Diversity and Technology - Challenges for the Next Decade in Personnel Selection

Introduction to the Special Issue "Job Search, Attraction, and Selection: Challenges for the Next Decade"

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Introduction

The world of work is changing quickly. An aging workforce, large-scale population migration, the democratization of remote work following the COVID-19 pandemic, and technological advancements, currently most famously driven by advances in artificial intelligence (AI), are just some of the driving forces of the changing world of work. Research is needed to properly understand those changes and their potential consequences on job seekers, employees, organizations, and the society more broadly. This Special Issue brings together a series of six original and insightful articles, based on research that was initially presented at the 6th small group meeting of the European Network of Selection Researchers (ENESER) organized by Martin Kleinmann and Annika Wilhelmy in Zurich in 2021. Together, these articles span two topics central to the changing world of work: Diversity and Technology. In this introductory article, we emphasize the growing importance of those two topics in relation to personnel recruitment, selection, or assessment. We then provide a brief overview of the six articles, and highlight how they contribute to enhancing our understanding of the role that diversity and technology play in various stages of the hiring process, from job applications to selection decisions. We conclude by providing suggestions about opportunities for future research in recruitment and selection that continues examining diversity and technology as well as their increasingly important overlaps.

Diversity

Due to globalization, migration, increasing rates of paid employment by women, an aging population, advances in reducing barriers for people with disabilities, as well as further societal changes, the labor market is becoming increasingly diverse. It is important for organizations to build a workforce that reflects this diversity to avoid litigation, serve the needs of diverse customers, and stimulate creativity, innovation, and high-quality decision making (e.g., Galinsky et al., 2015; Jackson et al., 2003). Building a diverse workforce starts with designing a hiring process that prevents adverse impact, meaning that it provides members of minority groups (regarding, e.g., race, sex, age, and national origin) an equal chance to be selected as members of majority groups (Uniform Guidelines on Employee Selection Procedures, 1978).

To prevent adverse impact, selection research has traditionally focused on identifying selection tools that predict future performance and minimize subgroup differences or on combining outcomes of different selection tools to optimize decision making (Van Iddekinge et al., 2023). However, less attention has been paid to earlier (recruitment) phases of the hiring process, while these phases determine the quality and diversity of the applicant pool. Only with a high-quality and diverse applicant pool, selection tools can identify equal numbers of talented candidates among different subgroups. Thus, to prevent adverse impact, organizations should carefully consider the different ways in which they can stimulate more diverse groups to apply for their positions. Another under-researched area is multiple-group memberships or intersectionality. For example, we know that unstructured interviews are prone to biases based on race, gender, and disability (Levashina et al., 2014), but we know relatively little about how being a member of multiple of these stereotyped groups simultaneously affects interview outcomes. More research on the effects of multiple-group members is important as isolating one stereotyped characteristic (e.g., sex) while ignoring others (e.g., race or age) may oversimplify the reality of many job seekers who have multiple identities and therefore may face intersectional biases. The papers by Koçak et al. (2023) and Krings et al (2023) in this Special Issue address these two important gaps in the literature.

Technology

The evolution of personnel selection approaches is closely intertwined with the evolution in technology: from paper-and-pencil testing, to online testing, to adaptive testing based on machine learning algorithms (Barney & Fisher, 2016); from face-to-face interviewing to telephone interviewing, to (a)synchronous videoconference interviewing (Basch et al., 2022; Langer et al., 2021; Lukacik et al., 2022); from conducting job analyses for every selection process, to having a searchable database of KSAOs for every job (O*Net) (Dye & Silver, 1999), to having generative AI (e.g., ChatGPT) automatically produce job descriptions. The technological changes may vary substantially but the questions for personnel selection may remain fairly similar: (how) can we effectively capitalize on new technological developments? What are the implications regarding the psychometric properties of selection tools? How do different stakeholders react to the use of novel technology? The papers by Bill and Melchers (2023), Bangerter et al. (2023), Kares et al. (2023), and Köchling and Wehner (2023) included in this Special Issue address such questions.

Summary of the Papers Included in the Special Issue

What is often a central part for an introductory paper to a Special Issue is to provide an overall summary of papers included in the Special Issue and to identify common concepts in these papers as well as summaries of the individual papers. The authors of this introductory piece had an about 45-minutes long discussion about the papers and tried to identify common topics. After this session, we identified the two topics diversity and technology. In line with the current hype surrounding ChatGPT, we thought we could try to input all the abstracts of the included papers into ChatGPT to compare the result of the authors' discussion with the output by ChatGPT. Here is the prompt that we used: "Please write me a one paragraph summary of the following abstracts of scientific papers in the area of personnel selection and industrial and organizational psychology. Please also identify two to three common topics in these abstracts that can be used to write an editorial for a Special Issue that includes the papers that are described in these abstracts. (*Then the abstracts were added*)."

Here is the result that ChatGPT produced (we only added the references to the respective papers): "The six abstracts all relate to personnel selection and industrial and organizational psychology. The first study examines the impact of negatively metastereotyped information in job ads on application intention and self-efficacy of both older and younger job seekers (Koçak et al., 2023). The second study examines the impact of self-promotion on interview performance ratings, finding that both older female and younger male candidates who engage in high self-promotion are regarded as less interpersonally warm and less likely to be hired (Krings et al., 2023). The third study investigates the effectiveness of countermeasures against faking in interviews and finds that none of the countermeasures tested could reduce faking intentions or faking (Bill & Melchers, 2023). The fourth study uses machine learning algorithms to predict storytelling in responses to past-behavior questions in a simulated selection interview, with potential implications for automatic provision of feedback to applicants (Bangerter et al., 2023). The fifth study compares trust, trustworthiness, and trusting behavior for different types of decision-support (automated, human, hybrid) across two assessment contexts (personnel selection, bonus payments) and examines trust violations (Kares et al., 2023). The sixth study investigates ways to alter applicant reactions to AI-supported selection processes (Köchling & Wehner, 2023). Two common topics that emerge across the abstracts are (1) the need to avoid or mitigate negative stereotypes in personnel selection and (2) the use of technology, including machine learning and automation, to improve selection processes."

We now provide the summaries written by the editors of the Special Issue that are organized in line with the two common topics of the included papers: diversity and technology.

Diversity

Koçak et al. (2023) investigate the effects of negatively metastereotyped personality requirements in job advertisements on both younger and older job seekers' self-efficacy and application intentions. Metastereotypes refer to people's beliefs about stereotypes that out-group members hold about one's group (Vorauer et al., 1998). For example, younger people believe that others think they are relatively irresponsible, while older people believe that others think they are stubborn (Finkelstein et al., 2013). Koçak et al. show that negatively metastereotyped personality requirements in job advertisements reduce older job seekers' application intentions and that this effect is mediated by self-efficacy regarding that personality trait. The authors did not find any effects of negatively metastereotyped personality requirements on younger job seekers' self-efficacy and application intentions. Thus, if organizations want to increase the diversity of their workforce, they not only have to administer bias-free selection tools, they also have to consider the wording of their job advertisement.

Specifically, this study shows that using adjectives related to the personality trait of agreeableness (e.g., obedient, flexible, friendly) causes older applicants to select themselves out of the applicant pool, making it difficult for the organization to create an age-diverse workforce. This paper convincingly demonstrates that to actually achieve diversity, all parts of a selection system need to be aligned with each other in a manner that supports the organization's diversity goals.

The research by Krings et al. (2023) focuses on two important diversity elements: gender and age. They take an intersectional lens to examine whether applicants' characteristics influence how their attempts to use impression management are viewed by interviewers. Building on past work showing that applicants generally benefit from engaging in self-promotion, by emphasizing their true job qualifications and relevant past experiences, Krings et al. explored whether such a strategy can backfire for certain applicants. They designed an experiment where a job applicant, described as either male or female and younger, middle-aged or older, would describe the same successful work experience, but either in a very modest way or in an immodest and very self-promoting way. They found that two types of applicants were mostly at risk of backlash when they engaged in extensive self-promotion: older women and younger men. In both cases, although the applicant was viewed as competent, they were perceived as less interpersonally warm and thus were evaluated more negatively and were less likely to be hired. Krings et al. argue that when older female applicants display high levels of assertiveness, it contradicts stereotypical expectations (i.e., older women are expected to be modest), thus explaining the negative evaluations. They further argue that the negative evaluations for younger male applicants could be attributed to recent societal changes, whereby excessive assertiveness is associated with toxic masculinity and dominance. Overall, their findings contribute to the literature on both impression management and discrimination or bias in selection contexts, by highlighting that interviewers have different behavioral expectations depending on who the applicant is.

Technology

The paper by Bill and Melchers (2023) combines the role of technology in personnel selection and the issue of applicant faking in employment interviews. In an initial study, they identified a series of potential counter-measures to faking for technology-mediated interviews (e.g., algorithms described as detecting non-verbal or para-verbal cues of deception) and face-to-face interviews (e.g., using questions asking about objectively-verifiable information). This was followed by three experimental studies (one imagined video-conference interview, one with a simulated video-conference interview, and one with an imagined face-to-face interview) where participants were presented with information about the faking counter-measure(s) that would be used by the organization. Participants felt their answers would be more likely to be verified in the presence of the counter-measure(s). However, across all studies, none of the examined counter-measures influenced faking intentions (in the imagined scenarios) or self-reported faking (in the simulated interview). In addition, some of the counter-measures were associated with more negative justice perceptions. Overall, Bill and Melchers' findings suggest that organizations should carefully consider the (possibly large) risks and (limited) benefits associated with integrating counter-measures to limit faking in interviews. They also highlight that more research is needed to identify truly-effective ways to deter or detect applicant faking, and especially research conducted with actual (and ideally high-stakes) interviews.

Bangerter et al. (2023) investigate to what extent it is possible to automatically identify storytelling behavior in responses to job interview questions. The findings show an accuracy of up to 78% for classifying whether a response includes a story. However, an accurate automated detection of smaller subcharacteristics of stories (i.e., classifying utterances in responses as situation, task, action, or result in accordance with the STAR method) may be more difficult to achieve. The authors argue that automatically detecting whether a response includes a story could be used to offer applicants automated training opportunities. This paper is an excellent example of what it involves to train supervised machine learning algorithms: gathering high-quality training data, annotating this data (e.g., regarding whether a response includes a story), checking for quality in annotations (e.g., calculating interrater reliabilities), choosing between different algorithms, and applying appropriate validation strategies (e.g., nested-cross validation). It is also an excellent example of the fact that machine learning methods can be used for various tasks beyond automatically evaluating interview performance (Naim et al., 2015) or beyond evaluating applicant personality (Hickman et al., 2022).

Kares et al. (2023) examine the perspective of the people who receive decision support by algorithm-based systems with a focus on the burgeoning area of trust in algorithmic decision support. The authors propose that beyond trust in a human *or* an automated system as decision support, there may also be trust that focuses on the combined entity of a human closely working together with an automated system (what the authors call hybrid human-system decision support). Across two studies in different selection settings, they compare trust in a human vs. in an automated system vs. in hybrid human-system decision support when the respective decision support agent provides either a gender-balanced or a predominantly male preselection of applicants (manipulating possible unfairness reflected in the preselection and thereby examining reactions to a possible trust violation). The findings show that trust in the human and in the human-system decision support seems to be similar and comparably higher than in the automated support. The authors highlight that hybrid decision support may be interpreted as a human who uses a tool to make their decisions which may lead to similar reactions. They also emphasize that having a human oversee an automated system may thus alleviate negative reactions that can result from fully automating decisions. This paper's findings are also interesting in the context of current calls for having humans oversee AI-based systems in high-risk domains (Green, 2022) such as personnel selection. Although human oversight may be targeted towards reducing risk in the operation of AI-based systems, it may first and foremost alleviate people's possible concerns regarding automating important decisions (without actually reducing risk; Green, 2022).

In a similar vein, Köchling and Wehner (2023) investigate ways to improve reactions towards AI-supported selection systems by another important stakeholder in personnel selection: applicants. In their study, they presented participants with either an AI-based selection without any information, with written information, or with video information. The authors found that video information can alleviate some negative applicant reactions to the extent that those may even be on par with reactions to a traditional human-made selection. Thus, the authors present a possibly effective way to improve reactions to automated selection processes and highlight that it may not only be the content that matters (e.g., whether to provide applicants with information about what is done and why exactly an AI-based system is used; Langer et al., 2021) but also the presentation format. Presenting a video of a company representative that informs applicants why the company uses an automated selection system was well-appreciated by applicants in contrast to having the same information presented in text form. Possibly, this kind of a video introduction serves to increase the social presence that applicants may sometimes miss in highly-automated selection contexts (e.g., in asynchronous video interviews [AVIs]; Basch et al., 2022), may signal extra effort that a company has put into the selection process (Bangerter et al., 2012), and may thus improve applicant reactions.

Future Research and Conclusion

The increasing diversity in the labor market and technological advancements are two driving forces of the changing world of work. The articles included in the present Special Issue illustrate the importance of examining issues associated with these two important forces in recruitment and/or selection separately. However, more research is needed at the intersection of diversity and technology. Indeed, of the articles included in this Special Issue, only the paper by Kares et al. (2023) touches upon this intersection: while focusing on technology in personnel selection, the authors examined evaluators' reactions to possibly unfair (i.e., gender-biased) outputs by an algorithm-based system.

Figure 1 presents an overview of the hiring process and the different steps in which research at the intersection of diversity and technology might contribute to considerable improvements in terms of the quality and diversity of the applicant pool and the ultimate hires. Although we believe that research on the intersection between diversity and technology has potential across the entire selection process, below, we focus on examples for promising research avenues within three specific steps in the hiring process.

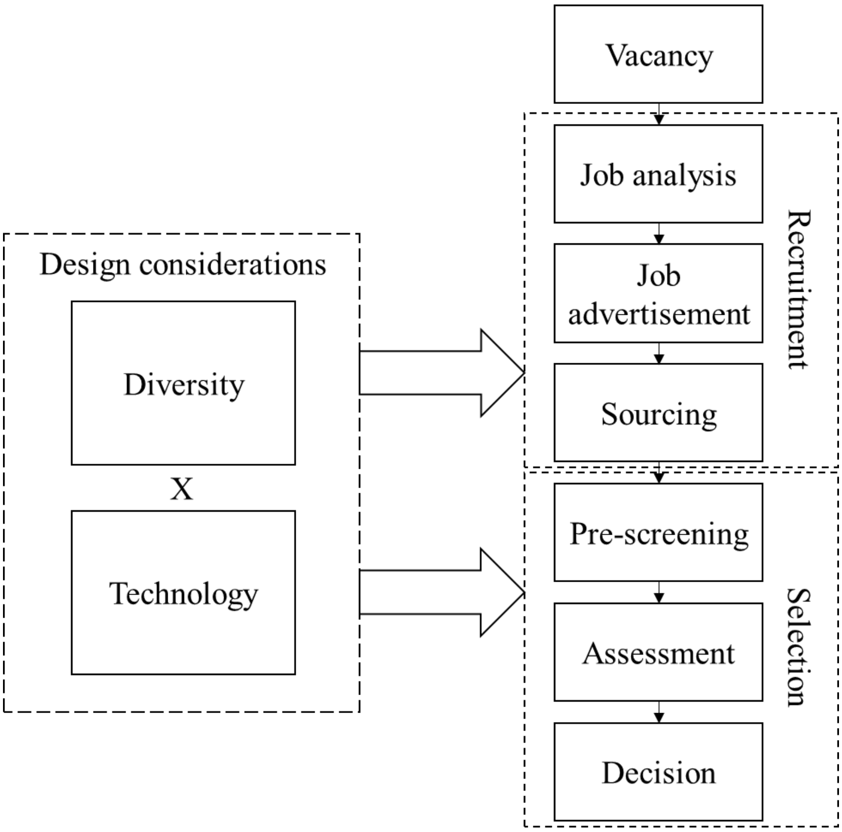

Figure 1. Diversity and technology considerations in the hiring process.

Job Advertisements

The research by Koçak et al. (2023) in this Special Issue, as well as prior work (e.g., Wille & Derous, 2017), shows that specific wording used in job advertisements can impact who will apply for the job, and thus the diversity of the applicant pool. Optimizing job advertisements can be facilitated by recent technological advancements. For instance, natural language processing can already be used to help effectively automatize the job analysis process (e.g., Putka et al., 2023). It could arguably also be applied to rework job requirements or specific language used in job ads that could discourage individuals from various groups to apply. There is also preliminary work in computer science showing that conversational AI tools like ChatGPT can be used to reduce biased language in job ads (Borchers et al., 2022). Taken together, examining the effects of technology-based support to make job ads more attractive to diverse applicants represents a promising avenue for future research.

Pre-screening

Recent work in the context of video interviews –an increasingly popular pre-screening tool– also illustrates the importance of research at the intersection of diversity and technology. For instance, Roulin et al. (2023) examined how video interviews create unique opportunities for traditionally invisible applicants' characteristics (such as parental status, sexual orientation, or political preferences) to become available to hiring managers via background elements observable in video recordings, and thus possibly bias decisions. Arseneault and Roulin (2023) described how the flexibility of AVIs might help organizations attract more culturally-diverse applicants (i.e., breaking barriers associated with time zones and availability), yet showed that AVI raters might still evaluate applicants more positively when they are more culturally-similar to them.

These examples showcase that more research is needed to identify how organizations can harness the benefits associated with technological advancements in pre-screening without reproducing inequalities observed with traditional selection methods or creating new ones. For example, AVIs could be advantageous for job applicants in need of more flexibility, such as those with parental responsibility, working irregular hours, or living in remote locations, because they can complete their interviews where and when they want (Lukacik et al., 2022). However, we still know very little about the reactions, behaviors, or performance in AVIs for such individuals specifically. Similarly, AVI responses automatically rated by AI could potentially reduce biases associated with human judgments, and thus contribute to creating more diverse workplaces. But research on the predictive validity and bias of such tools is still very limited, and some preliminary findings suggest that AI can indirectly reproduce some human biases (e.g., Zou & Schiebinger, 2018), and that careful considerations of prediction accuracy, bias, and fairness are needed (Booth et al., 2021).

Decisions

Many studies showed that mechanical, algorithmic decision-making is often equally or more valid than holistic decision-making (e.g. Kuncel et al., 2013) which is largely due to a consistent use of information in mechanical decision-making (Yu & Kuncel, 2020). Recent shows that people do recognize this important benefit of algorithms, which may stimulate their use in selection contexts. For instance, people seem to believe that algorithms ignore demographic characteristics (Bonezzi & Ostinelli, 2021), have less discrimination motivation (Bigman et al., 2022), and expect consistency from algorithmic decisions (Langer et al., 2020). All of this may show that people expect that algorithms have the potential to foster diversity in selection. However, at the same time, there is also evidence that people seem to be concerned with unfair discrimination that is hard to control with algorithmic decisions (Mirowksa & Mesnet, 2022). Combining those two issues, Koch-Bayram et al. (2023) recently showed that applicants who had experienced prior (human-based) discrimination tend to view algorithmic decisions more positively than applicants without such experiences. Overall, there is still much to learn about what are the conditions for fostering the potential and for controlling the risks associated with algorithmic decision-making, especially with respect to (perceived) fairness and diversity.

Collectively, the six included articles in this Special Issue have the potential to inspire new research on diversity and technology in personnel recruitment, selection, and assessment. Importantly, the changing world of work has brought new research problems and opportunities, and may require both scholars and practitioners to revisit certain steps in the hiring process. Beyond a series of inspiring and thought-provoking articles, this Special Issue also offers a set of recommendations for scholars engaging in research at the intersection of diversity and technology that serves to advance our current knowledge of how technology can be used to increase workforce diversity.

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