# 8 Digital technologies and artificial intelligence (AI): implications for using intuition and analytics in personnel selection

Robotics and other combinations will make the world pretty fantastic compared with today. (Bill Gates, 2016)

## 8.1 Digital technologies and AI in personnel selection

The age of digitalization is bringing about significant changes and new opportunities for' HR practices in companies. New technologies, such as cloud technologies, blockchain, algorithms, artificial intelligence (AI) chapter 8, and other technological innovations, are causing profound changes in HR practices (Michailidis, 2018, p. 169).

Today, online applications and applicant management systems are the standard in many personnel departments, often integrated with an overall HR or people IT system. In addition, digitalization offers new recruitment possibilities to support hiring managers in selecting suitable candidates. This process of digitization was accelerated by the Covid-19 pandemic in 2020–2022.

AI could ultimately have the ability of software and machines, such as robots, to perform specific HR tasks better than humans. The so-called machine learning is of central importance and distinguishes AI from rule-based expert systems such as simple algorithms. Rule-based expert digital systems cannot learn independently.

We, therefore, only speak of AI when, using machine learning, the software autonomously generates rules and knowledge, recognizes patterns, and, thus, becomes a self-learning and self-supervised learning system. Thus, machine learning is "the machine's ability to keep improving its performance without humans having to explain exactly how to accomplish all the tasks it's given" (Brynjolfsson & McAfee, 2017, p. 2).

Like human intelligence or cognitive abilities, which require specific experiences and learning opportunities for its development, AI is also based on experience and learning. Solutions are then derived from machine learning.

AI systems can learn from their own experience. The independently learning networks train themselves to win against human beings in games like GO, chess, or videogames, or when self-propelled vehicles take over human decisions. Open AI, for example, boasts that the new training units go through all past versions of themselves. Each hero in video games is currently controlled by an LSTM (long short-term memory) network that enables the networks to remember earlier experiences.

One subarea of machine learning is the so-called deep learning, in which attempts are made to emulate the learning behavior of the human brain, using artificial neural networks. Machine learning tends to continuous deep learning, based on input and


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self-generated data or algorithms and improves decision-making through experience growth (Kreutzer & Sirrenberg, 2019, pp. 3–5). Thus, high-quality (training) data should be available to successfully train AI systems (Teetz, 2018, p. 238).

AI, as an approach to simulate the human brain and the cognitive and emotional (or maybe intuitive) abilities of machines, is regarded as the key technology of this century, due to its successes in recent years. AI has enormous potential to solve complex problems independently and improve HR/People management, especially personnel selection. In addition, the supply of information to decision-makers will be expanded and improved, if implemented appropriately.

Although "so much about the brain is still a mystery" (Barrett, 2017a, p. 290), recent developments in AI try to emulate processes of the human brain and reproduce sensitive artificial synapses. For example, computer chips, such as neuromorphic processors or the so-called memristors, try to work the same way as does the human brain, but are somewhat faster than conscious cognitive processes in the human body. Memristive cells and devices are basic units for future nanoelectronic architecture targeting alternative data processing approaches, such as cognitive or neuromorphic computing and alternative logic operations (Lübben et al., 2020). However, further developments will show whether the unconscious processes in the human brain or the use of implicit knowledge and, thus, everything on which human intuition is based can also be mapped accordingly.

AI tools can record, process, and analyze immense volumes of data to learn underlying patterns, enabling computer systems to make complex decisions, predict human behavior (predictive analytics) and employee performance, and recognize images, nonverbal expressions, and human speech, among many other things. Moreover, AI-enabled systems continuously learn and adapt to changing circumstances and requirements. As a result, AI-enabled platforms can help organizations simulate work environments better and create on-demand labor forces. Potential success areas can be those that seamlessly combine and integrate AI with human judgment, (intuitive) experience, and the emotions of HR managers. Thus, a "successful AI-centered operating model needs to integrate human judgment and experience at its core" (Candelon et al., 2020).

In practice, there is need for time- and cost-efficient procedures that nevertheless demonstrate – from a psychometric perspective – compliance with scientific quality criteria such as validity or objectivity. In addition, the perceived professionalism of selection methods and the associated impact on the candidate experience also represent a decisive criterion in the choice of AI-based procedures (Merkle et al., 2009, p. 157).

In personnel selection, the central goal of AI is to make personnel decisions more information-, knowledge- and evidence-based and less based on human intuition or feelings. As a result, AI-based algorithms promise time and cost savings for companies and applicants, increased objectivity, and reduced discrimination (Youyou et al., 2015, p. 1039; Michailidis, 2018, p. 169; Weitzel et al., 2019, p. 17). Thus, AI-based tools are expected to reduce or even eliminate biases and stereotypes from personnel selection processes and minimize the number of wrong or poor hiring decisions and the associated costs (Petry, 2018, pp. 46–47; Petry & Jäger, 2018, p. 44). Thus, digital technologies and AI can create economic added value for the company (Merkle et al., 2009, p. 156).

Due to these advantages, digitally and AI-supported personnel selection procedures are increasingly becoming an integral part of personnel selection. In addition, several study results illustrate that decisions made using algorithm-based data can be superior to those made by human decision-makers (Grove et al., 2000, p. 26; Petry, 2018, p. 49).

However, the challenge is that AI gets trained by using data, and if these data are biased, then the implemented AI (e.g., algorithm) will be biased. Or the data is wrong or outdated and, therefore, not very useful for future decisions. At the same time, data protection, ethical concerns, and user-friendliness must be considered (Bauer et al., 2006, p. 616); and technologically, applicants must be prevented from cheating, when applying it digitally.

In machine learning, rules are created, based on previous data applied to new situations. Therefore, to avoid discrimination, decisions made by AI-supported algorithms should be transparent and monitored by an independent authority. Furthermore, differentiation should be statistically detectable. Finally, the data sets should also be examined to determine whether an algorithm's training is being carried out with data reflecting stereotypes, biases, and so on.

Although the topic of digital technologies and AI in personnel selection has received a great deal of attention in academia and at conferences of practitioners, and despite research showing that digital and AI-supported selection methods are noticeably advantageous for the selection process, AI-based selection procedures have been implemented relatively little in practice, until the beginning of 2020 d. Nevertheless, the use of digital technologies in recruitment, active sourcing, applicant tracking systems, or personnel selection processes is rated positively, overall, by the HR managers and is seen as having great potential for improving HR work; HR/People managers can no longer imagine practice without them (Weitzel et al., 2019, pp. 17 and 23).

The fact that humans increasingly rely on digital technologies can be seen in many examples, such as navigation systems in cars replacing the process of finding a route intuitively or, for example, in partner exchanges that support the preselection of matches, with the help of self-learning AI systems.

In the following, the possibilities of AI-supported personnel selection will be discussed more concretely against the background of rational-analytical and intuitive aspects of the process.

## 8.2 Algorithm in personnel selection

One possibility of implementing AI in selection processes is using algorithms (Uni Global Union Professionals & Managers, 2020, pp. 6–7). Algorithms can be seen as general digital procedures to screen and evaluate application documents or data on social media. They can be implemented, for example, in:

- Textual analysis algorithms used in designing the wording of job advertisements.
- Targeted placement of job advertisements online.
- Automated background checks on social media to look for appropriate candidates (active sourcing); thus, algorithms play a role before submitting an application. Comparable to social networks such as Facebook, Tinder, or Google search engines, algorithms play a significant role in deciding what content is displayed to users on job boards or career networks ("programmatic advertising").
- Chatbots that are used to guide candidates through the application process.
- CV screening and scanning job applications for keywords and phrases and filtering candidates for the next selection steps. In this preselection process, for example, essential data is automatically read and analyzed from the CV, online profiles, or other application documents (CV parsing). CV screening is a very widespread practice around the world, for example, in large companies with thousands of online applications, where a vast majority of applicants are automatically rejected in an automated screening process before human recruiters assess the remaining candidates.
- Competency-based or other psychometric tests such as cognitive ability tests to provide a further screening filter for candidates.
- Various kinds of automated interview systems (e.g., chatbots) that can ask candidates prerecorded interview questions. without the need for a human interviewer and/or attempt to assess candidates. based on an analysis of their facial expressions, voice, or the answers they provide.

The use of algorithms could, on the one hand, serve as a system for Automated Decision Making (ADM). It can reduce the time expenditure for screening processes and, on the other hand, provide more objectivity and, thus. less arbitrariness or even discrimination in the selection process.

It is possible to distinguish between static and dynamic self-learning algorithms. While a static algorithm constantly evaluates application documents according to the same criteria, a learning algorithm can also learn and develop, on experience. Thus, programming is not only about writing rules into algorithms, but dynamic algorithms are also about learning and applying new rules based on goals.

People can quickly lose track of large amounts of data, and due to limited cognitive processing capacity, it is often difficult for humans to recognize correlations and patterns in the data. Algorithms help generate decision proposals from large amounts of data, quickly.

Dynamic algorithms help analyze, link, and correlate vast quantities of data (big data) in no time, and they can support the fast recognition of patterns or legal requirements, establish correlations, and so on.

These dynamic algorithms represent a form of AI, since they are self-learning systems. By recognizing specific patterns in already evaluated data, they can fall back on these learned patterns in the future, without the need for additional human input. If, for example, the analysis of employee data reveals that other selection criteria than those previously used are required for successfully completing tasks, a dynamic algorithm can recognize this and change the requirement criteria, accordingly. In this way, a dynamic algorithm is a learning system.

While static algorithms are relatively easy to program and implement in practice, dynamic algorithms require vast amounts of high-quality training data. The quality of an AI system depends on the quality of this training data. And, they are mutually dependent: the data and the algorithms improve each other. When past decisions and, thus, used data are affected by prejudices and stereotypes related, for example, to gender, age, skin color, or ethnicity, there is great risk of making wrong or unfair decisions. For instance, in the United States, federal regulations state that a hiring tool can be biased, if it is job-related. Job-related could mean specific characteristics of successful employees. But if all successful employees are white men, then it is almost certain that a job-related hiring assessment will be biased in favor of white men and against women and minorities (Polli, 2019).

Indeed, if correlations between specific candidate characteristics and job performance are identified, they can be helpful for future predictions. Thus, such an approach seems legitimate and logical. If current job holders have specific characteristics (e.g., a certain age or a particular gender), the dynamic algorithm could derive that only applicants of a certain age or gender should be selected. Therefore, such discriminatory possibilities must be excluded, when programming the algorithm.

Thus, contrary to the assumption that an algorithm always processes data in an unbiased and exclusively rational fashion, it can generate biased decisions. Another example is an algorithm that may generate biased decisions if sensitive data are (deliberately) ignored and not captured by the IT system. For example, an algorithm can reduce discrimination by ignoring data that allow social categorization (e.g., gender, age, and ethnicity). Still, it cannot always avoid it, because discrimination can occur even if appropriately sensitive information, such as an applicant's ethnicity or gender, is not explicitly collected (Williams et al., 2018, p. 79; Silva & Kenney, 2018, p. 10). On the other hand, collecting and handling data that allow for social categorization can help make discrimination transparent and, thus, minimize it (Williams et al., 2018, p. 79).

Or, when automated text analysis methods are used, it is not always clear which data and algorithms are used for the analysis. Therefore, there is a risk that the training data used could reflect the biases of a specific society, organization, or even managers and, thus, have an undesirable discriminatory effect. The results of the system, then, can lead to an objectivity illusion.

Thus, rational-analytical personnel selection procedures and instruments, for example, based on standards such as the DIN 33430 or ISO 10667, or ethical principles, legal and diversity requirements should be integrated into the set of rules of an algorithm. In addition, successful heuristics, such as decision trees, can also be translated into algorithms. The data entered into the algorithm should be subject to qualified validation and evaluation.

**Transparency of algorithms:** Transparent, explainable, and understandable AI is a success factor and quality criterion for accepting selection procedures, namely, by applicants and the selection managers. Thus, recruiters and hiring managers should understand and comprehend from which data the algorithms learn and how they work, for example, in automated personality assessments in video interviews. Combining algorithmic literacy with transparency is, thus, necessary for acceptance (Osoba & Welser, 2017, pp. 23–24; Simbeck et al., 2019, p. 27).

Kuhn (2019) shows that the efficiency of heuristics can be improved by using human intuition. A significant problem is operationalizing the intuitions and feelings that arise during personnel selection and developing measurable indicators. If AI and algorithms try to integrate human intuition into rational heuristics and, then, into algorithms, the underlying indicators for intuition should be transparently shown and, at the same time, justified and explained.

The selection decisions based on algorithms should be made transparent by an evaluation. Feedback loops to self-learning systems are desirable, for example, due to the problem of "shortcut learning," that is, the propensity of an algorithm to seek desired results in the simplest possible way. In doing so, it may take undesirable shortcuts. Therefore, users of test data should not be lulled into a false sense of security (Geirhos et al., 2020; Schramowski et al., 2020). Thus, the quality of an algorithm should not only be evaluated by the results of a decision-making process, but always against the background of the quality of the data, especially when these data reflect indicators of intuitions and feelings.

## 8.3 Active sourcing and applicant tracking systems

Various procedures can already be used in personnel selection. These procedures range from so-called recommender systems, which automatically bring together applicants and vacancies (Weitzel et al., 2019, p. 13), to techniques that assist in the preselection of applicants, by comparing their skills with the requirements (Weitzel et al., 2019, pp. 13 and 17), to AI-based procedures such as machine learning, (chat-)bots, or video systems (Landers & Schmidt, 2016, p. 3; Weitzel et al. 2019, p. 23).

Specific digital technologies and AI help design and place job advertisements, support recruiting and employer branding, and are used in active sourcing, for example, in professional social networks and addressing fitting candidates, who cannot be reached by passive job advertisements in newspapers or other online job offers. In addition, based on requirement profiles or job descriptions, these digital applications bring together (potential) applicants and jobs with a high degree of matching requirements (Albert, 2019; Verhoeven, 2020, p. 121).

Software-based applicant tracking systems allow companies to track vast amounts of information, for example, cover letters, motivation letters, or resumes/CVs, for specific content such as keywords. If no matches are found, applications are sorted out. However, applicants can adapt their applications to the digital requirements quickly and, thus, improve their chances for the next application. Also, applicants (but also IT systems) learn that, often, it is enough to use phrases and specific keywords from the job advertisement to convince the computer to invite them for an interview.

This may result in inviting less suitable applicants. Here, it is essential to implement systems to avoid such errors, as far as possible. However, it often remains a matter of human competence to recognize, for example, in (telephone or video) interviews, that invited applicants do not have the necessary competencies to fill the position successfully.

## 8.4 Big data in personnel selection

In HR/People management, larger amounts of data can improve the accuracy of measurements in personnel selection processes and, thus, increase the quality of personnel selection decisions (McAfee & Brynjolfsson, 2012, p. 62; Guilfoyle et al., 2016, p. 128). AI can help better navigate these large amounts of data and the increasing complexity of decisions; a single person may not be able to regularly achieve this, due to limited cognitive capacity. However, it is a matter of processing more and more data, analyzing and weighing it, and ultimately extracting information from it, so that it can be used for decision-making.

Algorithms help analyze data of applicants found in social networks, application forms, or internal company documents such as competence profiles, performance data, appraisals, or completed training (Meißner & Nachtwei, 2017, p. 58). In addition, unstructured personal data such as blog posts, entries in chats, photos, or "likes" on social media can be collected and evaluated (Petry & Jäger, 2018, p.110). Kanning et al. (2019, p. 57) emphasize that data collected in an unstructured and subjective-intuitive way can be analyzed systematically, in this way.

AI can not only be trained with vast amounts of data, but it can also integrate them or apply them to new data, as in CV parsing.

Data-driven recruiting and selection is not only a question of available data. More critical is the quality of data, and hence, finding and assessing the correct and valuable data. Thus, there is a risk of using inaccurate or poor test and training data. In personnel selection, data should not be accepted uncritically. If HR managers want to make good decisions in recruiting and selection with data, they should start from the decision they need to make and then ask which data they need to make a good decision.

## 8.5 Digital analysis of written words

Specific innovations in AI deal with the analysis of written texts (e.g., choice of words and the structure of the language/sentences), the evaluation of the spoken language or voice of the applicant (Chamorro-Premuzic et al., 2016, p. 627; Fellner, 2019, p. 4). For example, the start-up "100 words" (100 Worte, 2019) analyzes written rather than spoken language and tries to create a personality profile. However, other companies claim that less than 150 words are enough to generate a valid personality profile, according to the Big Five theory or the DISC model and arrive at conclusions about an applicant's maturity level, using machine learning and psychological language processing. They assure to psychometrically analyze all relevant facets of human languages, such as word choice, semantics, speech patterns, syntax, and word contexts (Greple, 2021). This is somewhat reminiscent of the statement of some hiring managers who are very critical of rational-analytical selection procedures and are firmly convinced of their ability to assess applicants correctly, with the help of three questions or in thirty seconds.

Campion et al. (2016, p. 958) analyzed written language in success stories using natural language processing. Natural language processing is "an area of research and application that explores how computers can be used to understand and manipulate natural language text or speech to do useful things" (Chowdhury, 2003, p. 51).

In their study, Campion et al. (2016) asked participants to write success reports of 200 words. From reports describing past performance, conclusions about six defined competencies are drawn (Campion et al., 2016, p. 961). In addition, information on educational background, practical experience, and results of previous tests were included in the evaluation (Campion et al., 2016, p. 961). The reports and scoring of candidates were analyzed using natural language processing by a machine and by qualified and experienced recruiters (Campion et al., 2016, p. 961). In the study, the judgments generated by the machine were very similar to those of human judges. On average, the interrater reliability of the individual human judges attained $r = 0.61$, very close to the value of the machine at $r = 0.64$ (Campion et al., 2016, pp. 966 and 969). The construct validity of the computer-based scoring was also confirmed (Campion et al., 2016, p. 973). Neither the human evaluation nor the automated analysis disadvantaged people based on gender or origin (Campion et al., 2016, p. 973).

The authors uncovered limitations of the investigation regarding the data used (Campion et al., 2016, p. 974). A large amount of text-based data was available in the study, which provides an ideal database, especially for mechanical evaluation. However, it is doubtful that every company will have similar data sizes, when applying that procedure. Therefore, to provide information on the generalizability of the results, a similar study should be conducted in a different environment (Campion et al., 2016, p. 974). Furthermore, it must be considered that the preparation, especially the software training, requires a great deal of time, although the effort for such a study must always be classified as high (Campion et al., 2016, p. 974). Finally, this procedure might allow applicants, who would otherwise have been excluded by simple keyword queries, to remain in the selection process (Campion et al., 2016, pp. 973–974). All in all, the method can be a good option to preselect large numbers of applications, quickly and cost-effectively (Campion et al., 2016, p. 973).

## 8.6 Likes in social media and personality

Social media channels are used not only for recruiting and employer branding purposes or to advertise available vacancies; social media analysis also enables organizations to automatically compare job requirements and candidate profiles, such as personality (Guilfoyle et al., 2016, p. 138).

On the one hand, computer-assisted analysis allows conclusions about the personality traits of social media users and, on the other, statements about the accuracy of the results compared to human decision-makers. In various studies, Kosinski et al. use the digital traces of the test persons, more precisely Facebook likes, and relate them to personality traits (Kosinski et al., 2013, p. 5802). Kosinski et al. (2013, pp. 5802–5803) used distinguishing attributes of over 58,000 participants based on their likes, including gender (93% agreement), political orientation (85%), and sexual orientation (88%).

They show that individual traits and attributes, ranging from sexual orientation to intelligence, can be predicted to a high degree of accuracy based on records of users' likes. This also applies to some personality traits, such as openness. The results show that the evaluation of Facebook likes as digital footprints can identify "openness" (as one of the Big Five traits) as accurately as a personality test (Kosinski et al., 2013, p. 5804; Youyou et al., 2015).

Büttner also analyzed social media data. For this purpose, he took information about more than 700 part-time students from the XING platform. Using various algorithmic methods, he examined their predictive validity for the Big Five personality traits. The analysis yielded a predictive validity between $r = 0.31$ and $r = 0.46$ for personality traits (Büttner, 2016; Büttner, 2017, p. 25). This shows that data from the social media platform, XING, allows predictions about users' personalities (Büttner, 2017, p. 25). However, Büttner (2016) criticizes his research design, because the personality profiles were only measured based on the Ten Item Personality Inventory (TIPI). Further personality tests with a more differentiated approach should be included in future studies. Furthermore, considering data protection regulations, the used information could not be extracted directly from XING but by interviewing the participants, which Büttner also considers disadvantageous.

Youyou et al. (2015, pp. 1036 and 1039) compare the results of a personality assessment by close relatives of the test persons with an automated, computer-aided analysis of the corresponding Facebook Likes (the study aims to investigate the accuracy of the measurements concerning the current personality profile of the subjects) (Youyou et al., 2015, p. 1036). A correlation of $r = 0.56$ was found between the automated approach and the assessment of the subjects' personalities by their relatives. Furthermore, the correlation between self-disclosure and the assessment of relatives is $r = 0.49$. Likewise, the interrater reliability of the automated approach ($r = 0.62$) exceeds that of the human decision-makers ($r = 0.38$) (Youyou et al., 2015, p. 1038). The same applies to external validity (Youyou et al., 2015, p. 1039).

The results show that a computer-based assessment can more accurately evaluate a person's personality than humans (Youyou et al., 2015, p. 1039). However, according to the authors, limitations arise from the fact that here, too, only the personality traits of the Big Five model are included, and other personality traits are ignored.

> According to the Realistic Accuracy Model, the accuracy of the personality judgment depends on the availability and the amount of the relevant behavioral information, along with the judges' ability to detect and use it correctly . . . Such conceptualization reveals a couple of major advantages that computers have over humans. First, computers have the capacity to store a tremendous amount of information, which is difficult for humans to retain and access. Second, the way computers use information – through statistical modeling – generates consistent algorithms that optimize the judgmental accuracy, whereas humans are affected by various motivational biases. Nevertheless, human perceptions have the advantage of being flexible and able to capture many subconscious cues unavailable to machines. Because the Big Five personality traits only represent some aspects of human personality, human judgments might still be better at describing other traits that require subtle cognition or that are less evident in digital behavior. Our study is limited in that human judges could only describe the participants using a 10-item-long questionnaire on the Big Five traits. In reality, they might have more knowledge than what was assessed in the questionnaire (Youyou et al., 2015, p.1039).

The benefits of computer-based analysis and deducing personality traits based on social media data can represent a valuable approach for personnel selection (Youyou et al., 2015, p. 1039; Chamorro-Premuzic et al., 2016, p. 629). They represent a chance for personality assessment that is automated, accurate, and cost-effective (Youyou, 2015, p. 1039). The amount of personal information available on the Internet is increasing immensely. Due to further developments in technology and the increasing amount of data, it can be assumed that the significance of this information will increase (Youyou et al., 2015, p. 1039).

## 8.7 Online test in personnel selection

Digital technologies and AI offer the chance to implement online-based tests. Thus, companies conduct various psychometrically valid tests such as skill tests, knowledge tests, cognitive ability tests, integrity tests, personality tests, and so on. Also, AI helps conduct digital role-plays, case studies, or interactive and multimedia task designs. This increases the simulation capability and, thus, the mapping of tasks (Fellner, 2019, p. 17).

If valid cutoff scores are available in the company, for example, these tests can be used for personnel preselection. Science-based tests used for preselection increase the validity of the selection process and, thus, the probability of inviting only candidates who fit the preselection job requirements to the interview. At the same time, time and costs can be saved, as fewer applicants must be invited to interviews, and selection managers, thus, gain more time for other tasks, such as personal interviews with the shortlisted candidates. In addition, companies can use the results of personality tests to generate specific questions for the interview guideline and/or to reflect on the results, with the candidates in these job interviews.

However, when using test procedures, hiring managers should know which occupational group, country, and so on, a test was designed for, as different competencies or personality traits may be the focus (Danks & London, 2017, p. 4694).

One of the main reasons for the skepticism surrounding AI-based personality tests is that, from a scientific perspective, there are no clear correlations between personality traits and performance on the job. Although some studies show a (moderate) correlation between the personality traits conscientiousness and emotional stability and performance, especially in highly complex jobs (Le et al., 2011), concrete personality test results for personnel selection must be reflected on, critically. As mentioned in other parts of this book, using the results of a personality test as a basis for reflection in interviews can be recommended.

Gamification and recruitainment are also examples of online tests. Using the example of consumer goods manufacturer, Unilever, Feloni (2017; see also Gärtner, 2020) describes a procedure where applicants first have to upload their LinkedIn profile to participate in up to 12 online games, which are then evaluated. Next, the AI-based software compares the results of these computer game players (applicants) obtained with successful employees. Finally, applicants with scores comparable to scores of successful employees are invited to the further selection procedure, for example, a video interview. Research by Gkorezis et al. (2020; see also Nikolaou, 2021) shows that the gamified method has a positive effect on organizational attractiveness, which, in turn, positively predicts recommendation intentions, but only for those who have a high level of video gaming experience (Potočnik, 2021, p. 170).

The company HireVue uses software that analyzes keywords, word choice, intonation, body language, facial expressions, and gestures (Black & van Esch, 2020, p. 7; Feloni, 2017). If candidates also pass this video analysis, they are invited to an on-site applicant day, after which a final decision is made (Feloni, 2017). Unilever sees a positive result from the changeover to this process. According to the company, an increase in diversity in hiring was observed. In addition, the company recorded a doubling of the number of applications received and, at the same time, a reduction in the time-to-hire ratio (time to fill a position) from four months to four weeks. This is primarily due to efficiency improvements. Recruiters spend 75% less time screening resumes and have cumulatively saved 100,000 interview hours globally, since implementation (Feloni, 2017; Gärtner, 2020, p. 76). According to internal data, the organization has cut recruiting costs by $1 million through streamlining (Booth, 2019). A specially conducted survey of 25,000 applicants shows a high level of satisfaction in the process (Gärtner, 2020, p. 76). According to internal evaluations, the acceptance rate of contract offers increased from 64% to 82% (Feloni, 2017).

## 8.8 Digitally based video or telephone interviews

### 8.8.1 Analysis of video interviews

For selection purposes in practice, it is possible to record face-to-face interviews or use video interviews. These are either time-shifted or asynchronous, one-way video interviews, where selection managers can put predetermined questions and tasks to candidates, who can answer and solve these on video, without being tied to a specific time and place. Another possibility is conducting a recorded or nonrecorded online interview (synchronous or live interview), for example via telecommunication and video applications such as Skype, WebEx, Teams, or ZOOM, to assess the candidate, including analyzing the facial expression, emotions, authenticity, personality, and so on.

Due to technological improvements and encouraged by the Covid-19 crisis in 2020–2022, selection video interviews have become more popular.

In the case of time-shifted interviews, applicants receive a link. The candidate has a prescribed amount of time to answer standardized questions on various topics. Depending on the company, the time allowed and the number of questions to be answered varies; there are programs where three questions have to be answered within 45 s, and others require recordings that take 30–45 min (Barsch & Trachsel, 2018, p. 83).

Asynchronous videos offer several advantages, such as cost and time savings due to reduced scheduling, global interviewing, and travel, since applicants do not have to be at the interview site. Further advantages are standardization, lower interviewer influences on candidates, and the possibility to replay and review the recording, instead of relying on memory and/or notes. But, where there is light, there must be shadow, and where there is shadow, there must be light. As a result, there is lower information richness due to the inability to ask questions or give feedback and lower media richness through the candidates' limited visibility. In addition, inaccurate conclusions may be drawn due to technical problems or visual cues, such as the design of the visible background (the applicant's home/personal living spaces), and performance in the interview can be compromised by unfamiliarity with technology or a specific selection tool. Also, the lack of personal interaction can lead to relatively low acceptance and skepticism among applicants and hiring managers (Hendrix, 2021, p. 4).

Both forms of interviews can be evaluated by humans or by AI. Video analyzing software or humans can, for instance, evaluate applicants for call centers. Based on data that, for example, successful job holders make frequent eye contact, use specific words and words with more emotional impact, act less fidgety, and show (in Western cultures) positive emotions, for example, through facial expressions, attention is paid to appropriate signals when evaluating an applicant's behavior in the video (Stulle & Thiel, 2018).

Synchronous or live online video interviews are conducted by an interviewer and are designed – as far as possible – like a regular face-to-face interview. However, if the interview is recorded, AI can analyze the candidate. For example, Suen et al. (2020; see also Suen et al., 2019) show that the automated assessment of a candidate's personality based on facial expressions and movements and audio cues in asynchronous video interviews can accurately predict the personality as perceived by experienced observers (Chen et al., 2017). For this purpose, it usually requires many already classified patterns created from (other) video analyses. The evidence base for AI-based video analyses, for example, validity, should be proven (Woods et al., 2020).

The validity of personality judgments can increase if – besides evaluating verbal communication systematically – a structured analysis of visual cues, either by the selection manager alone or with the help of algorithms or other AI support, is included. Judgments, thus, improve when human and computer-based assessments are conducted complementarily (Hendrix, 2021, p. 38). However, for hiring managers, it's often a matter of time and resources, whether they'll watch the video again. Usually, they rely on their impressions during the synchronous interview. Also, an analysis of the applicant performed by AI provides additional information about the candidate.

### 8.8.2 Analysis of voice

The idea that people's personalities and character could be analyzed via language and that, for example, the Big Five personality traits could be diagnosed via characteristics of the human voice and used words, goes back to the sedimentation or lexical hypothesis, first investigated by Francis Galton in 1884; his approach assumes that differences in characteristics are represented in words used in a society (Fellner, 2019a, p. 4).

Today, such analysis can be conducted via a telephone interview, in which applicants answer standardized questions on various topics (Schaumlöffel et al., 2018, p. 62). To enable a linguistic evaluation, software providers proceed in different ways. Sometimes, the content of what is said is not considered in the assessment. Instead, the speed of speech, the structure of the sentences, the grammar, and the words used are examined closely (Schweizer, 2017, p. 38). In that case, an analysis of the content of the statements is intentionally avoided, because the speaker can easily and consciously control the content.

In such an evaluation, the focus is on the structural analysis of the words used, breaking them down into their parts (Schaumlöffel et al., 2018, pp. 9 and 62–63) and investigating them to uncover linguistic and acoustic peculiarities, with the help of a mechanical procedure (Linnenbürger et al., 2018, p. 23). Other techniques focus on the linguistic content of the applicants' speech (Schossau et al., 2019, p. 30). Finally, the fully automated execution of these methods is carried out to assess the applicant's personality.

Other companies develop speech recognition software to analyze the personality, to evaluate spoken words and expressions, language breaks, and so on. Currently, popular examples of the practice in German-speaking countries are PRECIRE or JobFit (Schaumlöffel et al., 2018; Schmidt-Atzert et al., 2019). Based on language analysis, characteristics, personality traits, or the professional fit of applicants are assessed (Linnenbürger et al., 2018; Bärschneider, 2019). A specific feature of such software is that no questionnaires must be filled out in writing, since the focus is on recording and assessing spoken words (Verhoeven, 2020, pp. 122–124). After checking the application, a potentially suitable candidate gets a phone number and pin code that can be used to submit a language sample. During this automated call, applicants are asked questions to elicit language examples. When enough language examples have been collected, the call is terminated. The software then analyzes the sample and compares the result with a representative comparison group. In addition, a voice check can be performed to test stress and workload capability, or learning areas can be identified.

The analysis of speech or voice is currently also used to assess employee satisfaction in an organization, because the way people speak can tell something about their job happiness and their performance (Marr, 2018, p. 78).

Research in AI-assisted analysis of human speech continues to progress very rapidly. For example, research results have identified a connection between speaking and diseases. Software offered by the company audEERING (2021), for instance, offers algorithm-based software that claims to be able to detect a speaker's level of emotional excitement and to identify over fifty emotional states via analyzing audio data beyond the content of spoken words, for example, vocal timbre, intonation, speech rhythm or pitch, as well as to diagnose health symptoms at an early stage (Köhn, 2021, p. 26).

Example: An applicant converses by phone or video call for about 15 min with a computer voice (bot) and answers questions that have nothing to do with actual job requirements: "What did you do last Sunday?" can be one of them. The responses are recorded and then evaluated by AI-based software. The AI deduces personality traits by analyzing the choice of words, voice pitch, volume, and other language components. In the end, the test persons can read six single-spaced pages, detailing whether they are rather optimistic or pessimistic, neat or chaotic, and so on.

According to Schimansky-Geier (2017, p. 48), such procedures allow filling vacancies, based on objective requirements. Unlike a questionnaire, where people give information about themselves, the software provides more objective results. The result is more objective than what psychologists can measure, because people can hardly consciously control their speech as soon as they speak for more than a few minutes (Hummel, 2015).

Characteristics such as the gender or age of applicants are disregarded by the system, so that subjective distortions of judgment by a human decision-maker are prevented. Thus, selection can be carried out more fairly, and broader diversity can be achieved (Schossau et al., 2019, p. 30).

Although the first software for speech and voice analysis software is already in use, and there is a large branch of research in personnel diagnostics, there is a lack of scientifically valid, evidence-based research on this subject (Fellner, 2019a, p. 4).

### 8.8.3 Selection support by chatbots or messenger systems

Several companies have implemented the use of chatbots (chat robots or bots). However, non-self-learning chatbots are programmed to respond to specific keywords with a predefined action or response. The risk of such a bot misinterpreting human questions is, accordingly, high. On the other hand, an AI-controlled chatbot can learn to understand the context of the questioner and, by analyzing the reactions of questioners, also recognize their emotions and take corresponding action (Petry & Jäger, 2018, p. 47).

Especially by imitating human speech (and partly emotions), they are used to handle initial contact and arrange appointments with candidates, answer simple and frequently asked questions from applicants, for example, about earnings, hiring requirements, or application procedures.

Research shows that bots can answer about 75% of candidates' questions. The 25% that remains are often questions that require individual advice (Albert, 2019, p. 218), and the bot forwards these inquiries to the appropriate HR employees. Some chatbots even offer applicants individual tips, such as which job advertisements might be attractive.

Further developments of bots allow for conducting preselection interviews or the so-called prescripted interviews. In this case, all applicants are asked standardized questions, but they do not have the opportunity to ask anything themselves. Both HR managers and applicants repeatedly complain about the lack of interaction, here. It leads to a feeling of lack of appreciation, but this can nevertheless be a first opportunity to make contact at the beginning of a selection process.

At the same time, these systems are constantly improving through self-learning, so that both sides can ask and answer questions individually. A practical example is IBM Watson Candidate Assistant, where applicants have the opportunity to engage with an AI-based chatbot to share information on interests, skills, and potential job fit. The tool analyzes resumes and recommends jobs suited to the applicants' skills and goals. The job seeker can talk with Watson, ask questions, and find out about employment opportunities (IBM, 2017).

Likewise, work is being done on topics of automated communication via messenger systems such as e-mail, WhatsApp, or Signal, which are increasingly individualized and personally tailored to the applicant. In addition, both chatbots and other communication systems are accessible from anywhere in the world (without the applicant needing any special software), are not limited to typical business hours and, can communicate 24 h a day, and can usually answer an unlimited number of queries at the same time (without, as with humans, possibly getting stressed or sick) (Verhoeven, 2020, pp. 106–107; Pasenau, 2021, pp. 65–66).

Chatbots and other digital technologies can have a filtering function by only suggesting jobs to interested parties based on essential criteria such as existing skills and work experience, work location, or working hours, enabling a preselection for applicants.

## 8.9 AI as an intuitive and emotional system

AI aims to operationalize human intelligence and make it available through IT systems. Human intelligence can be understood as recognizing, making judgments, grasping possibilities, comprehending contexts, and gaining insights (Görz & Wachsmuth, 2003, pp. 1–2). Therefore, AI aims to map not only conscious cognitive abilities but also intuitive and emotional ones.

Intuitions and emotions are human capacities for holistic, associative, and nonlinear thinking. Intuition helps people get inspiration and solve problems in complex and unknown situations. For many years, researchers have advocated a clear division of labor between managers and machines: computers should do what computers could do best – to calculate and process data according to formal logic – while managers should stick to what humans do best, namely to perceive information holistically, seek patterns in data, or in intuitive and emotional impulses. Nowadays, AI research focuses intensely on developing systems and robots that exhibit human intuitions and emotions. In addition, robots with the capacity for emotional expression could be beneficial, because no human being can live without emotional attention.

Dolls that can speak for children, cuddly animals for older people in nursing homes, and social robots in public life or at home or intimate partners such as sex or love dolls that express specific emotions and empathy are just at the beginning of their development. These humanoid machines learn not only to look like humans but also to move like humans, communicate with, and like humans, learn from them, read and understand their emotions, and show specific forms of emotions themselves. For example, in the field of eldercare, Prescott & Caleb-Solly (2017, p. 22) predict that "AI personal assistants and social robots may be able to provide a form of synthetic companionship that people may find engaging, but this will never replace human companionship." Thus, whether these products can replace humans' feelings of closeness and warmth can be questioned, but they are increasingly used.

In this field of AI, the researchers are often not primarily interested in these robots showing real human emotions but rather in what they can do for human beings. For example, robots should convey the feeling of being empathetic by laughing along, rejoicing, looking curiously, mourning, touching, or simply listening, when appropriate. Advancements in Social Signal Interpretation (SSI) help robots recognize and interpret interpersonal interactions' emotional and social dimensions. Such applications can be used in personnel selection and for therapeutic and medical applications (see, e.g., the research and publications of Elisabeth Andre; e.g., Schiller et al., 2020a and 2020b).

It is becoming apparent that whatever is technically feasible and for which there is a market (e.g., sex dolls) will be produced, despite all sorts of ethical debates.

It is essential to wait for further developments and see to what extent such systems, also as humanoid hiring managers (e.g., avatars), can show appropriate intuitions and emotions to job applicants and, thus, shape their behavior.

However, whether machines controlled by AI can think and feel like human beings do, for example, in a holistic and associative way, or can simulate and replicate intuitions and emotions in unconsciously stored experiences can be critically questioned from today's perspective. Currently, AI systems are still far from feeling and showing intuitions and emotions as humans do. And, if possible, which intuitive and emotional capacities could and should be outsourced to machines or which of these remain uniquely human capacities (Lussier, 2018)?

## 8.10 AI and candidate experience

Since personnel selection aims to acquire and win the best-suited people for an organization, it is essential to consider the applicant's perspective and how AI affects the candidate's experience. Thus, the applicant's perspective on AI in recruiting and selection processes must be discussed more thoroughly.

Employee reactions to technology have become an important research topic in recruiting and selection. For example, Nikolaou (2021) explores new recruiting and selection technologies. He discusses the impact of cybervetting and applicant tracking systems, asynchronous digital interviews, and gamification/games-based assessment on candidates. Also, Langer et al. (2017, 2018, 2019), Wang et al. (2020), or Woods et al. (2020) reviewed applicants' reactions toward digital and internet-based selection methods. For example, a study by Langer et al. (2017) shows no difference in organizational attractiveness levels, but further studies (2018, 2019) state that candidates considered digital interviews less personal, reporting increased privacy concerns. Gamification can be a reliable and valid selection method raising positive reactions among candidates and increasing organizational attractiveness; gamification can promote fun, interaction, and challenge, especially among younger candidates.

Research by Proost et al. (2020) states that reactions to video interviews show that applicants fear having fewer opportunities to show their potential and use their nonverbal behaviors, compared to in-person interviews. Thus, in digital interviews, especially the lack of personal and face-to-face interaction with the interviewer, and the candidates' perception of being unable to influence the outcome of the interview process, maybe a significant drawback of digital interviews, and it will be difficult to change this in the future, despite the apparent advantages they offer (Nikolaou, 2021, pp. 3–4).

A more time-efficient selection of personnel can positively affect the satisfaction of applicants, as they receive feedback on their applications and a decision, more quickly. In addition, an application can be submitted, regardless of time and place. This can be a strategic advantage in the competition for suitable candidates. In addition, applicants may feel they are treated more fairly, as objectivity increases by eliminating bias, stereotypes, and so on, because AI treats all applicants equally, regardless of the individual selection manager.

In addition, chatbots, video, and other AI-based conversations conducted independently of time and location can increase candidates' perception of control. As a result, the selection process can be perceived as more individual, user-friendly, and less time-consuming. Research shows that younger applicants, in particular, are interested in self-determination and want to influence the selection process actively. In addition, digital and AI technologies are considered innovative and modern (Black & van Esch, 2020, p. 7; Hamilton & Davison, 2018, p. 417).

AI allows recruiters to perform routine tasks using machines and focuses on process quality and relationship building with shortlisted candidates (Albert, 2019, p. 217; Lochner & Preuß, 2018, p. 199). Thus, opportunities for appreciation and individuality conducive to a positive candidate experience are seen. However, it must be noted that a more intensive relationship-building only occurs. later in the process. with shortlisted candidates and. thus. not with all applicants. equally.

Thus, the candidate experience can be optimized but also degraded through AI's use. For example, Knobloch & Hustedt (2019, p. 18) speak of dehumanizing the selection process due to the lack of personal relationship building, making it challenging to create trust. In addition, the AI-driven process could be perceived as a black box lacking transparency due to the independent learning of the software and an unclear decision-making process (Fesefeld, 2018, p. 26).

Based on Gilliland's model (1993; see for details Sections 3.2.5.1 and 3.7.9), Dineen et al. (2004, p. 138) examined applicants' perception of fairness in the selection process, depending on whether an algorithm or human experts made the decision. Five criteria of organizational justice were examined (type of decision-maker; availability of information; consistency; possibility to provide feedback; the speed of feedback) to assess the perceived fairness of a computer-based recruiting system. The most significant factor was consistency ($r = 0.45$), followed by the provision of information ($r = 0.27$). However, suppose the selection criteria in an algorithmic assessment are not transparent, applicants experience these evaluations critically, because they cannot identify the assessed requirements and are, thus, not able to adapt their behaviors to requirements (Rahman, 2021).

Overall, participants considered humans more fairly in procedural terms than automated decision-makers. The procedural justice model helps explain this (Lind & Tyler 1988). This model states that fair treatment signals the inclusion or confirmation of group members. Thus, applicants may associate feelings of inclusion or confirmation more with the fairness shown by human recruiters, while automated personnel selection systems are usually unable to communicate these types of signals (Dineen et al., 2004, p. 139).

Although it has been shown that AI can lead to less discrimination regarding personnel selection decisions, human experts are perceived more positively than their digital equivalents. Even if digital systems can better predict a candidate's suitability (Dahm & Dregger, 2019, p. 252; Fortmann & Kolocek, 2018, p. 163), personal contact is expected, especially at management levels (Fellner, 2019, p. 12). Candidates value subjective control and the feeling of influencing the selection results with their behavior, which is possible through personal contact (Fellner, 2019, p. 13).

Applying Davis' (1989) Technology Acceptance Model (TAM) to using AI in personnel selection, research shows that general trust, a willingness to innovate, or even the familiarity with a specific technology promote the acceptance of new technologies; at the same time, perceived risks such as a lack of transparency or privacy concerns reduce acceptance (Lancelot Miltgen et al., 2013, pp. 103 and 110; Black & van Esch, 2020).

On the other hand, younger generations, or digital natives, evaluate the use of AI differently than older applicants or senior managers.

Besides trust in technology and computer playfulness, Dahm & Degger (2019, p. 264) identified five measures that promote the acceptance of AI in personnel selection in Germany (percentage of respondents want):

1. Human contact person (70.6)
2. Detailed explanation of how the system used works (70.2%)
3. Applicants themselves decide which data is made available and stored (63.9%)
4. Detailed explanation of the advantages of the system by the company (50.5%)
5. Shortening of the application process (49.5%)

A further problem is that computer-based systems today are not (yet) capable of capturing moods (Fellner, 2019, p. 12).

Thus, despite the advantages of digitally supported selection procedures, personnel selection procedures carried out and accompanied by people are perceived more positively, by applicants. One of the reasons for this is that machines cannot – although algorithms and robots can reproduce some aspects of human social interaction and despite all the progress made in the development of humanoid robots – replace genuine interpersonal human feelings and recognition of natural human emotions (Frey & Osborne, 2013, p. 26).

In addition, it is questionable whether the current generation of hiring managers will accept these technologies, fearing that the human-empathetic approach to recruiting will fall victim to digital opportunities. However, the possibility of authentically representing human emotions or even responding to the emotional state of applicants using AI tools is seen very critically. Digital technologies cannot recognize the person-organization-fit by intuitive feeling. Thus, human interaction, especially in final selection decisions, particularly interviews, remains critical during a selection process.

To promote a positive candidate experience, companies look at how digitally supported selection procedures meet with applicants' acceptance. However, several interviewed managers argue that the use of language analysis software or the creation of personality profiles based on social media data may deter many applicants: "In the end, it has an impact on the image of our company . . . . That's why I would never rely only on such tools because it could lead to certain people not applying for a job in our company" (Flörke, 2020, p. 60).

While the hard facts in a selection process can be evaluated much faster with the help of AI, as soon as the soft factors, such as the cultural fit between candidate and company or the team fit, are involved, the human element is essential (Mülder, 2018, p. 112). As early as 1976, Schmitt and Coyle (1976, p. 190) showed that personal contact is crucial for candidates and significantly influences their choice of organization. Nothing has changed so far and will probably not change soon.

Although there is currently a lack of valid research on the topic of AI and candidate experience conducted by independent researchers, in summary, critical for the acceptance and, thus, a positive candidate experience with AI are:

1. Trust in the technology: This trust is supported by transparency and comprehensibility concerning the intention of using this AI tool and the process flow, easy comprehensibility and simple operation of the tool, openness of the evaluation

criteria and the decision-making process, and compliance with data protection and ethical standards.
2. A human contact person is available during the recruiting and selection process and should make the final decision.
3. It is essential to clarify the added value, benefits, and goals of using AI-based tools at the beginning of the selection process, such as high speed, more objectivity, fairness, and less discrimination, ensuring high-quality personnel selection.

And to get detailed and constructive feedback is essential for the acceptance of digital selection procedures.

4. Most important: A human being should make the final selection decision based on personal contact, especially in an interview. In addition, applicants want to know how they performed in an interview or specific exercises and their individual scores.

## 8.11 Limitations of digital and AI-based selection procedures

### 8.11.1 Data from the past

A problem with using AI or algorithms in management and personnel selection is the quantity and quality of the underlying data. With increasing data quantity and higher data quality, the algorithm's results improve (Tambe et al., 2019, pp. 10–16; Knobloch & Hustedt, 2019, p. 15).

In many organizations, especially SMEs, there is no usable digital data for defining successful employees, or according to which criteria the attribute "successful" can be determined, AI-supported data-driven decisions are based on data that usually reflects the past. Thus, data from the past is subject to the risk of recommending the past, repeatedly, for the future. In this self-reference learning and self-replicating way, algorithms possibly create a future with the past image. However, it is questionable whether the past success principles will also apply to the future because of rapid environmental changes (Klopprogge et al., 2019, p. 208; Klopprogge, 2022, p. 92).

In order to derive a reliable projection for the future, the past-related data would have to be typical for the present and the future. However, this may not be the case. As a result, there is the risk that the algorithm will automatically perpetuate the past and past mistakes, for example, a lack of diversity – in the future.

Suppose the requirements for new employees correspond to the suitability profile of those who were successful in the past, the success principles of the past have a normative character. In this way, the existing practice is repeated in an endless loop, and the "chance of something new, unknown, or disturbing is smothered in the conservative slime of self-referenced entropy" (Klopprogge, 2022, p. 85). Therefore, organizations' ability to change will be jeopardized, if attempts are made to predetermine and clearly define all required criteria for personnel selection by past data.

An algorithm based on past data presents an ethical and business problem, because it may lead to suboptimal selection decisions and not necessarily a desirable future (Diercks, 2021).

Despite all the advances in data analysis, pattern recognition, natural language understanding, and so on, another big problem of AI is still to capture a very complex world to grasp and describe completely what is very fuzzy, contradictory, ambiguous, and constantly changing. Hence, it is about building systems that navigate the hard-to-model real world and learn to make decisions directly, on rich sensor data.

An algorithm is only as good as the data used. Therefore, one of the critical challenges in implementing AI is to provide a large amount of high-quality training data.

An algorithm should not only learn from the past but also be "fed" with data that are particularly important for the future and reflect requirements for future challenges and tasks. This is critical in a rapidly changing world and changes employee requirements.

### 8.11.2 Huge amount of data and organizational resources

Self-learning systems such as dynamic algorithms must be filled with training data. However, since the quantity of data is constantly growing due to the explosion of machine-generated data and human involvement in social networks, it is questionable which of these data are relevant for personnel selection, to what extent companies have access to this data, or whether they have the resources to generate such data. Large companies have an advantage because they regularly have the resources to use or develop these data; and they process large numbers of applications for specific positions that must be filled repeatedly. Therefore, the development and use of appropriate algorithms are more worthwhile for such companies than SMEs. But, SMEs can be supported by employer associations, consulting companies, or informal cooperation between SMEs to develop appropriate algorithms.

### 8.11.3 Static algorithms

A deterministic algorithm proceeds according to a predetermined pattern from which it does not deviate, and it does not learn independently. The use of such a tool carries the risk that applicants with atypical CVs but who are certainly interesting for a company (e.g., lateral or "out of the box" thinkers, "colorful applicants") will be sorted out by the algorithm and rejected. The use of algorithms can favor standard profiles and lead to unintentional homogenization of the workforce.

A hiring manager interviewed in our empirical research stated that preprogrammed algorithms could potentially reject highly interesting applicants who fall through the traditional selection grid, because they do not meet the preselection criteria.

> Well, if decisions are only made according to previously defined criteria and programmed algorithms, there is a risk of losing flexibility. Moreover, if one does not also and especially rely on the recruiter as a human being, certain personalities will no longer have a chance to join the company (Flörke, 2020, p. 63).

It is vital that a diverse team of personnel managers, executives, and others should be assembled to discuss and develop criteria for programming the algorithm.

In practice, it is often found in selection procedures that applicants are not eligible for the position to be filled but for other positions. However, if the algorithm rejects such candidates, they are no longer available to the company. Unlike human recruiters, algorithms do not completely view other advertised positions or those that may need to be filled soon.

### 8.11.4 Biased data

Although algorithms and other digitally supported procedures for personnel selection contribute to greater objectivity, the involvement of humans in programming can lead to the inclusion of personal views, values, and other things, and, thus, to the transfer of stereotypes, prejudices, and other unconscious biases to the algorithm (Petry & Jäger, 2018, p. 112). Thus, training data of the algorithm can be based on information that may not be objective and, therefore, automatically reproduce existing distortions, biases, or even discriminations. “Discriminatory patterns can be reproduced, scaled, and social inequality can be reinforced by all algorithmic systems” (Knobloch & Hustedt, 2019, p. 13).

Flörke (2020, p. 33) notes that independently of the influence of the programmer (Brynjolfsson & McAfee, 2017, p. 16), the algorithm itself can recognize patterns that are anchored in a specific context or society (Langer et al., 2018, p. 35). For example, an algorithm can be based on past decisions, and, therefore, persons who are less strongly represented in the data, possibly members of ethnic minorities, could be overlooked, in future evaluations (Liem et al., 2018, p. 198). The question is: has the machine made an assessment based on a meaningful and also ethically and legally correct correlation of data or based on wrong or impermissible correlations? The more autonomously the system learns and develops new algorithms, the fewer the possibilities for intervention (Diercks, 2021).

An algorithm may be discriminatory by using information such as age, gender, or origin (Buxmann & Schmidt, 2019, p. 16; Stachl & Bühner, 2018, pp. 25–26). Companies could suffer legal consequences if such cases occur and become known (Stachl & Bühner, 2018, p. 26).

Telephone or video interviews, for example, in which the speaking habits of applicants are compared with sample databases, can have discriminatory consequences. Eliminating candidates with a speech impediment or accent or giving them a poor evaluation because the program or the microphone cannot classify speech correctly can mean discrimination based on disability, ethnic origin, gender, or background.

Video and speech analytics by AI can be affected by several factors. The results of speech analysis, in particular, are highly dependent on the task and the situation. For example, the sitting posture of a candidate, a cold, or too much alcohol the night before can lead to a distortion of voice pitch. In addition, nervousness in selection situations can influence the pitch of the voice, the choice of words, or even the speed of speech. Such influencing factors must be considered, particularly against evaluating the reliability of AI-supported selection procedures.

There may also be significant correlations between language characteristics and various personality traits. However, the question is how strong these correlations are. An exclusive (internal) validation of language-analytical procedures by calculating correlations with established personality tests is of only limited value. Even in the case of external validation, in which the language characteristics of applicants are compared with the language characteristics of particularly successful job holders (reference group), it must be critically questioned whether the recorded (language) characteristics of the successful employees are related to their performance. It would have to be demonstrated, beforehand, that language characteristics are directly related to success in a specific job (Schwertfeger, 2015, pp. 33–34). For example, Siegert and Niebuhr (2021) show that during the Covid-19 pandemic in 2020, video conferencing systems have thinned out frequencies of high female voices to save data volume. This could lead to discrimination against women because these female voices were perceived as less expressive, competent, or charismatic.

What data an algorithm is fed with and how it is programmed depends on the respective company and its goals. The nondiscriminatory use of AI is essential; an algorithm must be trained with unbiased, nondiscriminatory data sets, and programming codes and result interpretations should not reproduce possible discrimination. Furthermore, from a legal and ethical point of view, programming must ensure that discrimination based on age, gender, religion, or ethnic origin is avoided. Thus, even if a dynamic algorithm recognizes patterns, for example, that certain positions have only been filled with people of a specific sex or age, it must not select only applicants who correspond to this recognized pattern in terms of age or sex. Therefore, discriminatory criteria such as gender or age should be kept out of the training data. For this reason, the training data should be evaluated and – if necessary – adjusted regularly by diverse and independent teams.

In order to ensure high-quality personnel selection, algorithms should be checked for compliance with scientific quality criteria such as objectivity and reliability.

### 8.11.5 Limits of (verbal and nonverbal) language analysis

Despite the chances of AI-based language analysis, some scientists have concerns about such methods. There is not yet sufficient research-based evidence of the predictive power of the analysis of personality traits (Schwertfeger, 2015, p. 33). More research is needed to investigate how accurately and validly, automated AI-based video or speech-based assessments can capture a candidate's personality and/or competencies and predict performance on the job to be filled.

Standardized (or semi-structured) job interviews and an automated evaluation of the collected data offer the opportunity to improve the selection process. However, only vague statements concerning reliability or validity can be made, since precise information on the methods used in practice is only available to the public and researchers, to a limited extent. Also, usually, the algorithm is also not transparent to applicants (Buxmann & Schmidt, 2019, p. 16; Stachl & Bühner, 2018, p. 25). Therefore, scientific quality criteria are only partially fulfilled. As long as companies developing and selling AI tools do not subject their data to independent testing, validity statements should be treated critically (Schmidt-Atzert et al., 2019, pp. 19–20). Methods of language analysis can offer advantages, especially concerning objectivity and increased efficiency (Flörke, 2020, pp. 29–32), as shown, for example, in the studies by Campion et al. (2016) or Suen et al. (2019, 2020). On the other hand, scientifically based research is required to make an all-encompassing evaluation of such software.

Practitioners report of recognizing emotions in faces of applicants and using them to form their judgments. However, perceptions and analysis of gestures, facial expressions, voice, and emotions are usually subjective and unstructured. This is where AI and corresponding software-based tools can assist. Research on affective computing is engaged in attempts to detect and measure people's emotions accurately and build AI systems that can recognize and appropriately respond to these emotions.

In AI, there are increasing efforts to develop systems that perceive and accurately assess emotions in other people. This type of special AI-based software claims to be better than humans at recognizing verbal and nonverbal behaviors, including emotions in other humans.

Researchers analyze facial expressions using AI trained on images of faces and develop an algorithm. Using these algorithms, they try to determine the intensity of facial expressions and type of emotion. A research group from the Max Planck Institute of Neurobiology reports in the journal, *Science*, that they have already succeeded in analyzing and developing algorithms for analyzing facial expressions in mice. Particular stimuli, such as drinking water containing sugar or salt, triggered different reactions. Using their algorithms, they could determine the intensity and type of feeling in the facial expressions of the animals, in a fraction of a second. In parallel, the relevant neurons could be identified with two-photon microscopes. In the view of researchers, a significant advantage of discovering mouse mimicry is the possibility of understanding the processes in the brain behind emotions. Unfortunately, this is precisely where the problem has been up to now: without a reliable measurement of emotions, it has hardly been possible to investigate their development in the brain (Dolensek et al., 2020).

Thus, AI-based facial recognition software and software designed to recognize various emotions such as disgust, surprise, anger, joy, sadness, or even fear are constantly being improved (Desoi, 2018, p. 24). Video analysis by face-reading occurs during the interrogation of suspects by the police, during security checks at the airport, and in market research. In addition, the software is used to identify micro expressions that indicate, for example, whether suspects are lying or not (AI as a lie detector). However, these facial and emotion recognition methods are still in their infancy.

Such AI technologies can also be used in personnel selection. As a result, specialist companies see the enormous market potential in this area and promise employers great success in selecting suitable job candidates.

On the other hand, people who know that they are being observed and their emotions analyzed by an AI system may behave differently than when talking to a real person. In addition, the question arises as to what extent applicants experience interaction with a machine as “natural” and authentic.

However, using AI to analyze facial expressions, the tone of voice, and so on to predict certain personality traits accurately can be a helpful tool in selection. On the other hand, skepticism is called for, if AI analyzes body language, clothing, or whether someone wears glasses and pretends to derive personality analyses from this data. However, suppose the results of personality analyses vary depending on whether someone wears glasses, how the visual background of the video is designed, or what clothes someone is wearing, then, there is still considerable potential for improvement in AI development.

Therefore, most of the selection managers surveyed in our empirical research are firmly convinced that correctly perceiving and evaluating applicants’ verbal and nonverbal expressions remain one of their core competencies as human beings.

### 8.11.6 AI and lack of “human eye” and intuition

Practitioners interviewed in our empirical research also point out that the algorithm lacks the human eye for detail and intuition and cannot recognize or depict emotions. The subjective-emotional experiential content of a mental state or a particular human perception is linked to emotionally charged experiences connected to other individual concepts, memories, and experiences. Also, currently, there are limitations to AI being able to replicate that. For example, recruiters often have many years of experience, which allows them to read between the lines and distinguish nuances in application documents and behaviors. However, from the perspective of hiring managers interviewed, these subtleties, or the authenticity and the overall impression, can only be recognized to a limited extent by an algorithm or AI.

HR professionals want to demonstrate their competencies in assessing these human characteristics. Also, they resist thinking and feeling like a machine. Kloprogge et al. (2019, pp. 224–227) even call digital personnel selection inhumane, because it wants to take away from selection managers and treat as a disruptive factor, what human beings are particularly good at and what creates the competitive advantages of companies, in the first place. It's about the human factor in personnel selection and, thus, about deciding which people you want to work with, who you experience as authentic and credible, and, ultimately, who you trust. Trust is the breeding ground and the protective space in which new and additional things can emerge. Trust is an interaction and a resonance, which, in turn, generates trustworthiness. Those who do not trust will never be able to reap the returns of a trusting relationship. Hence, personnel selection is not primarily a decision between two requirements and suitability profiles, but between people.

Harari (2014, pos. 2055) states that computers have trouble understanding how people think, feel, and talk; so humans learn to think, feel and talk in the language of numbers, which computers can understand.

Hence, digital tools in HR or People Management should be designed to support and use the success factors of human decision-making behavior instead of trying to eliminate them as disruptive factors. There is a risk that AI or software will force human decision-making in a particular way or that people have to organize work processes according to software requirements. On the one hand, this can help make good decisions. On the other hand, it can lead to a situation where the focus is more on the correctness of adhering to processes and rules and less on what may be correct from a business perspective. In this way, people's scope for decision-making and, thus, for action and responsibility can be narrowed by AI and software.

For this reason, digital processes and AI should always be critically reflected upon in terms of the extent to which they narrow people's scope for decision-making and responsibility and, thus, possibly prevent people from learning to think independently and assume responsibility. Moreover, as open systems, organizations should be able to cope successfully with the complexity of the demands of their environment, and this requires opening up areas of responsibility for employees and placing decisions, as far as possible, at lower or decentralized levels, following the principle of subsidiarity. Therefore, AI and associated digital processes should always be reflected against the backdrop of the freedom and, thus, responsibilities they leave for people. This is made very clear in the Digital HR Manifesto (Goinger Kreis – Initiative Zukunft Personal und Beschäftigung e.V., 2019).

The Digital HR Manifesto calls for digital tools to support people in thinking about alternatives and allowing for diversity, not to demand a static fit from applicants, and, in particular, not to be an unwilling performer incapable of personal responsibility. Thus, the Digital HR Manifesto calls for increasing the range of options and perspectives rather than reducing them to a single instant solution, and digital instruments should make visible, the full range of different ideas and problems, rather than streamlining behavior. Furthermore, digital tools and AI should encourage active thinking and experimentation at all levels of activity, rather than reducing individuals to mere passive executants; they should allow for individuals to develop, rather than portraying them as consistent and unchanging; they should deliberately allow for exceptions and offer scope for off-piste ideas; they should ensure transparent criteria and methods for evaluating and assessing individuals and their performance, they should encourage the empathetic relationship between people, and strengthen the responsibility of each individual (Goinger Kreis – Initiative Zukunft Personal und Beschäftigung e.V., 2019; Klopprogge et al. 2019, pp. 276–277; Klopprogge, 2022, pp. 489–491; Koenig, 2019).

Thus, algorithms and AI are seen as a support in the decision-making process, which can give a score to applicants, after the first assessment of the application documents or deliver test results, which are then checked and evaluated by the recruiter, for example, in an interview.

"What algorithms . . . do not provide are imaginations and visions. They know neither emotions nor worries, no hope, and no trust. But these are precisely the central resources for decisions that point the way, and thus the entire field of entrepreneurial decision-makers. . . . For entrepreneurial decisions (and personnel selection decisions are one of the most important entrepreneurial decisions, J.D.), in which individual judgment is important, a human decision-maker is still needed" (Hutzschenreuter, 2022).

### 8.11.7 Ethical particularities of AI

AI tools can significantly support personnel selection but fall short, if not used responsibly. AI, per se, is neither good nor bad: it depends on what it is used for. Technology is usually developed for a specific purpose, for which it is better suited than others, and, therefore, it is not neutral. How digital technologies are used depends not only on programmers, developers, or coders but also on computer science developments and other factors such as law, economics, politics, philosophy, or ethics.

Using AI to analyze candidates' "digital footprint," for example, by examining data on private social media, could limit freedom of expression due to fears that certain information might be interpreted negatively by hiring managers.

Apart from the problem that facial recognition software can be used to monitor certain population groups or people and that AI can be used for "social scoring," it must be critically questioned whether such systems actually identify feelings. AI-based systems may capture someone's behavioral or body-language patterns, classify them, match them with images associated with specific emotions, and infer their emotional state. Specifically, this involves correlating recognized behavioral or body-language patterns to the seven basic feelings of happiness, anger, disgust, fear, contempt, sadness, and surprise. The AI-based systems detect these patterns and micro expressions in the face, but the question remains to what extent emotions can be identified correctly. In addition, the software may have difficulty recognizing signals in certain groups of people, such as people of color. Thus, the risk is that the data used to train the computer programs may reproduce human inadequacies and biases rather than overcome them (Scheer 2021). Barrett et al. (2019, p. 48) conclude: "Efforts to simply 'read out' people's internal states from an analysis of their facial movements alone, without considering various aspects of context, are at best incomplete and at worst entirely lack validity, no matter how sophisticated the computational algorithms. Nevertheless, these technology developments are powerful tools to investigate the expression and perception of emotions . . . Right now, however, it is premature to use this technology to reach conclusions about what people feel based on their facial movements."

AI actively interferes with people's self-image. Therefore, the topic of AI must also be examined from an ethical perspective. There is the question of whether the goal of being objective and less discriminatory by using AI leads to releasing humans from the responsibility of making selection decisions. Or do we want to leave those decisions with humans?

To get a trustworthy and accepted application of AI, many ethical guidelines have been established recently, including in Germany, by the HR Tech Ethics Advisory Board. According to these guidelines, the goal of using digital technologies such as AI must first be defined, before they are used, and the key stakeholders should be involved in this goal-setting process, which should be as transparent as possible. Anyone using AI solutions must ensure that a human has the final personnel decision (Ethikbeirat HR Tech, 2020).

Also, the European Commission has established the High-Level Expert Group on AI. This group has developed an EU-wide framework for using AI that complies with fundamental rights. Among other things, this involves user transparency and also human control. Furthermore, ethics guidelines for trustworthy AI were published. Respect for human autonomy, fairness, transparency, and harm prevention are particularly important. In addition, it is crucial to protect vulnerable people exposed to a particular risk of exclusion in the labor market (e.g., people with disabilities) from discrimination in personnel selection. The guidelines put forward a set of seven key requirements (European Commission, 2019):

1. Human agency and oversight: AI systems should empower human beings to make informed decisions and foster their fundamental rights. At the same time, proper oversight mechanisms need to be ensured, which can be achieved through human-in-the-loop, human-on-the-loop, and human-in-command approaches.
2. Technical robustness and safety: AI systems must be resilient and secure. They need to be safe, ensure a fallback plan if something goes wrong, and be accurate,

reliable, and reproducible. That is the only way to ensure that unintentional harm too can be minimized and prevented.
3. Privacy and data governance: besides ensuring full respect for privacy and data protection, adequate data governance mechanisms must also be guaranteed, taking into account the quality and integrity of the data, and ensuring legitimized access to data.
4. Transparency: the data, system, and AI business models should be transparent. Traceability mechanisms can help achieve this. Moreover, AI systems and their decisions should be explained according to the stakeholder concerned. Finally, humans need to be aware that they interact with an AI system and be informed of its capabilities and limitations.
5. Diversity, nondiscrimination, and fairness: Unfair bias must be avoided, as it could have multiple negative implications, from the marginalization of vulnerable groups to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders through their entire life circle.
6. Societal and environmental well-being: AI systems should benefit all human beings, including future generations. It must, hence, be ensured that they are sustainable and environmentally friendly. Moreover, they should consider the environment, including other living beings, and their social and societal impact.
7. Accountability: Mechanisms should be implemented to ensure responsibility and accountability for AI systems and their outcomes. Auditability, which enables assessing algorithms, data, and design processes, plays a key role, especially in critical applications. Moreover, adequate and accessible redress should be ensured.

These fundamental requirements are prioritized for human action, responsibility and accountability, and human supervision. However, the question remains whether technological systems are accountable from a legal perspective. Therefore, care must be taken to ensure that people remain accountable, that people make (final) decisions, and do not leave them unchecked to machines.

### 8.11.8 Legal aspects of AI

In many countries, data protection laws apply, especially when generating personality profiles using algorithm-based methods. For example, in Germany, the Federal Data Protection Act states that if assessments of personal characteristics lead to a candidate's rejection, this decision may not be made solely using automated procedures (Büttner, 2017, p. 26).

Big data analysis relies on a vast amount of data; thus, compliance with data minimization principles, storage limitations, or informational self-determination can be challenging (Weitzel et al., 2019, p. 27).

It must be possible to use employee feedback and evaluation data to determine how applicants have performed. Here too, data protection regulation rights must be considered.

Another influencing factor in implementing these digital or AI-based selection procedures in countries like Germany is the codetermination rights of employee representatives such as works councils or social partners. The works council must agree to use technological instruments that can assess the behaviors of employees. One of our interviewed selection managers says: "If (. . .) the social partners have the right of codetermination, it is always a great challenge to incorporate things like algorithms, personality tests, or video interviews into the selection process" (Flörke, 2020, p. 50).

To help employee representatives navigate the complex field of AI in management, recruitment guidelines and critical negotiating demands for unions have been developed. From the UNI Professionals and Managers (2020) perspective, the first step is to understand algorithms, how they are being used properly, and the key risks and opportunities that unions need to bear in mind. Unions must verify the legality of using such tools of data collection. A company that is programming or purchasing management algorithms needs to be adequately aware of the risks of bias and discrimination and take all possible steps to mitigate them. Decisions affecting employees should always be based on transparency. Thus, algorithms should use publicly known criteria, and their decisions should be explainable in clear, understandable language, not technical jargon. Clear records of what decisions have been made and why these decisions have been made should be referred to, in case of future challenges. To avoid biased or discriminatory outcomes, algorithms should also be regularly audited by independent third parties and chosen jointly by employers and unions. The results of such audits should be available to anyone affected by algorithmic decisions, including union representatives. "Human in command" should be the overriding principle. It is never acceptable to pass responsibility for critical decisions to nonhuman agents.

> Algorithms should advise, humans should decide. Algorithms should be used to support managers but never to replace them.

Thus, employers and unions should ensure that selection managers do not use algorithms to avoid taking responsibility for their decisions (Uni Global Union Professionals & Managers, 2020, pp. 22–24).

The ethical topic of the responsibility and imputability of judgments on people is also discussed in jurisprudence, along with the extent to which AI can help process legal cases faster and more competently. AI can learn how judges make decisions in certain situations and specific issues. However, strong voices in the judiciary advocate preserving the human element in decision-making. AI can, if necessary, assist in reducing discriminatory and incorrect judgments. The decision-making process can also be shortened by using AI to help generate data from previous judgments and other decisions, commentaries, and so on, to apply to new cases. Judicial decisions are also about discretion, appreciation of the individual case, and social skills, such as empathy. Therefore, there is great skepticism about automatic judgments by "legal tech" and demands that human judges make judicial decisions. Even though there may be a temptation to allow machine judgments due to time pressure and the large number of cases to be processed, robots as judges, who pass sentences nonstop, are questionable from today's perspective (Nink, D., 2011; Ebers & Navas, 2020).

### 8.11.9 Limits of using data from social media

Within social media, such as Facebook or LinkedIn, users present information. This means that information can be deliberately withheld from the public or removed from a profile. Therefore, when assessing the quality of data in social media, it should always be considered that making (private) data public may be influenced by factors such as social desirability and deliberate misrepresentation (Kosinski et al., 2015, p. 548). In addition, it is not only that information can be deliberately withheld. It is possible, for example, to falsify a profile by incorporating specific keywords with the help of algorithms (Siemann, 2017). In this way, evaluations of social media data may be based on deliberately falsified data. For example, one of our interviewed managers stated:

> The data on Facebook or other social media are not necessarily more honest and authentic; especially when candidates assume that employers evaluate their statements on social media (Flörke, 2020, p. 56).

Another aspect relates to influencing people in the network within the platform. For example, users can include other users in contributions, leading to a distortion of their profile and its meaningfulness (Landers & Schmidt, 2016, p. 4). It is also essential to recognize that some data give insights into users' privacy (Kosinski et al., 2013, p. 5805). This could lead to findings regarding age, origin, skin color (Landers & Schmidt, 2016, p. 4), sexual orientation, or political views (Youyou et al., 2015, p. 1039), as well as personality (Büttner, 2017, p. 26) of the persons. These criteria can influence the selection decision (Landers & Schmidt, 2016, p. 4) and discriminate against specific persons (Büttner, 2017, p. 26).

Similarly, when using digital social media data, its relevance must be ensured, because it is to be expected that the predicted personality of users will remain relatively stable, but it cannot be assumed that people's likes of specific content, pages, events, pictures, and so on will also remain stable (Stachl & Bühner, 2018, p. 33). Thus, the age, timeliness, and, hence, validity of the evaluated data should be considered. Since the internet does not forget, the sins of youth and posts made at a young age may still be held against the writers in adulthood.

One of the main reasons interviewed selection experts oppose certain social media data is that they attach great importance to separating the private person from the professional person. In particular, data from networks such as Facebook, Instagram, Twitter, or Twitch belong to the private and personal sphere of the candidate:

> I find that it infringes very much on the individual's personal rights, and I would be very, very, very critical. . . . the private must remain private . . . what a person does privately should not be a selection criterion (Flörke, 2020, pp. 56–57).

However, some interviewees state that it is permissible to use data from applicants' social media accounts in professional networks such as LinkedIn, XING, or similar. But they do not rely on more private social media such as Facebook or Instagram (Flörke, 2020, pp. 56–57).

For example, a completely AI-based selection process is currently not legal under German law, so humans must always make the final decision (Fesefeld, 2018, p. 27).

AI methods that use social media data from private networks are ethically problematic, because they process personal data without the applicants' permission and may investigate characteristics that have nothing to do with the job requirements. Thus, many interviewed HR professionals fear that use of social media data by AI could violate the personality and privacy rights of applicants (Berthel & Becker, 2010, p. 341):

> Only when these tools are legally correct and produce results that have been scientifically tested, and a higher level of fairness and objectivity can be achieved, under these conditions I would consider using such tools (Flörke, 2020, p. 61).

Another critical point is that the personality tests based on the evaluation of data from social media should be evaluated scientifically and assessed in terms of their quality (validity, reliability, objectivity, etc.).

## 8.12 Advantages and disadvantages of AI in personnel selection

Although AI-based software still has several weaknesses in personnel selection (Woods et al., 2020; Tippins et al., 2021; Wall & Schellmann, 2021), AI and algorithms that do not generate one-size-fits-all solutions and recognize the limits of AI and algorithms, as well as the specific characteristics of the situation (individual employee, the particular tasks, team constellation, culture, legal system, etc.), could be very useful in supporting selection decisions. If AI can also identify processes and selection decisions that end discrimination, it can lead to more fairness and objectivity.

AI and algorithms, but also humans, achieve good results, particularly when trained with high-quality and high-value data. Human expertise and human expert experience (and, thus, intuitive and emotional knowledge) can be incorporated into AI. The exchange of information between humans and machines is a critical success factor in that humans tell the machine how they decided and why they decided in the way they did; or they evaluate decision proposals from the AI and report these evaluations back to the AI. On the other hand, AI gives information to humans and makes suggestions. Since human decision-makers, especially in Western cultures, want to know how AI gets specific analysis results and why it judges in a particular way, transparency is essential for accepting AI. In this way, the people and the AI learn through a so-called feedback loop. Woods et al. (2020, pp. 68–73) show evident advantages of digital-based personnel selection, for example, faster, easier, sometimes more vivid, and fun, while expanding the number of applicants by reducing distance, cost, and time barriers. In addition, Algorithms and AI help find possible inconsistencies and judgment errors, and they do not get tired, work 24/7, have no good or bad days, and are not subject to perceptual distortions like noise (see 3.5.2.4). However, their research also highlights significant limitations in understanding the effectiveness of these technologies. In their view, a multi-method scientific research program is necessary because, in some areas, organizations using these new technologies are rather "blind" to their validity, adverse impact, privacy, or impact on applicants.

Main advantages of AI in personnel selection:

1. AI can eliminate or reduce unconscious human bias (Albert, 2019, p. 217).
2. Algorithms and robot recruiting systems should be designed to meet legal and ethical specifications. Thus, the data sets with which AI is trained should be free of bias; furthermore, statistical methods can be used to check whether specific categories are adequately represented. AI should be designed to be audited and evaluated, for example, to find and remove biases. IT technologists, HR specialists, line managers, and legal experts should work together to create the AI software. An AI audit should function just like the safety testing of a new car before someone drives it. If standards are not met, the defective technology must be fixed, before it is allowed into production (Polli, 2019).
3. AI enables much faster assessment, processing more applicants than human recruiters with limited resources and cognitive capacities. AI can check the entire pipeline of candidates, without the risk of time-constrained humans implementing potentially biased processes to shrink the pipeline from the start.

Figure 17 shows a comparison of the old and new selection methods:
However, there are also some risks in using AI. Publications like the anthology "Fake AI," edited by Frederike Kaltheuner (2021), director of the European AI fund, show examples of dubious AI that promises more than it delivers. We can also find collections of such dubious applications of AI on the websites of nongovernmental organizations like Algorithmwatch.

Since people have a deep need for security and can hardly tolerate uncertainty, there is a risk that they will rely on AI in personnel selection, even though it is not yet mature. Delegating tasks to technical systems is called technology-solutionism:

| Old methods | New tools | Dimension assessed |
|---|---|---|
| **Interviews** | Digital interviews<br>Voice profiling | Expertise, social skills, motivation, and intelligence |
| **Biodata** | Big data (internal) | Past performance |
| **Supervisory ratings** | | Current performance |
| **IQ**<br>**Situational judgment test**<br>**Self-reports** | Gamification | Intelligence, job-related knowledge, and Big Five personality traits or minor traits |
| **Self-reports** | Social media analytics | Big Five personality traits and values (identity claims) |
| **Resumés**<br>**References** | Professional social networks (LinkedIn) | Experience, past performance, and technical skills and qualifications |
| **360s** | Crowdsourced reputation/peer-ratings | Any personality trait, competencies, and reputation |

**Figure 17:** Comparison of old and new personnel selection instruments (Chamorro-Premuzic et al., 2016, p. 627).

People feel overwhelmed and hope that technology will provide a solution that will take the decision away from them. As a result, the overburdened human being relies on the help of at least equally overburdened algorithms and AI that give a decision-making process the appearance of progressiveness, objectivity, and efficiency (Lenzen, 2022).

The evaluation of current literature and our interviews (e.g., Lindemann, 2020, pp. 50–53) clearly show that digital technologies such as software to assess video interviews, chatbots, or digital tests can help make selection processes more efficient, especially in the preselection process by HR-managers. However, AI cannot replace human contact.

Just as people don't only want to experience something digitally but also want to hike, climb, travel, cook and celebrate with others, people also want to meet and interact with real people in personnel selection.

Candidates and hiring managers, worldwide, want to have the opportunity to get to know each other and meet in person, which promotes trust and a sense of belonging. However, getting impressions about a company, the department, and the team via virtual or augmented reality is not enough for applicants. They want to meet personally and see if they like each other, if they fit together, professionally, and especially, humanly and socially. While providing applicants with a positive candidate experience may depend on the specific labor market situation, our literature analysis and empirical research clearly show that this is an important goal of personnel selection, across countries and cultures.

The difficulty with video-based verbal and nonverbal behavior analysis is that face recognition, verbal and nonverbal language, and even other human emotions are very complex. In different contexts, terms and specific body language expressions have different meanings. And, humor, irony, and sarcasm are individual, culture-specific, and complex (Kreutzer & Sirrenberg, 2019, p. 30; Lochner & Preuß, 2018, p. 194). To perceive and evaluate humor or irony accurately, humans draw on implicit knowledge and, thus, on their intuitions and emotions.

AI, currently, has some problems in dealing with ambiguity, irony, humor, or deviations from the expected. In addition, candidates react to the behavior of selection managers and vice versa. They use their experience, background knowledge, values, and interests, anticipate possible behavior and behavioral expectations of the counterpart, and so on. All of this is difficult to capture in rules and, therefore, challenging to map in AI and algorithms. Perhaps, it is not enough to try to imitate the human brain via AI, because there is a complex interplay of brain and body: there is no intelligent mind without the interplay with the human body or gut.

Dahm and Dregger (2019, p. 264) show that the acceptance of AI in personnel selection processes is higher, when human contact is available. In addition, ethical guidelines and legal concerns for AI state that human supervision and human decision-making should take priority (European Commission, 2019)

Despite all the possible advantages of AI-based video interviews, the human element is irreplaceable. The selection managers interviewed in our research rely on face-to-face interviews for the final selection decision. They want to take time for the candidate and directly observe verbal and nonverbal expressions such as facial expressions or gestures. They are convinced that only their intuitions and feelings help assess whether an applicant is empathetic and authentic, can form a positive relationship, and is, all in all, a good fit. AI can help obtain additional information about applicants but will not replace human decision-making.

Indeed, artificial neural networks and material techniques will become more potent in the future, data sets qualitatively and quantitatively better, computing power will be more powerful, and learning algorithms more sophisticated. Yet, some questions remain, for example, how AI can be meaningfully embedded in social, cultural, or even political contexts and developments. Also, some core questions concerning AI remain in personnel selection: How do we get AI to draw the correct conclusions from data? This is where AI continues to develop, including at the level of emotional and intuitive intelligence. But, someday, and no one can predict precisely when, we may have hardware and software to make human decisions as good as or even better than humans do.

However, even if the world will see more progress in AI in the next decade than in the past 100 years, and even if AI achieves increasing success in personnel selection, hiring managers should beware of inflated expectations and promises.

HR managers can and should use algorithms and AI for preselection. But when it comes to deciding whether a candidate is a good fit for a company or a team, line managers (superiors) and possibly team members should be involved. Candidates want to be won over by people. They are willing to work for their company, their managers, and their team, being highly motivated if they feel chosen by them actively (and vice versa) and not by a machine. Thus, humans will remain superior to AI for a long time, especially when it comes to implicit and contextual knowledge, associations, humor, irony, or evaluating and expressing intuitions and emotions.

Most managers we surveyed do not see the threat of recruiters or selection managers being eliminated. Instead, they see that digitalization and AI could upgrade the profession, making the work more exciting and people-oriented. Also, repetitive or routine tasks could be eliminated or reduced, and more time would be left for personal conversations with people (Pasenau, 2021, p. 48).

Thus, it is to be expected that AI will not replace human leadership, and final personnel selection decisions will continue to be made by humans: Recruiters and hiring managers should not hide behind data and AI. They are responsible for selection decisions. Suppose hiring managers concentrate on their human strengths and use their soft skills, intuitions, and emotions to understand people better and build positive relationships, while leaving technical skills or routine tasks to robots. In that case, they will gain the trust of their employees and candidates in their decisions.

Even if the development of human or even superhuman intelligence seems possible to some AI researchers, it remains to be seen as to what extent, for example, corresponding AI can succeed in understanding and mapping human interrelationships, or to what extent it can succeed in creatively developing novel solutions. Therefore, from today's perspective and an ethical standpoint, digital technologies and AI can best realize their strengths in personnel selection, when they complement human capabilities.

There is also the risk that AI as a self-learning system can develop its own intentionality and act autonomously. If these systems act according to their own rules, they, possibly, can no longer be controlled by humans. Therefore, they may make decisions contrary to humans' goals, and such an AI would no longer be humans' servants or partners (Klopprogge, 2022, p. 80). Then, we humans have to answer questions such as: Do we humans want to dominate computers and AI? Or do computers and AI dominate us? What do we want as humans?

HR or people managers and selection managers should never forget that organizations are all about people. People are the problem and also the solution. (Fernandez-Araoz, 2007, S. IX).