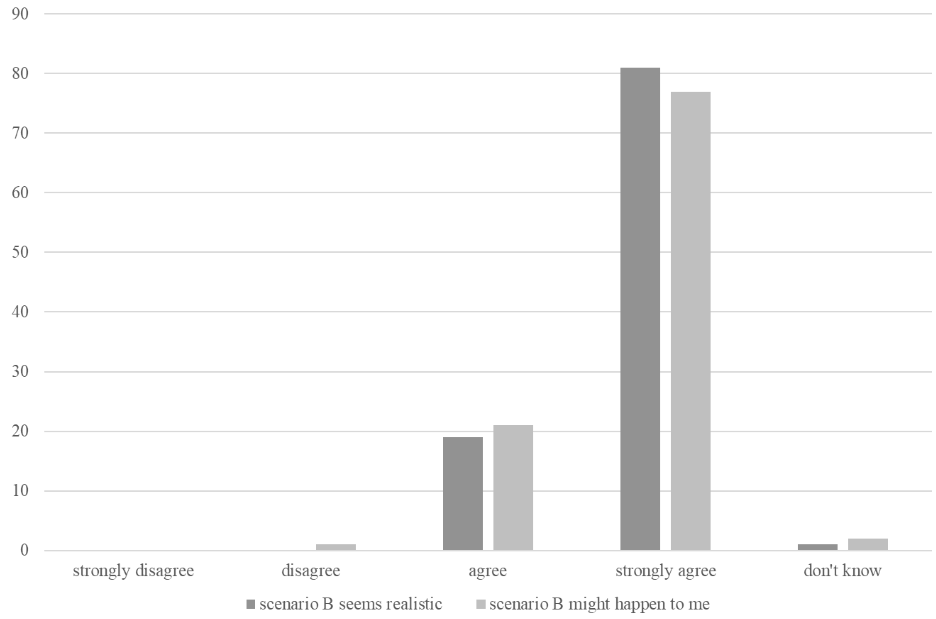
‘Selection information’ is assessed ambiguously with a tendency for approval. In total, 55 respondents voted for the agreement, while 26 chose a disagreeing option, and 20 took a neutral position. When analyzing ‘honesty’, the same tendency is visible. 69 respondents opted for “strongly agree” and “agree,” while only 13 went for a disagreeing option, and 19 were neutral. The statement about the ‘interpersonal effectiveness’ of AI shows completely different characteristics and a clear tendency towards disagreement. 70 respondents voted for disagreement, 29 for neutral, and only 2 for agreement. The statement regarding ‘two-way communication’ draws a more diverse picture: 47 participants opted for disagreement, 32 for the neutral option, and 21 for agreement. In turn, different again are the votes for ‘propriety of questions’. Here, 73 respondents chose an option for agreement, 18 were neutral, and 10 for disagreement. Therefore, a clear tendency towards an agreement is visible. The last statement is about fair treatment in total regarding AI being involved in personnel preselection. The majority, 54 respondents, chose agreement, while 13 opted for disagreement. Still, this statement was rated neutral by 34 participants. This is the highest expression of no tendency to take all eleven statements into account.



(Illustration 17: Distribution of responses, scenario A, A2.6 to A2.11. Own depiction)

6.1.4 Analysis of scenario B

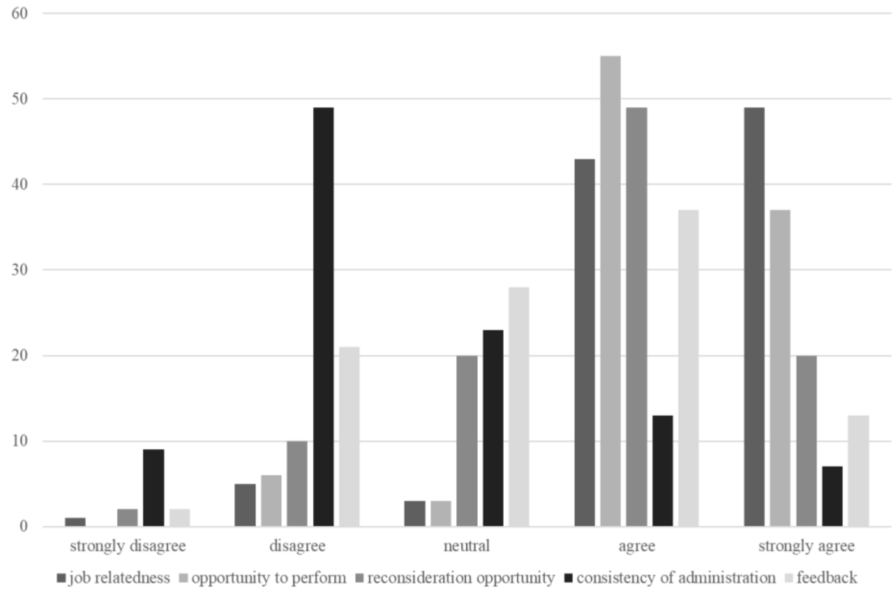
As already considered for scenario A, it accounts for scenario B as well that only two statements are left to be analyzed, namely “The described situation seems realistic.” and “The described situation might possibly happen to me.” Illustration 18 shows the frequency distribution of answers provided by respondents. Again, both statements show a similar trend in the distribution of votes. For both statements, the option “strongly agree” receives the biggest approval, with 81 votes for the first and 77 votes for the latter question. “Agree” accounts for the second highest vote count with 19 and 21 votes. The remaining options were only chosen to a negligible extent. Therefore, the first statement about the scenario’s realisticity reached a high of 100 responses of total agreement. The second one, regarding the likelihood of occurrence, culminates with 98 votes for agreement.



(Illustration 18: Distribution of responses, scenario B, B1.1, and B1.2. Own depiction)

Illustration 19 shows the distribution of responses regarding scenario B, so about human recruiters involved in personnel preselection. For clarity, only five out of the eleven statements were summarized in this depiction. The other six statements are shown in illustration 20 and will be addressed immediately afterward.

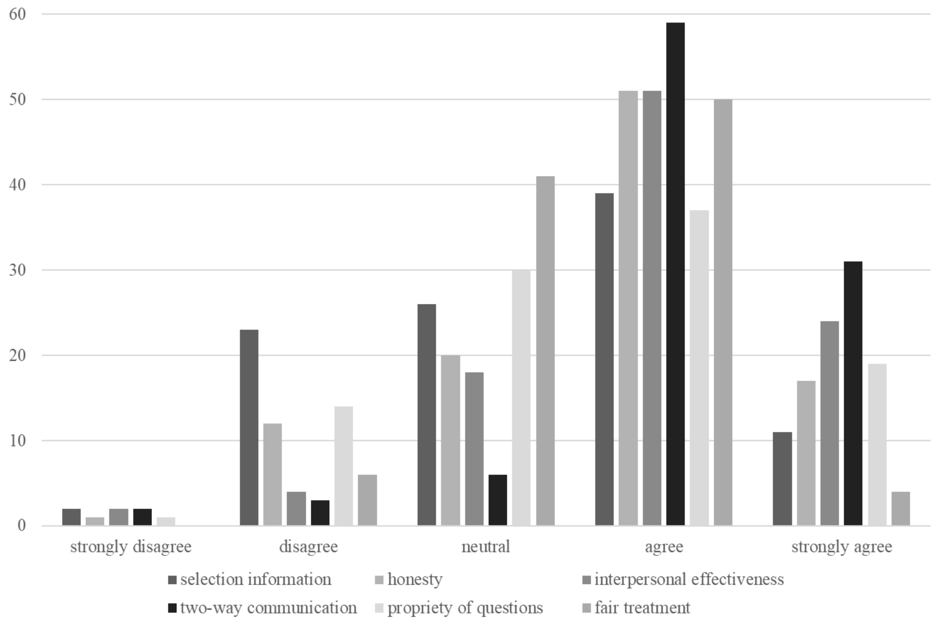
In illustration 19, the statements about ‘job relatedness’, ‘opportunity to perform’, ‘reconsideration opportunity’, ‘consistency of administration’, and ‘feedback’ are shown. The first statement about ‘job relatedness’ received the agreement of the major part of the respondents, namely 92 votes. This is the exact same for ‘opportunity to perform’: 92 votes for agreement. The statement about ‘reconsideration opportunity’ was more diverse, but with a majority of 69 respondents opting for agreement, 20 for neutrality, and 12 for disagreement. The fourth question addresses ‘consistency of administration’ and turns around the trend for high agreement of the last statements’ responses. Here, 58 respondents voted for disagreement, 23 for neutral, and 20 for agreement. The last pillars address the question regarding ‘feedback’. Analysis shows different tendencies here: 50 respondents opted for agreement while 28 chose the neutral option, and 23 took an option of disagreement for this statement.



(Illustration 19: Distribution of responses, scenario B, B2.1 to B2.5. Own depiction)

As already mentioned, illustration 20 deals with the six remaining statements for scenario B. These are ‘selection information’, ‘honesty’, ‘interpersonal effectiveness’, ‘two-way communication’, ‘propriety of questions’, and fair treatment.

In general, a tendency for agreement on all six statements is visible. The first statement addresses ‘selection information’. A majority of 50 respondents chose an option of agreement, 26 chose neutrality, and 25 disagreed. When asked about ‘honesty’, the tendency for agreement becomes intensified: 68 votes for agreement, 20 respondents voted neutrally, and 13 participants opted for disagreement. This continues with ‘interpersonal effectiveness’ and 75 agreeing responses, 18 neutral, and only 6 votes for disagreeing options. The next statement was about ‘two-way communication’. Here, results show 90 responses for “strongly agree” and “agree”. On the other hand, only 6 contributions were neutral, and 5 participants responded with “strongly disagree” or “disagree”. The statement concerning the ‘propriety of questions’ posed by human recruiters shows 56 votes for agreement, 30 for neutrality, and 15 for disagreement. In total, all five statements dealt with so far meet a great majority of respondents with approval. The last statement regarding scenario B addresses total fair treatment regarding human recruiters involved in personnel preselection. Interestingly, 54 respondents chose agreement, 41 neutral, and 6 voted for disagreement.



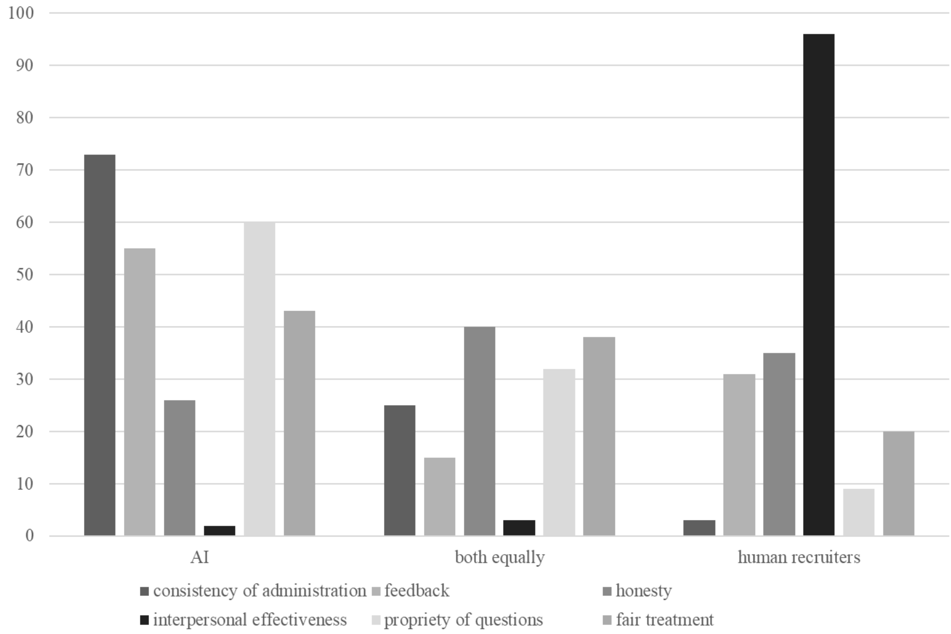
(Illustration 20: Distribution of responses, scenario B, B2.6 to B2.11. Own depiction)

6.1.5 Analysis of the comparison

The survey's last part concerning research content directly compares AI and human recruiters along six aspects that appeared to be most insightful on closer examination, these are: 'consistency of administration', 'feedback', 'honesty', 'interpersonal effectiveness', 'propriety of questions', and overall fair treatment. Therefore, respondents needed to decide whether they expected the indicated case to be more of an AI or a human recruiter or both equally.

In total, 606 answers were collected along the six statements posed. Out of this, AI received general encouragement of 259 responses, human recruiters achieved 194 votes, and 153 times "both equally" was chosen. This means that for these six statements, in total, 43% of expectations are set on AI, 32% are put on human recruiters, and 25% are assumed to be about both equally.

To be more specific, the statement about 'consistency of administration' was assigned to AI by a majority of 73 respondents. 25 opted for "both equally", and only 3 for human recruiters. The second statement concerned 'feedback'. Here, results are less widespread but still show a direction towards AI being assigned higher expectations of fairness: 55 participants chose AI, 15 both, and 31 human recruiters. 'Honesty' was mostly assigned to "both equally" with 40 votes. 26 respondents set higher expectations of AI, and 35 of human recruiters. Responses regarding the statement about 'interpersonal effectiveness' stand out. 96 participants voted for higher estimation on human recruiters, while only 2 chose AI, and 3 opted for "both equally". The statement about the 'propriety of questions' shows an inverse trend: 60 votes for AI, 32 for both, and only 9 for human recruiters. Finally, the last statement concerned overall fair treatment. Interestingly, the results of AI and “both equally” are rather similar: 43 for AI and 38 for both. For this statement, 20 respondents set their expectations of human recruiters.



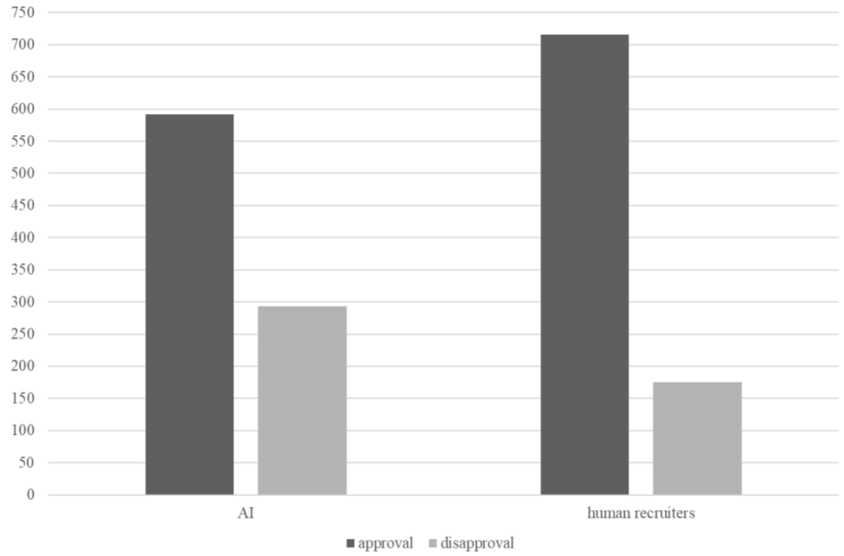
(Illustration 21: Distribution of responses, C1, Artificial Intelligence (AI) versus human recruiters. Own depiction)

6.2 Result interpretation

6.2.1 Comparing scenarios A and B

In this section, the analyzed results of the previous chapter will be compared and interpreted. At first, general approval and disapproval of AI and human recruiters being deployed in personnel preselection will be juxtaposed and compared. Therefore, the survey’s sections A2 and B2 are used as they both deal with the same nature of questions and track respondents’ approval and disapproval, along with eleven statements for each. For clarity, the options “strongly agree” and “agree” will be combined, “neutral” will be left aside as it does not track approval or disapproval, and “strongly disagree” and “disagree” will be merged as well.

In general, illustration 22 shows that approving options were preferred by respondents. Disapproval makes up roughly 33%, i.e., 293 votes for disagreement for AI, and about 20%, i.e., 175 votes for disagreement, for human recruiters. Furthermore, the overall approval of human recruiters is higher than that of AI as human recruiters reach 80%, i.e., 716 votes for agreement. On the other hand, AI receives 592 approving votes, which makes approximately 67%.



(Illustration 22: Total distribution of approval and disapproval, AI (A2) and human recruiters (B2). Own depiction)

The higher approval rating for human recruiters may be due to the fact that AI does not currently have a widespread role in personnel preselection. This might be why approval for a new approach like AI is more hesitant.

This assumption can be continued by the following figures. The first two questions after each scenario, A and B, show a general assessment of reality and the likelihood of occurrence. In general, both statements for both decision-makers, AI and human recruiters are viewed as realistic by respondents. The statement “The described situation seems realistic.” received 78 votes of agreement for scenario A and 100 votes for scenario B. Also, here, slightly higher approval for human recruiters as the traditional, well-known method is noticeable. The evaluation of ”The described situation might possibly happen to me.” shows that participants view the deployment of AI as rather unlikely. This might be due to AI still being deployed rarely in personnel preselection in Austria so far.

In the following paragraphs, scenarios A and B will be compared. This way, potential special aspects or anomalies can be identified. All results are summarized in illustration 23. The first procedural justice rule tested for both scenarios was ‘job relatedness’. Here both variants of decision-makers received an equal amount of approval. All in all, ‘job relatedness’ is expected by roughly 90% of respondents in total. Only a minor number of participants do not expect ‘job relatedness’ in order to preselect or reject candidates.

The second procedural justice rule concerns ‘opportunity to perform’. Comparing the results of both scenarios shows less approval of AI. While human recruiters receive more than 90% of respondents’ approval, AI is perceived differently. Only about 50% expect to have enough opportunity to demonstrate their skills and provide input for the

AI to make a fair choice. Maybe participants expect to be pressed into a rather fixed framework when AI is deployed. They may feel that an AI allows less freedom and deviates less from a predetermined agenda. Therefore, they might have the expectation of not being able to perform as they could with more freedom given. It might be their opinion a human recruiter acts differently and might take a more personal approach to them. This might be a reason why respondents preferred a probably more easygoing human recruiter concerning the aspect of ‘opportunity to perform’ and not a strict, rule-following AI. Perhaps, they expect a human recruiter to give some hints or advice on what to talk about or highlight for them to be able to perform especially well.

Next, ‘reconsideration opportunity’ was assessed. Here, human recruiters again receive higher expectations than AI. Roughly 70% of respondents expect to have different opportunities to prove their real capabilities and make the recruiter reconsider their first impression, while only about 40% expect this when AI is deployed. Maybe participants expect AI to be less flexible and stiff. They might think that recruiters might give them a second chance more easily if their first impression is not that good. Perhaps they fear that an AI should fulfill its strict process and not deviate from it. Moreover, they might think an AI forms its picture in the first few minutes based on fixed criteria that may evaluate a candidate worse than a human recruiter would. On the other hand, respondents might expect a human to be better at assessing the overall image of a candidate and to deviate more easily from their first impression if the person appears to be a better fit in other areas. It is possible that sympathy also plays a role here, which humans can be impressed with, but AI cannot.

Assessing ‘consistency of administration’ followed. The question addressing this procedural justice rule was about expectations regarding biases. Interestingly, AI is expected to make its decisions without biases about 70% of respondents. On the contrary, only approximately 20% of participants expect no biases in the decision-making of human recruiters. Respondents might trust AI more regarding biases or might expect AI only be deployed if fewer biases are its benefit.

The statement about the expected provision of timely and informative feedback after having made a selection of applicants is higher for AI (roughly 70%) but still about 50% for human recruiters. This result could be due to the fact that an AI is automated, is thought to have almost endless resources, and is therefore expected to give feedback more timely. On the contrary, the recruiter might be stressed and not be able to give feedback for a longer period of time. Maybe some of the respondents have already experienced this case by themselves personally.

Afterward, the procedural justice rule ‘selection information’ was assessed. Respondents did accredit AI with slightly higher expectations. The statement was about being well-informed about the selection process and the offer of reasonable explanations regarding the selection decision. Here again, respondents might have approved or disapproved hesitantly due to a lack of information about ‘selection information’ in the scenarios. Perhaps respondents expect, in case AI is applied, that they get a particularly detailed explanation in advance of how it works, assesses, and what exactly they have to do to start and end the process, but also what expects them. A reason for the rather high expected fairness to ‘selection information’ provided by a human recruiter might be the lower barriers when dealing with an actual human being. Respondents might think that a recruiter would explain the whole selection process to them verbally or written. They might expect to pose questions to make the selection process clear to them. Moreover, a selection process accompanied by a human recruiter is a well-established situation that is most likely not new to any of the respondents.

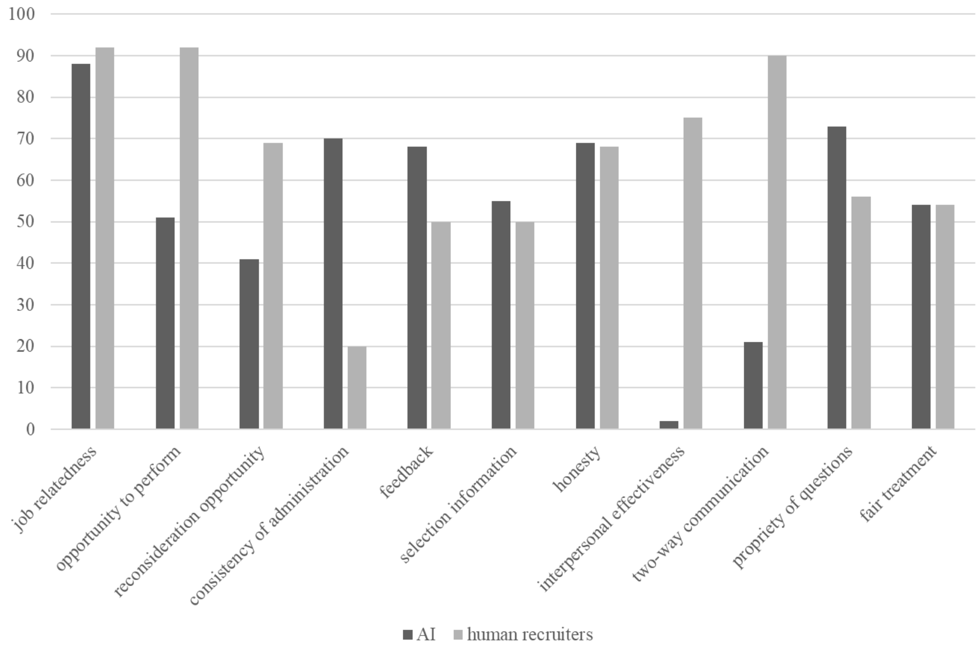
‘Honesty’ was addressed in the statement about credible and correct communication. Respondents’ answers did not reveal higher expectations by either AI or a recruiter. In general, about 70% of participants expect both to communicate credible and correctly. This might be about a general expectation towards a selection process. Respondents appear to have high confidence in the selection processes. Therefore, they might assume that they will not receive false information. Applicants know that in a selection process, not only they are looking for a job, but also the respective company is looking for an employee. Therefore, neither party is interested in manipulating the process to any great extent.

‘Interpersonal effectiveness’ is the most outstanding procedural justice rule addressed. About 75% expect to feel appreciated by a human recruiter, while only 2% expect the same by AI. Appreciation is thus not associated with AI. Therefore, this statement might have raised a new question for participants: Can AI actually appreciate? Can one, therefore, feel appreciated by AI at all? Moreover, respondents might think that AI does what it was programmed for and does not feel anything as if it is a machine. Respondents might not expect AI to do any differently. AI is not thought to be happy or sad when it finds a suitable candidate for an available vacancy. On the other hand, human recruiters definitely are.

Another aspect assessed is the procedural justice rule of ‘two-way communication’. Here again, the majority of respondents (approximately 90%) think they have the opportunity to add their input and their opinion when a recruiter is employed. Only about 20% of participants attribute the same to AI. This, again, might pay into the possible expectation of being pressed into a rather fixed framework when AI is deployed. Respondents might expect to be able to pose questions to a recruiter at any time during the process. On the other hand, AI might not allow this technically. Perhaps asking questions to an AI is only allowed during certain moments in the selection process.

Finally, the last procedural justice rule, ‘propriety of questions’, was addressed. The correlating statement was about the expectation of the questions provided in the video interview to avoid personal biases or topics raising concerns about privacy and illegality. Respondents indicated high expectations for both. 73 participants voted for approval regarding deployed AI, while 56 expect the same of an employed human recruiter. This might result due to the fact that every human has an unconscious bias automatically. Respondents might think that deployed AI does not have any bias at all.

The last statement of these two sections in the survey asked about overall fair treatment regarding the two scenarios of personnel preselection being either done by AI or a recruiter. Interestingly, both ways of decision-making are thought to perform equally well: 54 votes for both. Here, no preference regarding fair treatment is found.

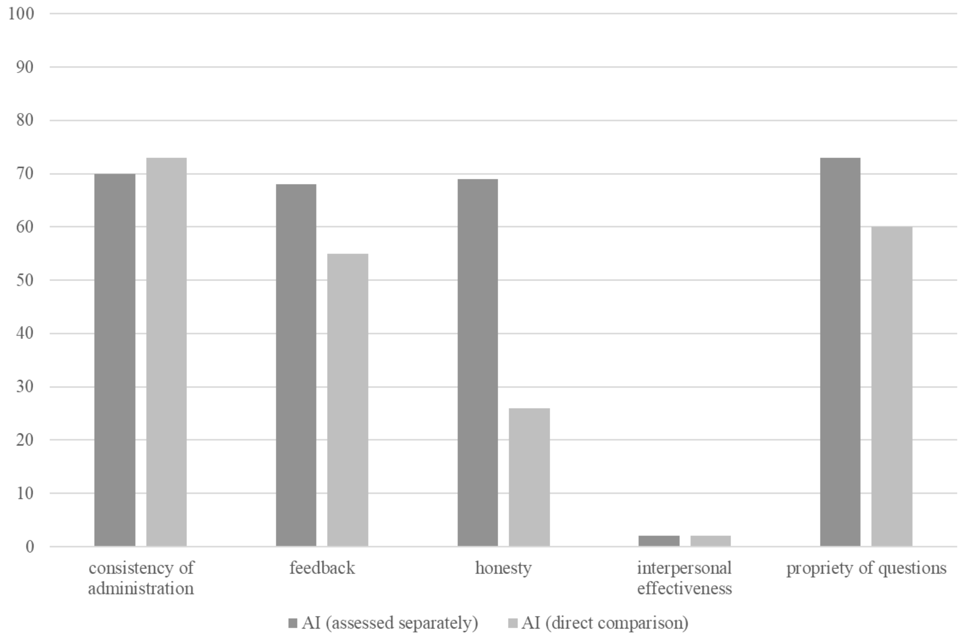


(Illustration 23: Distribution of overall approval regarding each statement separately, AI (A2) and human recruiters (B2). Own depiction)

6.2.2 Direct comparison vs. separate assessment

The last part of the survey assessing actual research content drew a direct comparison between the two modes of decision-making in personnel preselection. Five of the procedural justice rules and the last statement concerning overall fair treatment were assessed one more time. Illustration 24 shows each of the five aspects next to each other: The first bar of each group indicates the approval towards AI when assessed separately, and the second when assessed in direct comparison. Illustration 25 depicts the exact same for human recruiters. In illustration 26, all four bars regarding overall fair treatment are summarized.

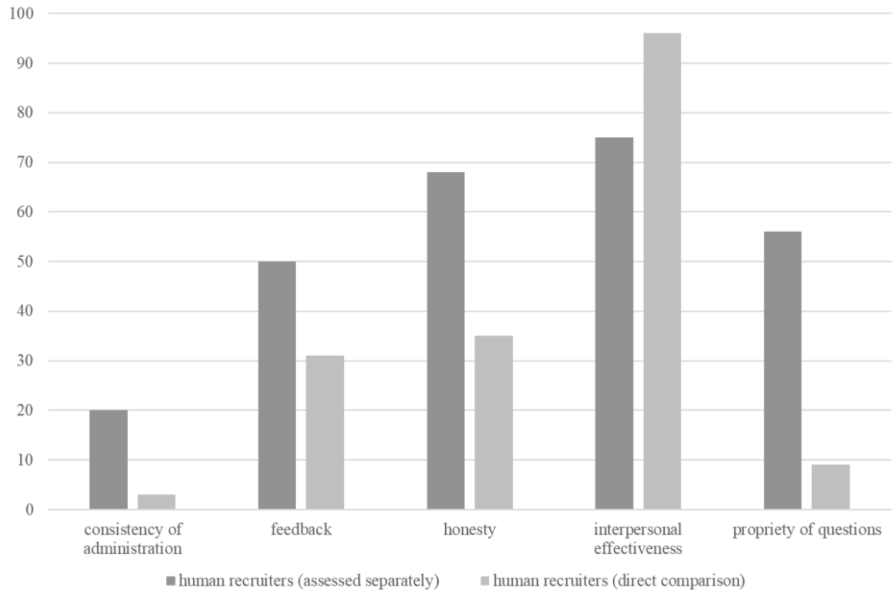
In general, respondents expected more of AI but did not stick to their original expectations when asked in direct comparison. The only exception is the procedural justice rule regarding ‘consistency of administration’. Here, fairness expectations were even a bit higher when asked in direct comparison. ‘Feedback’ and ‘propriety of questions’ experience only a minor decline in expectations. This can be partly explained by an increase of respondents voting “both equally” (‘feedback’: 15; ‘propriety of questions’: 32) when being asked in direct comparison. The justice rule ‘honesty’ shows a great decline when AI is not evaluated separately anymore but asked in the bigger picture. Possible reasons for this can be found in the group of “both equally” voters as well (‘honesty’: 40) or might be explained by people’s error of central tendency. Approval regarding ‘interpersonal effectiveness’ remains loyal and stays the same, namely vanishingly low.



(Illustration 24: Overall approval of AI when assessed separately (A2) and in direct comparison (C2). Own depiction)

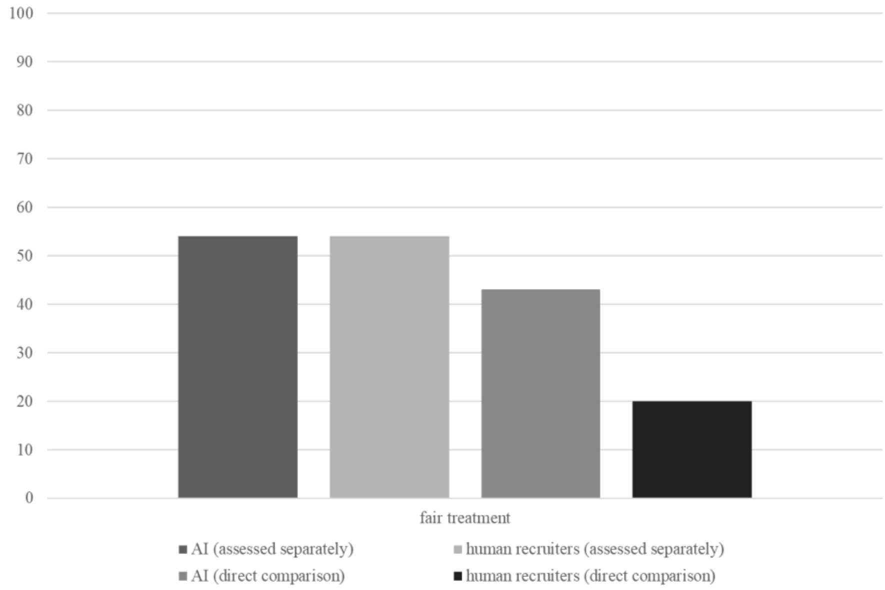
When asked separately, higher votes for human recruiters continue. Being assessed in comparison, a decrease in expectations regarding ‘consistency of administration’ for human recruiters is noticeable. This can be explained by higher votes for AI for the second assessment. Obviously, respondents expect higher fairness from AI in direct comparison, which is not the case for separate assessments. Feedback experiences slightly fewer expectations when being asked in direct comparison as well. Further procedural justice rules, ‘honesty’ and ‘propriety of questions’, were expected rather highly of human recruiters when being assessed separately. In the directly compared assessment, declines for both are visible as many respondents who were originally expecting human recruiters to communicate credible and correctly and to provide suitable questions jumped over to vote for “both equally”. Again, the procedural justice rule ‘interpersonal effectiveness’ stands out when respondents are asked about their expectations regarding human recruiters. This aspect is the only one that even shows an increase in votes of approval: from roughly 75% to 96% when asked in comparison.

‘Interpersonal effectiveness’ seems to be a characteristic only expected to be accessible to human recruiters.



(Illustration 25: Overall approval of human recruiters when assessed separately (B2) and in direct comparison (C2). Own depiction)

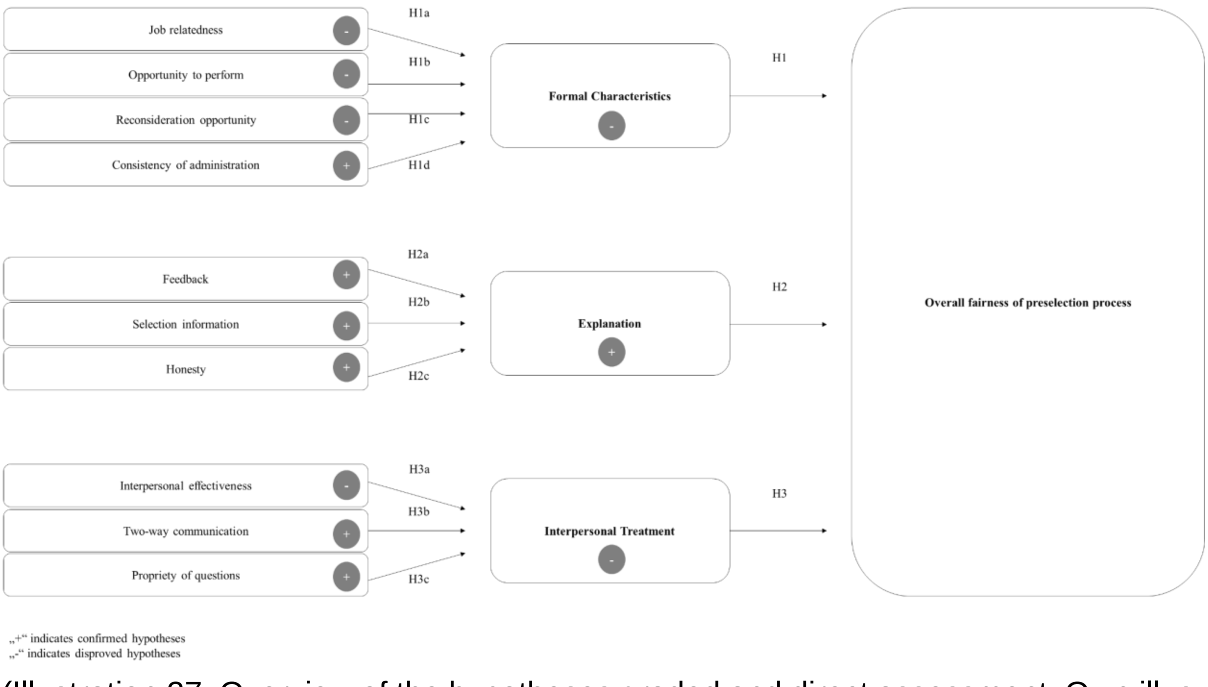
As already introduced a few paragraphs ahead, illustration 26 depicts all questions posed regarding fair treatment in general. This means two bars are for the two separately asked statements concerning AI and human recruiters. Moreover, two further bars show expectations towards both modes of decision-making when assessed in direct comparison. Both AI and human recruiters lost their original level of expected fair treatment when respondents were asked in direct comparison. A reason for this can be once again found in the group of “both equally” voters. Still, both decision-makers start from the same level of expectations, 54 votes. Along with the last question, the expectations towards human recruiters declined by 63%, while those for AI only declined by 20%. When directly compared and actually asked about expected fair treatment, this sample’s majority voted for higher expectations of AI than human recruiters. One possible explanation could be that respondents attribute high fairness to the idea and their expectations of AI. This comes to the surface in the direct comparison. However, if fairness is broken down into its individual aspects, this holds no longer. Then it is no longer the idea of the two decision modes that are assessed but the individual aspects that actually constitute fairness according to the model applied. Obviously, the respondents have higher expectations of AI in the direct comparison, which does not prove in the individual aspects.



(Illustration 26: Overall approval of fair treatment when assessed separately (A2.11, B2.11) and in direct comparison (C2.11). Own depiction)

6.3 Testing of hypotheses

In the following section, the results of the analysis and interpretation are combined. Therefore, all 13 hypotheses can be tested. Illustration 27 gives an overview of the hypotheses graded. The approach used is that the subordinated hypotheses are tested in the first place. Afterward, each main hypothesis is addressed accordingly. This way, all results flow into the research question, which can be answered as the very last step.



(Illustration 27: Overview of the hypotheses graded and direct assessment. Own illustration based on Konradt et al., 2013; p.157)

H1a The procedural justice rule ‘job relatedness’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

Testing this hypothesis is a very close decision. Still, it has to be negated as human recruiters received higher overall approval than AI.

H1b The procedural justice rule ‘opportunity to perform’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This hypothesis must be negated as well. Respondents clearly expect more ‘opportunity to perform’ when being assessed by a human recruiter in the preselection.

H1c The procedural justice rule ‘reconsideration opportunity’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This hypothesis could also be disproved. Human recruiters are expected to provide higher ‘reconsideration opportunity’ than AI.
H1d The procedural justice rule ‘consistency of administration’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This hypothesis can be clearly confirmed. The procedural justice rule ‘consistency of administration’ was assessed twice, and both times, the same result showed higher perceived fairness of an AI. In direct comparison, ‘consistency of administration’ could even achieve a slight increase.

H1 Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the ‘formal characteristics’ component of procedural justice rules.

All three subordinated hypotheses H1a to H1d pay into the main hypothesis H1. As H1a, H1b, and H1c were disproved, and only H1d could be confirmed, H1 cannot be confirmed either. This research comes to the result that formal characteristics do not result in higher fairness perception when AI is deployed.

H2a The procedural justice rule ‘feedback’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This subordinated hypothesis can be clearly confirmed. Still, feedback expectations towards AI did not increase throughout its second assessment in direct comparison. Nonetheless, it is in the lead when compared to human recruiters.

H2b The procedural justice rule ‘selection information’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This hypothesis could be confirmed. It is a close decision again, but in total, respondents expect ‘selection information’ to be higher when an AI is deployed.

H2c The procedural justice rule ‘honesty’ is satisfied less when deploying an algorithm instead of a human recruiter in personnel preselection.

Here, a more difficult case is opened up. When being assessed separately, the expected ‘honesty’ of AI is slightly higher than of human recruiters (the difference makes up only 1 vote). Later, in the second assessment comparing AI and human recruiters directly, the expected ‘honesty’ of human recruiters is definitely higher by almost 10 votes. Therefore, hypothesis H2c can be confirmed.

H2 Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the ‘explanation’ component of procedural justice rules.

The results of the subordinated hypotheses H2a till H2c pay into the clear confirmation of the main hypothesis H2. Hypothesis H2c signifies the exact opposite of the statement indicated in H2 and is phrased in favor of human recruiters and not AI. Still, the majority of subordinated hypotheses definitely qualify H2’s confirmation.

H3a The procedural justice rule ‘interpersonal effectiveness’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

Both assessments of this hypothesis regarding ‘interpersonal effectiveness’ clearly indicate it has been proven wrong. Therefore, H3a must be disproved. Expectations regarding human recruiters even became higher when being assessed in direct comparison to AI.

H3b The procedural justice rule ‘two-way communication’ is satisfied less when deploying an algorithm instead of a human recruiter in personnel preselection.

For this hypothesis, a very clear result is obtained, and it can be confirmed. Much higher expectations regarding ‘two-way communication’ are set on human recruiters than AI.

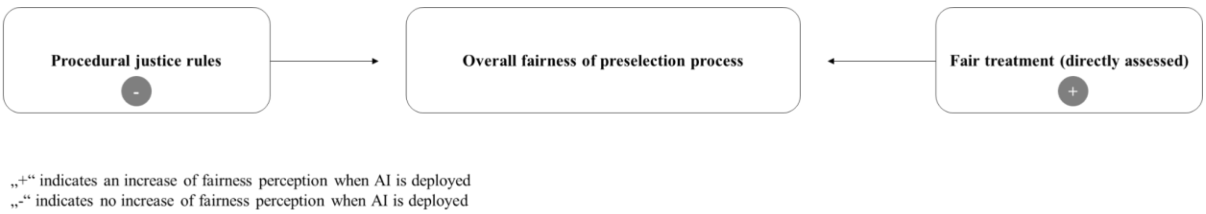
H3c The procedural justice rule ‘propriety of questions’ is satisfied more when deploying an algorithm instead of a human recruiter in personnel preselection.

This hypothesis can be confirmed. Throughout this justice rule's two assessments, expectations remained higher towards AI than human recruiters. Still, when being assessed in direct comparison, AI did not experience an increase in expectations regarding the 'propriety of questions'. Nonetheless, this does not influence its confirmation.

H3 Compared to human recruiters, the implementation of algorithms in personnel preselection results in increased perceived fairness in light of the 'interpersonal treatment' component of procedural justice rules.

This main hypothesis is composed of three subordinated ones. H3a was disproved. H3b could be confirmed but is phrased in favor of human recruiters and not AI. Furthermore, H3c was confirmed. Due to these results, the deployment of AI does not result in an increase in fairness perception regarding interpersonal treatment. H3 must be disproved.

In conclusion, the overall findings can be summarized as follows. Three statements in the survey assessed overall expected fair treatment directly. This led to the opposite result as the applied justice rules did: Overall expectations towards AI were higher than towards human recruiters. This was the case for the statement being assessed separately, but also in the direct comparison. Both factors, procedural justice rules and directly assessed fair treatment, need to be paid attention to in order to answer the given research question. Illustration 28 shows both factors that need to be taken into account and the result of each. The final conclusion concerning the research question is addressed in the following chapter.



(Illustration 28: Assessment of overall fairness of a preselection process. Own illustration based on Konradt et al., 2013; p.157)

7. Conclusion and outlook for further research

The research question is once again given as follows:

How is perceived fairness changed when implementing algorithms in personnel preselection?

Due to the results previously discussed, the research question cannot be answered clearly. When implementing algorithms in personnel preselection, fairness perception does not change clearly. This research comes to the result that neither AI nor human recruiters are perceived as a fairer choice in personnel preselection.

Still, there are some aspects that experience an increase in fairness perception regarding the deployment of either AI or human recruiters. AI is perceived as fairer regarding aspects concerning the mode of procedure. These are ‘consistency of administration’, ‘feedback’, and the ‘propriety of questions’. Additionally, AI is perceived as faster, more correct, more consistent, and expected to choose questions that avoid biases or concerns about privacy or illegality.

Moreover, there are some factors for which it does not seem to make a big difference regarding the deployed decision maker. These are ‘job relatedness’, ‘selection information’, and ‘honesty’. In general, respondents seemingly perceive both AI and human recruiters to base their decisions on information relevant to the vacancy, provide enough context regarding the selection process, and communicate credible and correctly.

Lastly, human recruiters cannot be beaten by AI for some factors influencing fairness perception. The human aspect is of importance when it comes to ‘opportunity to perform’, ‘reconsideration opportunity’, ‘interpersonal effectiveness’, ‘two-way communication’. To sum up, these are all factors where exchange among real humans is necessary and cannot be replaced easily. Possibly interaction with an actual person is perceived to be fairer regarding common sense in decision-making.

Further research might assess overall fairness by implementing all justice rules, procedural and distributive, of Gilliland’s model (1993). As indicated in the section *state of research*, many further models for measuring the fairness of selection processes exist. Further research might use a different model and compare the results to the ones resulting from the present analysis. Further research might also assess the final step of the selection process instead of the first step, namely preselection. Furthermore, not fairness but acceptance of applicants might be evaluated as well as these two components are most likely related.

Moreover, a more extensive and diverse sample might lead to more valid results. Further different insights might result from respondents of another age group or level of education. Additionally, assessing HR staff employed in recruiting might lead to different understandings. Another possible research might be focusing on a foreign country than Austria. Comparing the findings of similar samples from other countries might be a further interesting approach as well. Perhaps differences are measurable according to the technological progress of the countries surveyed.

In November 2022, OpenAI's ChatGPT was released (OpenAI, 2022). ChatGPT is a prototype of a chatbot (OpenAI, 2022). The release of the chatbot and further AI causes significant opportunities but also threats for many business sectors and is most likely only the beginning (Wittram-Schwardt & Bogs, 2021; Gordijn & Have, 2023; The Lancet Digital Health, 2023). Many competitors of ChatGPT already exist, and more are yet to be published (Mellow, 2023; Kim, 2023). Further research might pursue a similar approach as the present research and assess fairness perceptions before and after ChatGPT's release and the increasing public awareness of such powerful tools.

Probably the right choice between both modes, human recruiters and AI, lies in the middle, so in the mix of deploying both AI and human recruiters as both decision-makers have their benefits about fairness perception. Morse et al. (2021) have put it this way: "*Indeed, humans and machines must work together to alleviate unfairness in this new digital age of work."* (p.11).

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Appendices

Appendix A: List of abbreviations

AGI	Artificial General Intelligence
AI	Artificial Intelligence
ANI	Artificial Narrow Intelligence
ANN	Artificial Neural Networks
ASI	Artificial Superintelligence
CC	Cognitive Computing
HR	Human Resources
KI	Künstliche Intelligenz
NIST	National Institute of Standards and Technology
TAM	Technology Acceptance Model
VUCA	Volatile, Uncertain, Complex, Ambiguous

Appendix B: List of illustrations

Appendix C: List of tables

Appendix D: Survey

Thank you for your choice to participate in my survey!

My name is XXX and I am currently studying International Business Administration at the University of Vienna. In my Master Thesis I am investigating **fairness perception in AI enabled algorithm-driven personnel preselection.**

This survey addresses students and young professionals.

You will need about 7 minutes to complete this survey. The participation is voluntary. There will be no personal data collected and the analysis is strictly confidential and anonymous. The data will not be passed on to third parties and only used for my academic research purposes.

Thank you for your support already in advance!

SCENARIO A) Below, you can read the description of a fictional situation. Please imagine yourself being in the following scenario.

You are currently looking for a job at a company of your choice. It is your first application at the chosen company. You have already handed in your CV and a motivation letter. Moreover, you had to answer questions to an **AI (Artificial Intelligence)** enabled robot during a video recording.

Now it is the company's turn for its preselection of applicants like you. You know that the company will do this via deploying **AI** and not a human recruiter. The algorithm will review your CV, motivation letter and your online interview to determine whether you are suitable for the next round.

A1. Please, answer the following 4 statements, to make sure you have read and understood the described situation.

(From strongly disagree to strongly agree; don't know)

A1.1 The described situation seems realistic.

A1.2 The described situation might possibly happen to me.

A1.3 The described situation is about AI involved in personnel preselection.

A1.4 The described situation is about me deciding over applicants' suitability for a job.

A2. Along the following section, your fairness perception towards <u>Artificial Intelligence (AI)</u> in preselection processes is tested. Please, rate the following statements.

(From strongly disagree to strongly agree)

A2.1 I expect AI to use questions and criteria that are relevant and connected to the job in order to preselect or reject candidates.

A2.2 I expect I would have enough opportunity to demonstrate my skills and provide input for the AI to make a fair choice.

A2.3 I expect I would have different opportunities to prove my real capabilities and make the AI reconsider the first impression.

A2.4 I expect AI to make its decisions without biases.

A2.5 I expect AI to provide timely and informative feedback after having made a selection of applicants.

A2.6 I expect that I would be well informed about the selection process and would be offered reasonable explanations regarding the selection decision.

A2.7 I expect AI's communication to be credible and correct.

A2.8 I think I would feel appreciated during the selection process.

A2.9 I think the AI would give me the opportunity to add my input and my opinion.

A2.10 I expect the questions provided in the video interview to avoid personal biases or topics raising concerns about privacy and illegality.

A2.11 I think I would be treated fairly by the AI during my preselection process.

SCENARIO B) Below, you can read the description of a fictional situation. Please imagine yourself being in the following scenario.

You are currently looking for a job at a company of your choice. It is your first application at the chosen company. You have already handed in your CV and a motivation letter. Moreover, you had to participate in a video interview. During this interview, a **human recruiter** asked you some questions and vice versa you could pose questions to the company's recruiter who was happy to answer them throughout your interview.

Now it is the company's turn for its preselection of applicants like you. You know that the company will do this via deploying a **human recruiter** and not an AI. The company's recruiter will review your CV, motivation letter, their notes and impressions from your video interview to determine whether you are suitable for the next round.

B1. Please, answer the following 4 statements, to make sure you have read and understood the described situation.

(From strongly disagree to strongly agree; don't know)

B1.1 The described situation seems realistic.

B1.2 The described situation might possibly happen to me.

B1.3 The described situation is about human recruiters involved in personnel preselection.

B1.4 The described situation is about me deciding over applicants' suitability for a job.

B2. Along the following section, your fairness perception towards a <u>human recruiter</u> in preselection processes is tested. Please, rate the following statements.

(From strongly disagree to strongly agree)

B2.1 I expect the recruiter to use questions and criteria that are relevant and connected to the job in order to preselect or reject candidates.

B2.2 I expect I would have enough opportunity to demonstrate my skills and provide input for the recruiter to make a fair choice.

B2.3 I expect I would have different opportunities to prove my real capabilities and make the recruiter reconsider their first impression.

B2.4 I expect the recruiter to make their decisions without biases.

B2.5 I expect the recruiter to provide timely and informative feedback after having made a selection of applicants.

B2.6 I expect that I would be well informed about the selection process and have been offered reasonable explanations regarding the selection decision.

B2.7 I expect the recruiter's communication to be credible and correct.

B2.8 I think I would feel appreciated during the selection process.

B2.9 I think the recruiter would give me the opportunity to add my input and my opinion.

B2.10 I expect the questions provided in the video interview to avoid personal biases or topics raising concerns about privacy and illegality.

B2.11 I think I would be treated fairly by the recruiter during my preselection process.

C1. Along the following section, your fairness perception of <u>Artificial Intelligence (AI) versus human recruiters</u> in preselection processes is tested. Please, assign your tendency of the statements underneath either to Artificial Intelligence (AI), human recruiters, or both equally.

C2.4 I expect that ______ makes their decisions with less biases.

C2.5 I expect that ______ provides feedback more timely and informative after having made a selection of applicants.

C2.7 I expect that the communication of ______ is more credible and correct.

C2.8 I think that I would feel more appreciated by _______ during the selection process.

C2.10 I think that the questions provided by ______ in the video interview were more focused on avoiding personal biases or topics raising concerns about privacy and illegality.

C2.11 I expect that I would be treated more fairly by ______ during my preselection process.

D) Finally, please answer the questions related to your demographic data. Thank you!

D1 Age [to be filled in]

D2 Gender

D2.1 Female

D2.2 Male

D2.3 Other

D3 Highest education completed

D3.1 Finished school with no qualifications

D3.2 Still in school

D3.3 Secondary school-leaving certificate/Junior High Diploma

D3.4 High school diploma/Intermediate/General Certificate of Secondary Education, secondary school-leaving certificate or equivalent

D3.5 Completed apprenticeship

D3.6 Vocational baccalaureate diploma, vocational secondary certification

D3.7 A-levels/International Baccalaureate/Higher education entrance qualification

D3.8 Vocational university/university of applied sciences/university degree

D3.9 Other degree: ______

D4 Occupation

D4.1 Pupil/in school

D4.2 Training/apprenticeship

D4.3 University student

D4.4 Employee

D4.5 Civil servant

D4.6 Self-employed

D4.7 Unemployed/seeking employment

D4.8 Other: ______

D5 Current residency

D5.1 Austria

D5.2 Germany

D5.3 Switzerland

D5.4 Other: ______

D6 Field of study/work

D6.1 Business & Law

D6.2 Engineering & Technology

D6.3 Health, Medicine & sports

D6.4 Education, Administration & Social Sciences

D6.5 Languages, Culture & Humanities

D6.6 Media & Communication

D6.7 Computer Science & IT

D6.8 Design, Art & Music

D6.9 Natural Sciences

D6.10 Environmental & Agricultural Sciences

D6.11 No specification