Facilitating the co-creation of AI-enhanced HRM systems: A systematic literature review

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ABSTRACT,
Artificial Intelligence (AI) is increasingly implemented into various HR practices. Multiple stakeholders from very different backgrounds are involved in the design and development of these AI-enhanced HRM systems. But the distance between these stakeholders and the gap in knowledge regarding AI capabilities and HR domain processes hinder successful development. In the design of AI-enhanced HRM practices, co-creation is one approach to address these challenges and describes a process of relevant stakeholders co-creating the AI through processes of open discussions and collaboration. The approach offers various benefits but is yet to be effectively used in AI development projects in the HR domain. There is a gap in current literature regarding how to achieve this co-creation in AI-for-HR projects, as only few papers directly discuss how stakeholders would need to approach these projects and furthermore no clear framework for co-creation has been developed in the context of AI for HRM. This research addresses the gap by conducting a systematic literature review (SLR) and expert interviews in order to reach an understanding of how co-creation of AI-enhanced HRM systems can and should look like. The findings show four core themes of 1) stakeholder-involvement, 2) collaboration, 3) knowledge sharing and 4) iteration. These directly respond to four challenges regarding 1) various stakeholders affected by the AI, 2) the distance between stakeholders, 3) the knowledge gap and 4) the dynamic nature of AI. Through the framework created this study contributes to research developing a comprehensive methodology of co-creation for HR, as well as provides insights and recommendations for stakeholders, e.g. approaching the projects as continuous partnerships.

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1. INTRODUCTION

Artificial Intelligence (AI) is becoming increasingly relevant, also in non-technical fields like Human Resource Management (HRM). As companies integrate AI systems into their practices, new challenges, concerns and opportunities arise. For a lot of these companies, AI is a completely new venture, and they often lack an understanding of the subject (van den Broek et al., 2021). Based on multiple cases it seems that a common approach with AI projects is to hire an external agency to develop the AI for the company (Mayer et al., 2023; Miller, 2022; van den Broek et al., 2021). For example, Miller (2022) distinguishes between the "developing organization" (p.9) and "operating organization" (p.10). This means that two very different actors, AI designers and company representatives or domain experts, meet together to plan the integration of the AI system. Beyond these two actors, a variety of stakeholders are involved in the process of designing AI solutions for HRM practices including HR managers, line managers, AI designers, data scientists and employees (Einola & Khoreva, 2023; Liao et al., 2020; Park et al., 2022). The involved stakeholders often are confronted with a lack of shared knowledge and "common language" (Waardenburg & Huysman, 2022, p.6), which means new skills and knowledge need to be acquired (Tuffaha et al., 2022). On the one side, the AI designers have a very extensive knowledge of the creation, nature and risks of AI, but fall short when it comes to an understanding of the domain they are creating the applications for (Forsythe, 2001; van den Broek et al., 2021). A good example is designers underestimating the importance of how well the candidate connects to the recruiter or fits into the team in selection criteria. On the other side, the company has a better understanding of the nature of their work and practices, however, has little idea on how AI operates, functions and is developed (Tuffaha et al., 2022; van den Broek et al., 2021). For example, they often are unaware of the need for data production (Waardenburg & Huysman, 2022) and how that might prescribe changes in their practices.

Research has begun to look into how the development of these systems needs to look like to achieve the promises of objectivity, increased efficiency and helping the end users (van den Broek et al., 2021). Specifically to bridge the knowledge gap of the actors and ensure that the end system designed is adequately adapted to the business case and practices it is meant to improve, a co-creation process is recommended. While scholars call it by different names, strong characteristics like the involvement of multiple stakeholders (Miller, 2022; Park et al., 2022) or the "iterative" nature of the process (Einola & Khoreva, 2023, p.130) stand out. The co-creation of AI is meant to include a variety of necessary stakeholders, such as e.g. AI designers, line managers and HR managers, in the development to provide actors with the required knowledge to understand, discuss and create the AI solutions together. Waardenburg and Huysman (2023) explain the need for co-creation stating that creating "AI systems tailored to the user context requires developers and users to collaborate by mutually learning about each other's expertise" (p.2). The authors describe the "co-creating perspective [as] consider[ing] developer and user activities to be mutually dependent on each other" (p.2). The main benefit of co-creative AI development is that it allows stakeholders to communicate needs, challenge own beliefs and gain a new understanding of the technology and the practices the AI is meant to tackle. In cases where stakeholders fail to achieve co-creation and work together collaboratively, the project often fails to achieve its objective as the end system is not accepted by end users due to it not being fitted to the users' needs and processes, resulting in issues of mistrust (Mayer et al., 2023; Tuffaha et al., 2022). As Mayer et al. (2023) state, "AI systems may fail on the ground when they are not developed in collaboration with the experts they seek to bypass" (p.6139). In one of the cases they studied, collaboration failed and due to the often high amount of resources needed the project was scrapped and the organization decided to go for a simpler technology.

Much literature discusses the importance of co-creative development for AI in HR, however there is a gap when it comes to a clear understanding of what exactly co-creation entails especially in the HR domain. So while there are papers discussing the co-creative approach (e.g., Waardenburg & Huysman, 2022), the focus here is often not on the HR context. Only few papers explicitly discuss co-creation of AI for HRM (e.g., Malik et al., 2023) and often there the focus is not set on how the process has been approached or the co-creative aspect refers only to one step in the process (e.g., co-creating values). The question arises how the co-creative development can be achieved, specifically for AI-enhanced HRM systems. How should stakeholders interact in these process and how can it be ensured that the AI ends up serving the end users? Providing an overview of the underlying topics of co-creation of AI in the context of HRM this study allows actors and future research to gain a better understanding of how this method can be implemented and what is needed to ensure its benefits are reaped. The objective of this research therefore is to further help bridge the gap between different stakeholders in the process of designing AI-enhanced HRM systems and examine how a beneficial and realistic process of co-creation can be achieved. The following research question is proposed: *How can stakeholders interact to co-create AI-enhanced HRM systems?*. To provide an overview of how co-creation of AI for HR is and should be approached, a systematic literature review has been conducted. Furthermore, to deal with the gap of literature on the topic further insights have been gathered through experts interviews with two experienced experts, one holding a bridging position between the technology and HR side, and an HR manager with experience in AI implementation projects. This allows for a unique perspective and insight into how co-creation is realized in development projects of AI-enhanced HRM systems and what complications or benefits can be identified.

Ensuring a clear definition of stakeholders in the context of this study, Miller's (2022) classification of stakeholders in AI projects is used. Miller identified four groups; however the group of non-stakeholders is not included in this study as it refers to people from the AI community who "are not associated with or affected by the project" (p.8) and therefore hold no relevance for this research. Thus, a stakeholder is defined as anyone who belongs to one of the three remaining groups identified by Miller: Development stakeholders, usage stakeholders and external stakeholders. Furthermore, it is important to define what is meant by AI. Chowdhury et al. (2023) define AI in the HRM context as "the ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from the data sources to achieve specific predetermined goals and tasks" (p.2). As their definition is developed specifically for the HRM context, it provides a suitable definition for this study.

This study contributes to current literature by providing insight into how the concept of co-creative design of AI can be enabled. HRM, as a non-technical field with a focus on people and their relations, provides a specifically interesting ground for AI integration. Therefore, research has begun to examine the field's relation to and challenges with AI more closely. Nevertheless, there is still limited research into the topic of design particularly, especially when it comes to the role of AI designers co-creating AI with other stakeholders. As HRM implementation is characterized by a number of different stakeholders engaging with each other (Park et al., 2022), it is only natural that this characteristic of the field spills over into the concept of co-creative design. This study will provide insights into how co-creation can be approached in the HR context and therefore adds a new perspective to the discussion around co-creation, which has so far mainly been discussed in other domains. There is a gap in current literature on the exact characteristics of co-creation as well as the application of it in the context of AI development in HRM. There is much potential to gain further understanding of this and uncover possible concerns and opportunities.

This study contributes to the practical field by providing stakeholders interested in developing AI-enhanced HRM systems with an understanding of the co-creation approach. This will help these stakeholders, namely AI designers and the organizational actors, to better prepare for the AI development and integration process and unlock the full potential of co-creation. Lastly, the study provides the actors with insights into the views, needs and expectations of other stakeholders, which can further inform their approach of the development and integration process.

The study will be structured as followed. First, the introduction provides an overview of the topic at hand and explains the motivation for the research. The second part explains the methodology of the study, which includes e.g. research design and data collection. Thirdly, literature about identified characteristics of co-creation in development projects of AI-enhanced HRM systems, the related challenges and possible strategies is presented and a theoretical framework build. In the fourth part, the findings are further discussed, also in terms of contributions and possible limitations. Lastly, the main takeaways are summarized, and a conclusion formulated.

2. METHODOLOGY

2.1 Data collection

For this research two different methods have been used, and data has been analyzed in a qualitative way. A **systematic literature review** (SLR) has been conducted to provide an overview of co-creation and, to counter the limited literature available, new data has been collected through two semi-structured interviews with experts from the HR and AI domain to provide a fresh perspective on the current situation. Together the methods are able to address the research question effectively by providing both an overview through the analysis of literature as well as an understanding of how co-creation is and can be applied in designing AI for HR practices. The combination of both allows for a comprehensive picture to be painted.

A SLR relies on a highly systematic approach in order to be "transparent and reproducible" (Fisch & Block, 2018, p.104). Therefore, it is important to clearly define each step taken to search, select and analyze the literature. A common method to ensure the needed precision in reporting is through the PRISMA Statement (Sarkis-Onofre et al., 2021). The PRISMA 2020 statement consists of a checklist with recommended topics to be covered, as well as a Flowchart presenting the process of literature selection (Page et al., 2021). Both materials are used to explain the steps taken and provide the necessary context for the end results. The following section is structured according to the PRISMA checklist.

First, the **eligibility criteria** were decided upon. This includes both defining inclusion and exclusion criteria to assess whether a paper is relevant to and helpful for the research. Here, only published journal articles and conference papers written in the English language were included. As the integration of AI is a relatively recent development, only articles in and after 2005 were taken into account. This specific time limit relates to a study conducted by Jatobá et al. (2019), which showed that there was an increase in studies starting from 2005 and reaching a high of research on AI in HRM published in 2009 and 2010. To be relevant for this research, the paper had to include co-creation, or a comparable concept (e.g., Participatory Design, Collaborative Design, Knowledge sharing, or Stakeholder-centered Design), in the context of AI or ML development for HR practices.

Second, the Scopus, Web of Science and Google Scholar databases were chosen as **information sources** to collect papers from. Additionally, reference searching was conducted within the articles collected through the databases and identified as relevant. The databases were chosen based on their popularity and the amount of available literature. Google Scholar was added to increase the amount of literature found.

The **search strategy** included searching using keywords related to co-creation, and comparable concepts, of AI development for HR practices. To conduct the search the following keywords were used. For the concept of co-creation and comparable concepts the keywords cocreat*, codesign*, collab*, participatory, stakeholder-cent*, human-cent*, "knowledge sharing", "knowledge transfer" and "mutual learning" were used. Using the Boolean operators OR and AND these were combined with develop*/design* and Artificial Intelligence (AI)/Machine Learning (ML). The specific focus on HR was represented through the keywords Human Resources (HR), Human Resource Management (HRM) and HR practices. For the Google Scholar search, the keywords were combined into various phrases such as "Cocreating AI for HR". For the searches filters and limits were used based on the eligibility criteria defined. This meant setting the time span to 2005- and limiting the results to the English language and the mentioned document types.

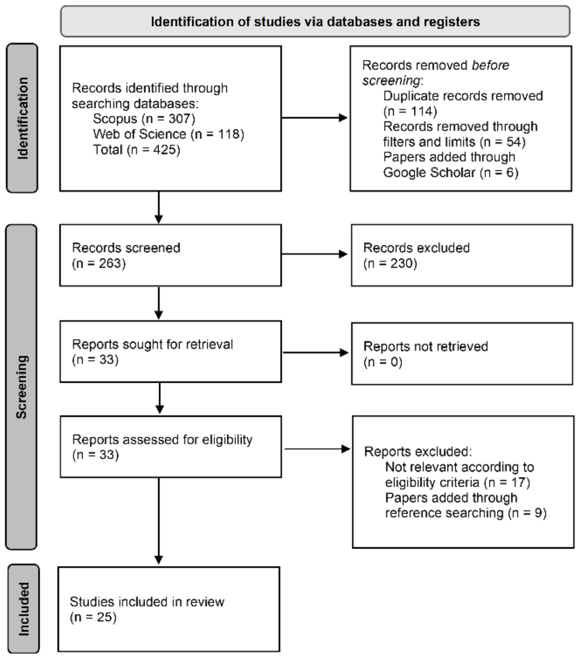

Figure 1: PRISMA Flowchart

Through an extensive **selection process** a total of 25 papers were found to be relevant. The initial search resulted in a total of 307 papers from Scopus (302 with set limits) and 118 papers from Web Of Science (114 with set limits). In the first step, the sets were combined, and duplicates removed. This resulted in a total of 263 remaining papers. Additionally, 6 papers were collected and deemed relevant from Google Scholar. The 263 papers were then screened based on the inclusion criteria through reading the title and abstract in Step 2. This process led to 33 papers. In Step 3, the introduction and discussion of the 33 papers were screened against the inclusion criteria. This led to a final sample of 16 articles relevant to the research. Through reference searching additional 9 papers were found and deemed as relevant. Table 1 and 2 give some insights into the final papers. Table 1 shows 16 different journals or conferences from either the HR domain, the management-business domain, ICT/systems domain or in mixed HR/ICT journals. Table 2 shows the number of papers per year. One can see that the number of published papers in the AI/HR design and co-creation domain is steadily increasing since 2005 and especially increasing since 2020, with more and more papers being published per year.

Table 1: Papers per Journal / Conference

Journal/Conference	Nr.
Human Factors in Computing Systems - Proceedings	7
Human Resource Management	2
Human Resource Management Review	2
AAAI/ACM Conference on AI, Ethics, and Society	1
Artificial Intelligence Review	1
Communications in Computer and Information Science	1
European Journal of Operational Research	1
Human–Computer Interaction	2
ICIS 2019 Proceedings	1
Information and Organization	1
Int. Journal of Business Science and Applied Management	1
International Journal of Knowledge Management	1
Journal of Occupational Rehabilitation	1
Journal of Service Management	1
MIS Quarterly: Management Information Systems	1
Hawaii International Conference on System Sciences	1

Table 2: Papers per Year

Year	Nr. of Papers
2023	6
2022	7
2021	5
2020	3
2019	2
2014	1
2005	1

The total identified 25 papers were then read, analyzed and compared based on their conceptualization and usage of co-creation. A synthesis matrix (Table 4) was created to analyze the papers and create a clear overview of each papers' contribution to the analysis, which is further discussed in section 2.2.

As only a few of the papers found through the SLR explicitly discussed co-creative development in the HR context and many did not focus on the approach or process but rather e.g. the effect and potential of the AI, there was a need to gather further insight to complement this and counter the limitation. Therefore, additional data was collected through semi-structured **expert interviews**. Experts are individuals who have "developed rich and coherent knowledge structures that allow immediate access to the relevant knowledge, strategies, skills, and control mechanisms" (van de Wiel, 2017, p.114). Because of this characteristic of experts they present a great source for gathering insights. Often whether or not someone counts as an expert is determined by "the experience of the professional and the presence of professional criteria, such as degrees, licenses, memberships of professional organisations, prizes, and teaching experience" (van de Wiel, 2017, p.114). Based on this, an important criterium is the professional experience and background of the person. Furthermore, identifying experts is closely related to the domain researched (van de Wiel, 2017, p.116). In the case of this study, experts are therefore someone with experience around co-creation (or comparable concepts) of AI in the HR context. Specifically, the expert should hold a role working directly with the various stakeholders.

The experts were selected through non-probability sampling, as specifically people with relevant experience were targeted. A total of two interviews have been conducted. Conducting interviews with experts provided important insights into the co-creation process of AI and the stakeholders involved. As the quality of expert interviews heavily relies on the extent of experience and knowledge the individual can bring to the table, a candidate with more experience in the designing and implementing of AI in HR was preferred. However, as AI is a very new venture, limitations in amount of experience had to be considered. Two experts were selected. Expert 1 works for a technology vendor in a bridging role in AI projects and is therefore in direct contact with a variety of stakeholders. Expert 2 is a HR manager and consultant for technology implementation with relevant experience in the application of AI within HR processes. Both experts have extensive experience and a background in the domain of HR enabling them to talk about the unique HR perspective. Expert 1 possesses additional knowledge of the technical development perspective and has worked in multiple development projects of AI-enhanced HRM systems. Expert 2 is a HR manager with specific expertise and knowledge of the needs and concerns related to AI in HRM as well as of how this can be addressed in the design process. The expert further works as a consultant in technology, including AI, adoption and integration and therefore fits the criteria offering relevant expertise. Both experts were able to answer multiple questions around the subtopics identified through the literature review.

Using interviews provided insights into experts' perceptions and perspectives of co-creation. The interviews followed a semi-structured approach as this best allows for interviewees to freely express themselves and bring up new factors yet to be uncovered by the interviewer (Adams & Cox, 2008). As this study aims to investigate the application of co-creation, allowing the experts to express what they experience and deem important is integral to the research design. The interviews built on a pre-defined set of questions structured according to multiple subtopics (Table 3). During the interviews the structure was kept flexible as the semi-structured approach calls for (Adams & Cox, 2008). Interviews were conducted virtually via Microsoft Teams and lasted around an hour. Before the interviews, interviewees were asked for consent and given a short introduction to the research to ensure that the objective was understood, and the interviewees were aware and content with the data collected. Giving context to the interview helps the interviewee focus on the topic and better understand the questions (Adams & Cox, 2008).

The interviews were then transcribed and analyzed coding methods with the ATLAS software. This allowed the researcher to identify patterns as well as relationships between different concepts. The following section goes into more detail on the analysis process.

2.2 Data analysis

For the analysis the methodology of thematic analysis was followed. This allowed for a unified analysis approach for both the literature and the expert interviews, which enabled the researcher to identify and connect the data collected through both methods. In this process the literature found was analyzed through the method of thematic synthesis as developed by Thomas and Harden (2008). The authors describe three stages of thematic synthesis: "the coding of text 'line-by-line'; the development of 'descriptive themes'; and the generation of 'analytical themes'" (Thomas & Harden, 2008, p.1). Accordingly, the papers were first uploaded into ATLAS.ti, read through and coded line by line. As suggested by the authors the coding was done inductively and followed the objective of "the translation of concepts from one study to another" (Thomas & Harden, 2008, p.5). ATLAS was chosen as it is a common software for coding and allowed the papers and transcripts to be uploaded and coded within the same project file. In the second stage of developing 'descriptive themes' the codes were then grouped into new codes based on found "similarities and differences" (Thomas & Harden, 2008, p.6). The third stage then revolved around the development of 'analytical themes'. Here, four core themes were found, which are presented in the findings section.

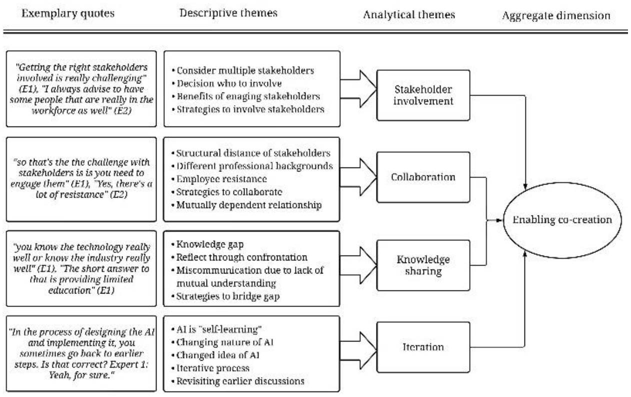

Figure 2: Coding process

The expert interviews were then conducted. As the four core themes were already fairly developed at the point of the interviews, it was possible to structure the interview questions according to the themes (Table 3). The interview transcript was uploaded into the ATLAS file and coded. Where possible already established codes were used, otherwise new codes were added and sorted into the developed groups and themes. Figure 2 presents an overview of the main codes and themes identified from the expert interviews.

3. FINDINGS

Through the analysis the findings around the challenges and strategies used to achieve the co-creation of AI in HR were found to revolve around four core themes. This section is therefore structured based on the characteristics found in the literature 1) stakeholder involvement, 2) collaboration, 3) knowledge sharing and 4) iterative process and relates each to the challenge it addresses, and the strategies used to achieve it. The following section therefore showcases how co-creation of AI is approached in the HR domain based on the literature analyzed with some added insights from the experts into real life, current applications and perspectives. Figure 3 summarizes the findings.

3.1 Stakeholder involvement

Most papers were found to agree on the fact that **various stakeholders need to be considered** in the AI design process (e.g. Charlwood & Guenole, 2022; Pan & Froese, 2023; Park et al., 2021, 2022). For one this was related to the need of different disciplines within the projects (Chowdhury et al., 2023) as both highly technical tasks, like the technology development (Drozdal et al., 2021; Mayer et al., 2023), as well as domain-dependent tasks, like mapping out the workflow (Zdanowska & Taylor, 2022), have to be covered in the development process. This complexity of the process was argued to require a diverse, multi-disciplinary team (Chowdhury et al., 2023; Drozdal et al., 2021; Waardenburg & Huysman, 2022). Secondly, various papers argued that when deployed the AI would not simply affect one group of organizational members, but rather change the way of work for many different stakeholders (e.g., Charlwood & Guenole, 2022; Cheng et al., 2019; Pan & Froese, 2023; Zdanowska & Taylor, 2022). Some papers highlighted this focus relating it to stakeholder tensions surrounding the role AI may play. Park et al. (2022) specifically emphasized the role these tensions play also in the development process. Furthermore, as the system is not always necessarily used by the same people designing it, it was perceived as crucial to understand how to ensure that it still would benefit and be used by the end user (Cheng et al., 2020; Zdanowska & Taylor, 2022). Zdanowska and Taylor's 2022 study about the perspective of user experience (UX) practitioners showed that this complexity, also due to the variety of stakeholders, was perceived as challenging by UX practitioners and members of the development team.

Expert 2 further elaborates on this described challenge:

"The risk is that if they don't involve the people that are in the day-to-day activities, you will forget about sometimes very important processes" (Expert 2)

To address these challenges most papers agreed on the benefit of **stakeholder involvement** (e.g., Park et al., 2021, 2022; Zhang et al., 2023). Stakeholder involvement commonly referred to including various stakeholders relevant to the AI or HR practice in the design process. In most cases the stakeholders involved seem to fall into two sides of the AI development team and the domain experts often coming from the company adopting the AI (e.g., Charlwood & Guenole, 2022; Mayer et al., 2023; van den Broek et al., 2019). Many papers argued for the involvement of employees based on the idea that those actively working in the practice or workflow meant to be improved would have the best knowledge of the process (Charlwood & Guenole, 2022; Zhang et al., 2023). Expert 2 also agrees with that, stating:

"I always advise to have some people that are really in the workforce to be there as well. Because what I found important is the more levels you have the more people don't understand anymore how processes work." (Expert 2)

Next to this another benefit, which was brought up by some, related to the positive effect stakeholder involvement was perceived to have on employees' trust in the AI (Mayer et al., 2023; Park et al., 2021; Zdanowska & Taylor, 2022). Zdanowska and Taylor (2022) deemed this as especially important in ensuring that the AI would actually end up being accepted and used by the end users. Few papers talked about the actual process of deciding who to involve and who was involved in this decision. Common stakeholders involved were members from the AI development team, here some made the distinction between AI developers, AI designers and data scientists, HR managers and employees, mainly when these were the end users of the AI system. Interestingly, papers written about the AI designers' perspective strongly focused on involving the user in the process (Calacci & Pentland, 2022; Liao et al., 2020; Zdanowska & Taylor, 2022). On the other hand, papers discussing the benefits of AI for HR focused more on the involvement of HR management and the relation to strategic decisions of the company (Charlwood & Guenole, 2022; Chowdhury et al., 2023; Pan & Froese, 2023).

The **strategies** used to involve stakeholders varied between papers with 4 papers specifically referring back to the Participatory Design methodology, 16 papers involving domain experts and users through testing and feedback methods and 5 papers using other strategies like open discussions (2) or design workshops (3) to involve various stakeholders. User testing and feedback was found to be the most commonly used method. It is important to note that who was involved and how the involvement was achieved heavily related to the context of the specific case. For example, Arakawa & Yakura (2023) discussed AI for human assessment, a highly complex process in "highly human contexts" (p.6). Their specific case meant that the users, here the assessors, already had to be involved in the very early stage of understanding where AI could improve and support the workflow, as the niche process required high expert knowledge to understand and map out.

Both experts interviewed found stakeholder involvement to be beneficial. Expert 1 further elaborated on his experience in deciding who to involve. Interestingly they go further than solely focusing on which groups to include by adding the element of the stakeholders' personality and opinion.

"Getting the right stakeholders involved is really challenging and having people that can think strategically about what are we really trying to do while also understanding how the system structured and how it works. And the big key is avoiding stakeholders who have been doing it for 15 years this way and they wanna keep doing it that way even in the new system." (Expert 1)

Expert 2 agrees with this added element explaining that they often focuses on including the "dreamers" in the early stages of design workshops and then later involves more hesitant groups. For them the hierarchical level or role of the stakeholder matters less than their curiosity and openness to the AI. Specifically in the initial design workshops Expert 2 explains:

"In this phase we need the people who allow themselves to dream and not think about the implementation or the dilemmas." (Expert 2)

This adds an interesting element of considering the personalities of stakeholders in the decision-making process of who to include the literature found did not address.

3.2 Collaborative interactions

Van den Broek et al. (2021) discuss a reoccurring issue writing that "human-ML [/AI] hybrid practice […] is difficult to reach – or at least develops more slowly – when developers are disconnected from the domains in which their tools operate" (p.1575). This **distance between the AI designers and the domain** and domain stakeholders presents another challenge prominent throughout the papers (e.g., Mayer et al., 2023; Park et al., 2022; van den Broek et al., 2021). Various reasons are given across the papers, e.g. a lack of common understanding (Cheng et al., 2020), conflicting ideas of AI's role (Park et al., 2022; van den Broek et al., 2019) and the different backgrounds of the stakeholders (van den Broek et al., 2021) to name just a few. Zdanowska & Taylor (2022) found that organizational structure also plays a role since often either a team from an external company comes in to develop the AI or, if done internally, the IT department is left to work with the HR department. Either case saw two very different groups or organizations coming together.

Specific to the HR context, the experts explained employee resistance as another challenge for the process. Expert 2 here gave an explanation from their perspective on why this is the case, stating:

"Because most of the people in HR start their job because they want to work with people […], so for them technology is interfering with that." (Expert 2)

The question therefore often arose how the stakeholders interact to bridge this gap. Almost all papers proposed the concept of **collaboration** here (Malik et al., 2023; Mayer et al., 2023; Soleimani et al., 2022; van den Broek et al., 2021). Collaboration as a core characteristic of co-creation relates back to the initial concept of stakeholder involvement by providing insight into how stakeholders are involved not just in the process itself, but specifically in the creating and interactions performed. Waardenburg and Huysman (2022) and Zdanowska and Taylor (2022) point out that this collaboration also needs to be sustained past deployment or launch of the AI. An important aspect of collaboration is found to be the idea of open discussions (Calacci & Pentland, 2022; Park et al., 2022) and collective decision-making (Mayer et al., 2023; Zdanowska & Taylor, 2022). Looking at perceived benefits, collaboration is seen as aiding with explainability and transparency of the system, ensuring that the AI is suitable for the practices meant to be improved (Liao et al., 2020; Waardenburg & Huysman, 2022) and as a crucial factor in mitigating biases (Park et al., 2021; Soleimani et al., 2022). Van den Broek et al. (2021) recommend stakeholders to "prepare to enter an interdependency relationship" (p.1575) showing that both developers and domain experts contribute to the process and depend on each others' contributions. In their example the authors found that developers depend on experts for their domain expertise used to design and evaluate the model, while experts depend on the developers to uncover insights into the processes and possible faults. Although not expressed in the form of an interdependency relationship, a similar notion can be found across the analyzed literature.

The most important **strategy** discussed to achieve this collaborative interaction has been found to be feedback. User feedback is here actively used to refine the AI and make sure that it fits the needs and understanding of the user (e.g., Chaturvedi et al., 2005; Soleimani et al., 2022). In some cases user testing was conducted through prototype testing (Arakawa & Yakura, 2023; Drozdal et al., 2021), mock-ups (Zdanowska & Taylor, 2022) or pilot studies (Drozdal et al., 2021; van den Broek et al., 2019). Collecting feedback was achieved through open discussions and various methods of testing or workshops. Additionally, multiple papers point out that it is important to build some sort of common ground to enable this collaboration (Mayer et al., 2023). This common ground can be achieved through e.g. using common files and documentation (Drozdal et al., 2021) or working to adjust language to be understandable for all stakeholders (Mayer et al., 2023). To illustrate, in some cases specific methods like mapping processes were used to visualize important concepts. Zdanowska and Taylor (2022) give additional credit to the fact that the involved stakeholders were still trying to figure out how to design for AI. They argue this allowed stakeholders to collaborate and move beyond their own domain to innovate together. One paper specifically focused on collaboration proposing three strategies to achieve collaborative development: "(1) Creating a shared vision, (2) building a common understanding, and (3) developing complementary abilities" (Mayer et al., 2023, p.6144). In this the authors explain strategies also found in other papers, however, add the importance of including domain experts in the initial discussions around what AI can bring to the day-to-day. The authors stress realistic expectations and suggest meetings and workshops to explore the possibilities of AI for the company or HR practice.

Particularly the positive effect of design workshops was also picked up by Expert 2, who reported on starting their process with imaginative workshops:

"The first workshop is about dreaming actually, because I think you need that. Dreaming about how work looks like in that specific company in the future. So I also challenge them, okay how do people interact in the elevator? How do they behave? Are they sitting behind a screen or are they walking around…" (Expert 2)

3.3 Knowledge sharing

The **knowledge gap** between AI developers and domain experts was found to be another crucial challenge in the development process (e.g., Liao et al., 2020; Mayer et al., 2023; Robert et al., 2020; Tuffaha et al., 2022). Most studies encountered this already at early stages of development, however it seems that the gap became most apparent when it came to translating practice-based values into the AI (e.g. van den Broek et al., 2021). Developers were found to make mistakes or incorrect assumptions around what was relevant to include in the model and a lack of skills and knowledge on AI made it hard for domain experts to communicate their values and processes and take part in co-creation. Park et al. (2021) also found this lack of knowledge to have a negative effect on the employees. The authors explained this as a mental burden causing employees to panic. Multiple papers agreed that the missing understanding directly hindered users' capability of trusting the AI, which in one specific case even led to the project failing (Mayer et al., 2023). Mayer et al. (2023) and Chaturvedi et al. (2005) further brought up the factor of inaccessible language. This describes the usage of domain-specific language either too technical or too context-related or practice-specific for the other side to fully understand. In some studies a further challenge came from developers approaching the project with the idea that they did not have to include domain experts and their knowledge, but rather actively aimed to exclude them in hopes of e.g. achieving greater objectivity (Mayer et al., 2023; van den Broek et al., 2021). Additionally, companies often underestimate the required resources, time and effort for these AI development projects (Liao et al., 2020; van den Broek et al., 2021). Specifically, in regard to the necessary training and learning process this underestimation is found to create a hindering challenge for the process.

Expert 2 dedicates one workshop in their process, after identifying objectives, to the questions surrounding required resources and skills asking:

"And then we say if this is what we want, what assets do we have in the organization? What skillsets do we need? What competencies do we need? What technology do we need? And how do they interact?" (Expert 2)

The corresponding characteristic of co-creation has been found to be **knowledge sharing** or mutual learning. Soleimani et al. (2022) define knowledge sharing in the AI development as a "process of exchanging task-related information, ideas, know-hows, and feedback" (p.2) and Waardenburg and Huysman (2022) describe it as "a prerequisite for co-creating AI systems" (p.4). This process can look like developers sharing the different elements and possibilities of AI or domain experts communicating their knowledge of the process and the related values they deem important. Van den Broek et al. (2021) talk about a similar process of mutual learning, where stakeholders learn from each other about each others' domains. Part of the process, according to the authors, is the learning through the confrontation with the system or model itself. In the case they discuss, stakeholders had to revisit their own ideas and concepts with domain experts questioning their values of e.g. what a good employee is and AI developers reimagining what AI can bring and, maybe more importantly, what it cannot bring to the table. Chowdhury et al. (2023) argue that knowledge sharing can further enable trust and therefore work against employee resistance or skepticism towards the AI. Another benefit is found by Soleimani et al. (2022) who present knowledge sharing as a way to mitigate biases.

When it comes to the **strategies** discussed by the literature, training is mentioned most often (e.g., Chowdhury et al., 2023; Mayer et al., 2023; Park et al., 2021; Tuffaha et al., 2022). Specifically training HR managers or domain experts in AI related knowledge and skills is often either recommended or used. The skills discussed here are broadly summarized in "AI literacy" (Park et al, 2021) or "Big data literacy" (Charlwood & Guenole, 2022, p.736), and include knowledge related to statistics, data science, general technical or digital skills and specifically AI design. Expert 1 agreed with this perspective of education or training as a vital strategy stating:

"How do you again bridge that gap between the knowledge of technical, clinical, operational, financial? And I think the short answer to that is providing limited education, because you can't go too deep in any one of those categories, right? You… you've gotta give people a basic ability to navigate and understand that area but you can't overload them because they're never gonna be able to understand and retain it." (Expert 1)

Zhang et al. (2023) made an interesting point focusing on the way the knowledge of employees is approached. The authors argued that "treating workers as experts can also help AI practitioners […] recognize challenges to consider" (p.14). This idea of recognizing the employees' knowledge was also present in the paper by Malik et al. (2023), who proposed "traditional and AI-mediated social exchanges" (p.111) as a way of knowledge sharing to include employees' knowledge. Overall, literature agrees on the importance of domain knowledge and most see benefit in bridging the knowledge gap through means of knowledge sharing.

Expert 1 sees communication as an important part of this knowledge sharing process:

"And again the other piece I should suggest too is communication. So I may not have any expertise in that area, but I wanna know about it. Before you made that decision so that I can at least weigh in." (Expert 1)

3.4 Iterative process

AI differs from other technology through its **dynamic and "self-learning"** (Waardenburg & Huysman, 2022, p.1) nature. This characteristic of AI is found to propose another challenge for AI development and implementation. The model has to be consistently improved and adapted to new changes or data (e.g., Arakawa & Yakura, 2023; Malik et al., 2023; Zdanowska & Taylor, 2022). Zdanowska and Taylor (2022) found that this need "to be monitored and maintained" (p.6) is rarely understood by the stakeholders, especially by organizations. Nonetheless, an emergent finding is that the AI designing and supporting does not end with the deployment of the model.

Responding to this challenge the concept of **iteration** was present in almost all studies. The iterative process included coming back to previous stages or steps throughout the whole process. For one, an iteration was often found to follow feedback given by domain experts or users (Drozdal et al., 2021; Faliagka et al., 2014; Lee et al., 2021; Soleimani et al., 2022). Lee et al. (2019) address this role of feedback in the iterative process describing the utilization of feedback "as guidance for future tool iterations" (p.723). Iterative steps found included refining the model (e.g., Faliagka et al., 2014; Soleimani et al., 2022), either in design or with new data, or revisiting the very idea of the AI in the HR practice (Arakawa & Yakura, 2023; van den Broek et al., 2021). Much of the iteration revolved around the user and therefore directly ties into characteristics discussed earlier.

When it comes to **strategies**, the papers frequently implemented ways of consistently evaluating the model and its effectiveness. User feedback, different ways of testing and translating the new insights into improvements to be made for the model were found as methods and tasks designed into the process (e.g., Chaturvedi et al., 2005; Soleimani et al., 2022; Zdanowska & Taylor, 2022). Park et al. (2022) suggest that designers should agilely reiterate the process to make sure stakeholder tensions are understood and addressed and thereby bring up another usage of iteration related to the underlying concepts and assumptions instead of the AI model or design. While this target of iteration is less discussed, it is still found to hold relevant value. To summarize, continuous feedback enabled continuous, iterative improvement.

Both experts expressed that they go back to earlier steps within their process, therefore following the approach of an iterative process. Expert 1 also found here the role of feedback important and describes a system used by them:

"The question is, is it good enough to function and and can we constantly improve it? […] You know, our clients want an opportunity to provide feedback and to say I don't like this, and I wish it would do this. […] So what we do then is we say, OK, you can submit an enhancement request, but you need to get others to vote for it." (Expert 1)

In this system user feedback only becomes visible to the developer side once it reaches a threshold of popularity. This is done to ensure that the wished for feature represents the interest of multiple users. So the expert perspective adds that while user feedback in itself is a strong strategy to inform iteration and improvement, it is also important to evaluate whether the feedback is relevant and beneficial to a sufficient number of users to justify the resources and efforts developing e.g. the new feature would take. In this process, the feedback given would then be prioritized.

3.5 Summary of findings

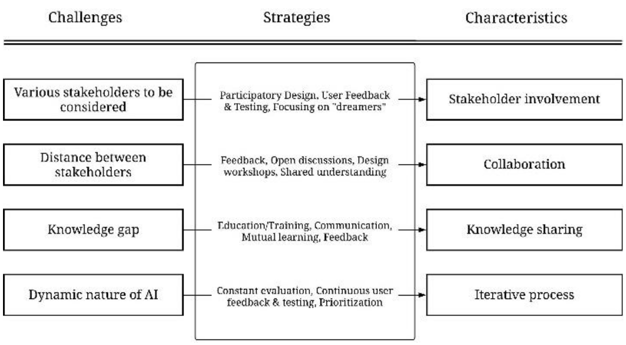

Figure 3: Findings summary

Figure 3 summarizes the findings of the analysis of the literature and expert interviews. On the left are the four challenges identified: 1) Multiple stakeholders are relevant to the AI design process and have to be considered, 2) there is often a distance between these stakeholders, whether due to organizational structure or the different professional backgrounds, 3) there is a clear knowledge gap between developers and domain experts and 4) the dynamic nature of AI calls for continuous improvement, proposing a challenge for the stakeholders involved. These four challenges are connected to the co-creation characteristics through the strategies identified in literature and by the experts. Important strategies include (user) feedback, design workshops and open discussions. Lastly, the four characteristics of co-creation for AI development projects in the HR context are presented: 1) Involving relevant stakeholders in the development process, 2) Collaboration between the stakeholders, 3) Both developers and domain experts sharing their knowledge with each other and 4) the iterative nature of the process to be able to revisit earlier concepts and system designs.

4. DISCUSSION

Addressing the question of how stakeholders should interact to co-create AI-enhanced HRM systems, this research conducted a systematic literature review and held two expert interviews. Four core themes responding to core challenges were found and presented. Stakeholder involvement, collaboration, knowledge sharing, and an iterative nature of the process are prominent elements throughout the literature resulting in a co-creative development process. Stakeholders should therefore interact according to the four characteristics. Furthermore, key strategies to achieve these were found, with feedback playing a major role in all four. It becomes clear that feedback combined with open discussions is a determinant factor for co-creation and should be considered as a necessary part of the co-creative process. Based on the results two key conclusions can be drawn.

4.1 The development process redefines work

AI has been widely accepted as technology with the capability to redefine work. Literature argues that through the automation and augmentation possibilities of AI the way of work will change in the coming years (Malik et al., 2023). In the specific context of HR, recruitment managers for example sometimes see their role changing to a final decision-maker instead of being directly involved in every step (e.g. searching and analyzing). This has been widely agreed upon in literature and aligns with the findings of this study.

What is less commonly included in this perspective though is that, as observed in the conducted literature review, the process of AI development itself often already leads to redefining and restructuring of the way and meaning of work for the various stakeholders. A good example are the required processes for data production. As AI is fed with data and further depends on the quality of it, data production is one of the most critical steps of the process (van den Broek et al., 2021; Zdanowska & Taylor, 2022). However, many organizations do not yet have data production processes set in place or the ones they do perform are insufficient for the amount and depth of data needed for AI development. This means that before AI is even deployed the stakeholders' day-to-day work already has to change and adapt. Another way in which the AI development process redefines work and meaning is through the occurrence of reflection through confrontation as discussed by van den Broek et al. (2021). Stakeholders here are confronted with the reality of their ideas of e.g. values embedded in their practices, and consequently oftentimes reflect and redefine or further develop their work processes and sense-making.

Through the process of AI development new meaning is therefore achieved and implemented. Further research would be needed to examine and validify this role of the AI development process as redefining, especially based on the perception of HR stakeholders.

4.2 Approach projects as partnership

The second conclusion that can be drawn based on the results revolves around the stakeholders' approach of the project. This specifically relates to their expectations. AI development projects are not alike other technology development projects (Zdanowska & Taylor, 2022). For example, they need closer collaboration, willingness to adapt and learn, long-term commitment and often more resources than initially expected. While literature around co-creation addresses a variety of these issues through the associated strategies and characteristics, this paper leads to assume the importance of the stakeholders' perceptions of the project. In the cases discussed co-creation is often focused on the development phase of the project. It begins with the interactions between stakeholders and often is deemed to end with deployment of the AI.

However, this perspective is limiting as it fails to address the perspectives of stakeholders before interaction begins and leaves out the crucial "sustained collaboration" (Waardenburg & Huysman, 2022, p.1) after deployment.

To enable co-creation and enter the projects with clearer expectations, stakeholders should approach AI-in-HR projects as a continuous partnership with various other stakeholders, namely the AI development or domain expert team. What this would achieve is a more accurate understanding of what these projects realistically entail and need to succeed, as realistic expectations have proven to be a challenge for the collaborative process (Mayer et al., 2023). Furthermore, approaching the relationship to the other stakeholders as a parentship rather than a project-based cooperation could influence the groups involved to communicate more effectively and invest effort into the collaborative relationship needed for co-creation. A continuous partnership, compared to entering one project together, is not designed to end with launch, which could possibly reap multiple benefits for the long run including a long-term improvement of the AI e.g. in response to changes within the organization (Waardenburg & Huysman, 2022). However, it is important to note here that such a partnership would require extensive amounts of resources and effort invested (van den Broek et al., 2019) and is therefore not always realistic for organizations to attempt. Future research should look into ways the required resources could be minimized or an effect and approach similar to a partnership achieved with less.

4.3 Contributions to Theory and Practice

By providing insights into co-creation in the specific field of HRM, this research contributes to literature aiming to understand how co-creation can be achieved in the HR context. Multiple studies have examined AI-in-HR projects and described the characteristics of co-creation found (e.g., Bromuri et al., 2021; Cheng et al., 2020), but have not explicitly related it to the co-creative approach or focused on the descriptive rather than relating the findings to the beneficial approach of co-creation. This finding aligns with Pan and Froese (2023) who argue that "the current field is perspective- and practice-oriented" (p.12) and further describe it as "rather weak in theoretical developments" (p.12). This lack of clear and prescriptive research leaves stakeholders with the question of how the success of the project described can be achieved and further causes confusion around what exactly co-creation entails. Co-creation of AI in HRM could instead be discussed and researched as a methodology with clear characteristics, guidelines and common practices. As Bailey and Barley (2020) state, research has a role in shaping the trajectory of AI, which means researchers should expand their objective to include providing clear guidance on how to achieve co-creation and the consequential benefits of an AI fit to the end users' needs and mitigated biases (Soleimani et al., 2022).

Furthermore, by examining important topics discussed in regards to co-creative development of AI for HR, this study adds to theory of co-creation for AI development. There has yet to be a clear understanding or framework of how this co-creative process should look like, which is likely due to the strong differences between cases and domains. For example, developing AI for law (e.g., Delgado et al., 2022) will come with very different needs and considerations than designing for HRM (e.g., van den Broek et al., 2021). Because of this it is important to examine co-creation and AI development domain specific. The conducted research follows this by focusing on the field of HRM and by providing insights into current practice and argumentation. Future research can build on the findings and conclusions discussed to further investigate real-life cases and use gained insights to build a comprehensive methodology. Specifically, the direction of a possible partnership approach would be interesting to further develop and research.

Lastly, this study agrees with various papers recommending research performed by multi-disciplinary teams to account for and reflect the multi-disciplinary constellation of the teams developing AI (e.g., Auernhammer, 2020; Bailey & Barley, 2020; Pan & Froese, 2023). Through the literature analysis it was found that many papers focus on a specific side based on the background of the researchers or journals. To elaborate, as found by Pan and Froese (2023) "CS [computer science] and EO [engineering and operations] papers focused more on developing AI tools to facilitate HRM, ME [management and economics] and OT [others] papers were more interested in general issues related to AI usage" (p.12). As co-creation is primarily a design concept it is often viewed from a technical perspective, however, as this research has found, a multi-disciplinary approach can allow a better understanding of the process as it enables the researchers to incorporate the various stakeholders and factors into their understanding and theoretical development.

When it comes to practical contributions, this research finds implications for various stakeholders. For one, all stakeholders involved in these AI development projects can benefit from understanding the identified challenges as it allows them to be aware and prepare to tackle these issues. For example, organizational stakeholders might want to invest in bridging the knowledge gap before project begin through training the stakeholders that would be affected by the AI or involved in the development of it. The framework identifies the correlating co-creation characteristic and identifies strategies used to achieve this. These insights can directly inform stakeholders' decision-making in the processes. Concretely, AI developers should prepare to include domain experts early on in the process. Ideally already in the initial exploring of possible applications of AI in the HR practice addressed. Domain experts should prepare to be involved in data production processes and should aim to garner an understanding of AI to be able to question its assumptions and bring up relevant domain knowledge. Both sides should prepare to engage in active collaboration, possibly through approaching the process as a partnership. Lastly, feedback was found to be the most important strategy as it plays a role in enabling within all four characteristics. Therefore, stakeholders should make feedback an integral part of the process early on and find ways to allow for and create meaningful feedback and insights from users.

4.4 Limitations and Future Research

There are a few limitations necessary to discuss. For one, the field of AI development in HR in general is relatively new and is still in the early stages of research. But in particular the concept of co-creation in this context presents a clear gap in research. Because of this only a limited amount of literature explicitly discussing the topic could be found. As only a few from the papers identified as relevant explicitly focused on the co-creation approach as applied in the HRM context, the expert interviews were added to collect further relevant data and gain insight into the real-life application and perspectives surrounding co-creation in AI-in-HR projects. Additionally, only two expert interviews were possible, partially also due to only a few having enough expertise in this domain to qualify as an expert. Future research could look to investigate and further validate the conclusions and findings of this paper. Based on the developed framework, AI development projects in the HR context could be examined for their usage of co-creation as defined in this paper.

Another limitation to be considered regards the keywords used in the search strategy. Comparable concepts were included as co-creation by itself has not been researched in the context of these AI-in-HR projects. Future research could be conducted into the explicit application of co-creation of AI in HR to be able to draw a fuller picture, possibly by interviewing the various stakeholders involved on their perspective and usage of co-creation and create a thought-out and comprehensive methodology surrounding it. As more organizations begin these projects, there will be further opportunities to e.g. conduct an ethnographic research and report on the real-life processes and challenges of these projects.

The interviews were conducted by two interviewers, which allows for some limitations in regard to bias to be addressed through peer reviews and discussions with the co-researchers and supervisor (Corbin & Strauss, 1990). While the high amount of experience of the experts interviewed aids to ensure precise and comprehensive insights, a larger empirical investigation would allow to see the extent to which the experts' perspectives are representative of the industry. Nevertheless, together with the SLR the expert interviews paint a clear picture of how stakeholders can work together to achieve co-creation of AI-enhanced HRM systems.

Lastly, as AI is still in a very early stage the formed conclusions might change with future developments of the technology and its adoption by HRM. It is possible that some of the themes found relate to the early stage of understanding around how AI can and should be developed for HRM.

5. CONCLUSION

This research focused on the question of how the co-creation of AI-enhanced HRM systems can be achieved. For this, a systematic literature review was conducted and, due to the limited availability of literature, complemented with insights from two expert interviews. Four core characteristics of co-creation were found that responded to challenges in development. Based on the findings stakeholders are recommended to approach the AI development projects as entering a partnership with each other. Furthermore, the findings hold value for future research by creating ground to establish a comprehensive framework of co-creation. Co-creation is highly valuable for ensuring that the AI serves the users and reaches its potential of improving work for various stakeholders.

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7. APPENDIX

Table 3: Interview questions

Gen Eral Ques tions	1. What is your educational background?
	2. How long have you worked in your field?
	3. What is your current position in the company?
	4. What are some AI projects that you have completed or are working on? a. How would you describe the process of a typical AI-HRM project?
	5. How would you describe your role in these projects? a. What are some typical tasks?
	6. With what expectations do you go into these projects?
	7. What are some challenges with integrating AI specifically for the field of HR?
Sta Ke Hol ders	8. What are the stakeholders typically involved in these projects?
	9. In your view, is stakeholder involvement a worthwhile endeavor in the AI design process? a. Why do you think so? b. Do you have an example from your working experience? c. Do you think your colleagues share your opinion? (if yes, why, if not, why not)
	10. How do you decide who to involve in these projects?
	11. Are there some relevant groups that might be left out?
	12. Would you describe the stakeholder involvement in the AI design process as smooth? a. If yes, why? If not, why not? b. Can you recall what this process looked like?
	13. Were there any disagreements or clash of perspectives (that may even persist or spill over?) a. How did you tackle the disagreements/clashes you just mentioned? b. Do you think this is an effective strategy, also for future disagreements/clashes?
Coll Abo Rat ion	14. How do you communicate your needs and expectations with the other stakeholders?
	15. How would you describe the process of working together with the mentioned stakeholders?
	16. What are some strategies you follow to ensure a successful collaboration between the different stakeholders?
	17. What challenges or hindering factors for this collaboration did you encounter? a. How did you tackle these challenges?
Know Ledge Shar Ing	18. What are some challenges you faced in these projects related to the expertise and knowledge needed?
	19. Would you say there is a knowledge gap between the AI development side and the HR side? a. If yes, how do you deal with this knowledge gap? b. If not, what do you think helped the sides find a common language / understanding?
	20. Could the process itself help the involved stakeholders bridge the knowledge gap? a. If yes, how could this be achieved? b. If not, what other measures could be taken to bridge the gap?
	21. What knowledge have you personally gained from these projects?
Iter- ation	22. Are you able to revisit earlier stages within the process? a. If yes, how are you able to do this? b. If not, do you think this could be a helpful tool?
Eth ics	23. In your opinion, what are the biggest ethical concerns integrating AI in the HR domain? a. Have you experienced any ethical issues related to implementing AI in HR? b. How would you go about mitigating these ethical concerns with AI implementation?
	24. As a HR manager involved in AI projects, what's your take on ethics during work? a. In your opinion, what are the most important ethical values in AI-HR implementation? b. How do you ensure that the mentioned values end up in the end design? i. Do you find this difficult to achieve? & Why is it difficult? ii. Do you have an example? c. What steps do you take to regularly monitor and evaluate the performance of AI systems used in HR processes to ensure they align with ethical standards?
	25. According to some studies, ethically responsible AI can only be achieved by constant stakeholder cooperation. How do you think stakeholder cooperation can result in ethically responsible AI-HRM systems?
	26. What measures are in place to ensure transparency and accountability in AI-driven HR processes, particularly when it comes to explaining the decision-making criteria used by AI systems?
	27. How do you balance the benefits of automation and efficiency that AI brings to HR processes with the potential risks of excluding certain individuals or groups due to algorithmic decision-making?
Bias	28. What biases do you think could be present in AI-HRM systems? a. Have you experienced forms of bias in AI-HRM systems? (IF YES, questions i and ii / IF NO, question i. How do you handle these situations where AI algorithms produce unexpected or unintended outcomes that could potentially discriminate against certain individuals or groups? ii. Were you able to mitigate these biases from the models in any way? iii. If so, how were you able to minimize/mitigate these biases? b. What steps do you take to address potential biases in AI algorithms, such as gender, racial, or age bias, during the implementation and ongoing use of AI in HR processes?

Table 4: Synthesis Matrix

Paper	Challenges	Stakeholder-involvement	Collaboration of stakeholders	Knowledge sharing & Mutual learning	Iterative process	Comments
The Design and Evaluation of a Chatbot for Human Resources (Drozdal et al., 2021)	Gap between "technical research and real world users" (p.246) Users not satisfied with (lack of) responses	Design team (researchers) and developers (comp. scientists) worked with the HR department / administration to create the chatbot Potential users of the chatbot were continuously involved through e.g. the pilot studies (user testing) or being asked to fill out a voluntary survey after using the chatbot which allowed the team to gather feedback on what they want / need improved HR department was involved in getting the right answers & will be involved in creating an understandable dashboard	Design team needed new input from HR department to get (better) answers for questions seen in the pilot studies Users are consistently giving feedback which is then integrated The design team and developers used common files (spreadsheet) to be able to collaborate Created a dashboard showing the current status of the chatbot → Want to involve HR department in the creation of this	Creating a spreadsheet showing what the chatbot was intended to respond and how it actually responded helped to create a "bridge in understanding between the designers and the developers" (p.245) Want to co-create a dashboard with HR department to make sure the team has a mutual understanding of the performance (ensure information is understandable for both lead AI researcher as well as head of HR)	New questions found in the pilot study 1 made design team go back and add more questions and answers After pilot study went back to change focus of answers (now less conversational, more concise and with links) The chatbot is consistently evaluated on it being able to meet "user needs and expectations" (p. 246)	
AI for human assessment: What do professional assessors need? (Arakawa & Yakura, 2023)	Because the process of human assessment is both complex and "sensitive" (p.1) the AI cannot just give a score but has to be explained and be trustworthy Researchers initially thought a scoring system based on e.g. nodding could work but assessors disagreed explaining that it would not serve their process "Highly human contexts" (p.6) regarding the human assessment domain	Professional assessors were involved by providing insight into their needs, being consulted on how different approaches could work for their process, testing the initial algorithm and later on evaluating the AI The researchers / designers took the inputs from the assessors, shared knowledge of possible algorithmic / AI solutions and developed these - Assessors guided researchers in understanding if detected cues were "actually	In initial workshops the researchers worked with assessors to see where AI could be helpful and what needs are there (assessors wanted humans to make the final decision but felt their objectivity could be enhanced) Researchers consistently consulted with the assessors: -With prototype testing the assessors were able to explain their perceived effect of the AI & give feedback for improvement	The assessors were consulted for their knowledge of the human assessment process helping the researchers understand this Assessors were asked where they could see a use for computers to help researchers understand where and how AI can help / improve the process Researchers shared knowledge of recent literature about human behavior analysis via computers	The idea of how AI could serve the process and assessors was continuously revisited throughout the process Following phases: Identify requirements, test algorithm, create and evaluate interface	Assessors "gained confidence" (p.6) if their own evaluations matched the AI's ones

		informative" (p.4) & gave feedback for improving the prototype	-Detailed conversations of what assessors look for etc. allowed researchers to derive characteristics to include in their design	Researchers had to revisit their initial idea Prototype made assessors "reflect on their evaluation" (p. 6)		
A study of UX practitioners roles in designing real-world, enterprise ML systems (Zdanowska & Taylor, 2022)	Existing (user-centered) design methods were used as a basis but needed to be adapted "Lack of understanding that AI/ML models needed to be monitored and maintained" (it is not a one time, here it is, now it works technology, but process of organizations didn't seem to reflect / understand that) Participants found "dealing with complexity" challenging (complex workflow, variety of stakeholders needing to be considered and "quality and availability of the data") Compared to traditional software designer is confronted with giving input into which variables are used "based on their user research" Companies often don't want tech. stakeholders involved in anything other than coding, which is both unfair to them and harmful for the further collaboration Current design methodologies do not include the post-launch need of AI/ML systems	Data scientist, software engineers (also grouped together as technical members) = propose technical solutions to problems UX practitioners asked users questions, designed, etc. & steer design back towards user needs (projects often started with user research) "Technical members should be involved in the early stage design discussions" (p. 8) Sales side of business initiated the AI/ML projects Original problem / question did not come from team → originated from client or other parts within the same business Business stakeholders as someone who has to be convinced Participatory design methods → involving users in design can be especially beneficial when fairness and explainability are very context-based "if the solution was not accepted by the end user then any real-world problem had not in fact been solved" (p.11)	Used mock-ups for user testing of the concept Collaboration or designers / developers involvement went beyond launch as AI needs to consistently be improved and some (chatbots) require user data and usage to validate and fine-tune 5/7 UX practitioners "used participatory design approaches to co-create AI/ML products and workflows" → ensure that end users accept, trust and understand design "Design decisions were made collectively" (p.8) → discussed all decisions throughout all stages "High level of collaboration was linked to the fact that teams felt they were still working out how to design for AI/ML" (p.8) Used diff. methods to encourage discussion (e.g. data journey maps, service blueprints) Strong importance of prototyping as a method, but adapted to AI; prototyping served to understand feasibility, understand users and see if AI is accepted	Members were aware of what the other team members can do and think about things Challenge each others understanding (e.g. "Would it be possible?" (p.8)) → also go into the others´ domains Including also technical details earlier would be helpful to not just rely on concepts and planning Non-tech. members observation and role-play exercises to understand tech. members and their decision-making, also used data as evidence in these conversations In-depth user research to understand the situation and be able to reflect complexity → included "mapping out workflows" etc. Could use evaluation techniques like Design Critiques to "challenge assumptions internally within interdisciplinary teams" (p. 12)	Created prototype first and then iterated with sample data (not iterative bc of user feedback) Some participants split the process into UX designing and AI development (two iteration circles) Iterated how documentation was delivered to developers to make sure requirements were well understood AI/ML models are continuously learning from data, which also means they need to be supported also after launch → "Designing for post launch" + Iteration post launch	

	Difficulty collaborating due to organizational structure (e.g. in different departments or diff. organizations)	Not involving tech. stakeholders can lead to collab. Issues down the road	(important for participatory approach)			
Unlocking the value of artificial intelligence in human resource management through AI capability framework (Chowdhury et al., 2023)	Organizations don't reap the benefits from AI yet Fear of losing jobs, bias, limited trust in AI "Limited knowledge, skills and understanding among the workforce […] about AI capabilities, limitations,…" (p.7); Four major HR challenges: "complexity of HR", "small data", "ethical constraints" and "reaction of employees" Transparency is especially relevant for HR context	Three new possible roles: Trainers (help development through finding data possibilities etc.), Explainers (have knowledge to understand AI output and evaluate it → enhance trustworthiness) & sustainers (develop AI governance structure & ensure effective and fair usage of AI) Involve employees in development team to help understand what AI adoption means for them	HR managers need to consider -supporting AI development team with multidisciplinary team w diff. skills, domain expertise, digital experience	Sharing knowledge to develop skills of workers can enable trust and understanding of AI and the AI-human role → strategy against resistance / skepticism AI socialization as strategy = process of training employees for AI knowledge, skills & expectations to introduce AI (also helps trust) Co-creating (employees & externals) expertise and knowledge can complement adoption & evolution	AI needs to periodically be assessed and maintained, adapted	More general and not fully about development, but also generally with stronger focus on capabilities from needed from HR side
Human-AI Interaction in Human Resource Management: Understanding Why Employees Resist Algorithmic Evaluation at Workplaces and How to Mitigate Burdens (Park et al., 2021)	Employees experience 6 types of burdens that could be addressed through e.g. transparency and interpretability Mental burden on employees to "guess, understand and adapt to unpredictable AI" (p.7) AI/HRM domain specifically needs high level of process transparency Employees had concerns regarding their AI literacy when it came to interpretability → match interpretability with their level of understanding	Employee burdens and wishes should be included in the designing process "Designing AI in HRM is complex by nature since multiple stakeholders […] are intertwined with various incentives in the operation process" (p.10) Employees want to be involved in the design process	Should tell employees who owns data, builds algorithms and changes them → mitigate bias burdens Discussions about design decisions with various stakeholders ("employees, AI designers, HR teams, and enterprises" p.11) Initial trial period to get employees "familiar with the system" (p.11) Suggest "co-designing AI work evaluation systems with multiple stakeholders" (p.11) → can build trust and help adoption	AI literacy training or some sort of training to help employees understand the tech. and use it good		

Participatory Algorithmic Management: Elicitation Methods for Worker Well-Being Models (Lee et al., 2019)		Managers & workers with diff. perspectives	Used preference elicitation to understand what employees preferred in scheduling → worked well to “enable participation and empowerment of users” (p. 723) Managers & workers updating system together	Workers preferences had to also be elicited → could not assume them to be fully formed (translatable to other values) → Elicitation methods as a way to help marginalized groups discover preference	Feedback used “as guidance for future tool iterations” (p.723) Importance of evaluating over time	Not as much about design process itself, insights into challenges and effect of participation on workers
When the machine meets the expert: An ethnography of developing AI for hiring (van den Broek et al., 2021)	“Tension between independence and relevance” (p.1558) Difference in how knowledge is embedded in system and how it presents in reality Technical focus of developers Required time & effort on experts side (e.g. data-related practices also of non-tech. actors) “Human-ML hybrid practice […] is difficult to reach […] when developers are disconnected from the domains” (p.1575) they design for	Developers offered more less bias etc., developed the AI and communicated with the experts to create a useful AI Domain experts (users) looked for increased “efficiency” (p.1571) and objectivity, communicated needs, provided feedback and questioned AI’s role Domain “experts need statistical education, knowledge about data legislation […] and understanding of moral concerns around the use of ML” (p.1575) Developers must “learn about practical domain’s local standards, values, and routines” (p.1575)	“Alternative trajectory” (p.1574) (to power struggle) of collaboration, where “actors mutually shape a new practice” (p.1575) Professional standards and priorities of HR experts to select data, build the models not just on historical data but also with the organizations’ vision Domain experts (and developers) should prepare (also in time and effort needed) to “enter an interdependency relationship” (p.1575) → “developers rely on experts to define, evaluate, and complement machine inputs and outputs” (p.1575) → Developers help experts uncover insights (e.g. biases)	Developers reflected on their ideas of what ML/AI can provide and how far it is actually objective Domain experts reflected on their own practices & values through confrontation with the AI and discussion with the developers → Reflected on own ideas through mutual learning about each others’ domains and engaging with each other HR professionals expertise of what variables are important for them, where they want to develop into and their reasons for how they make their final decision	Revisited own concepts regarding AI (designers) and the workflow (domain experts)	Very good for an overview of the whole process
Mitigating cognitive biases in developing ai-assisted recruitment systems: A knowledge-	Recruitment AI may still be biased (bc of training datasets based on past decisions and algorithms) Bias can come from developers not being able to objectively formulate user assumptions or	HR managers share their domain knowledge, communicate what they need, give feedback / evaluate AI AI developers ask right questions, translate domain knowledge / requirements,	AI developers & HR managers need to collaborate for AI to be less biased Collaboration through user feedback Came up with three phases (pre-development,	Knowledge sharing as a way to mitigate biases End users and developers need to share knowledge about “expectations, requirements and limitations” (p.2)	Software development is iterative HR managers test the model, give feedback and then the model is refined accordingly	Very good, especially for knowledge sharing

sharing approach (Soleimani et al., 2022)	use selection criteria that is not correct or relevant	develop and implement feedback Employees working in the actual position that is being hired for should be involved as they know the work Possible role of HR experts (academics) to help with data labelling and knowledge	development and post-development) Initial discussions around requirements and domain knowledge Bias “has to be solved through communication and collaboration” (p.10) Pilot as a strategy to evaluate the model and test the outcomes	Definition of knowledge sharing in software development: “process of exchanging task-related information, ideas, know-hows, and feedback” (p.2); multiple activities: participation, requirement gathering HR managers should tell what they know and what they need before developing AI begins		
Designing Fair AI in Human Resource Management: Understanding Tensions Surrounding Algorithmic Evaluation and Envisioning Stakeholder-Centered Solutions (Park et al., 2022)	Lots of unsolved tensions and different (subjective) definitions with no clear understanding on the role of AI Diff. intentions and usages of AI throughout stakeholders 5 identified tensions: “1) divergent perspectives on fairness, 2) the accuracy of AI, 3) the transparency of the algorithm and its decision process, 4) the interpretability of algorithmic decisions, and 5) the trade-off between productivity and inhumanity”	Participatory workshops involved employees, employers / HR teams, AI / business experts Recommend a “stakeholder-centered design” process: Actors should involve stakeholders & employees in process through open discussion and co-designing and help understand process Include other stakeholders to accurately reflect HRM context	When designing or adopting AI in HR companies should make sure to give space and cultivate “organic collaboration”, “open discussions” and “codesign sessions” Designers should identify diverse “stakeholders’ tensions in advance” by utilizing explained method (how their workshops were organized, coping strategies etc.)		Designers should be “agilely reiterating the process” to make sure all tensions are understood and addressed	
Stakeholder-Centered AI Design: Co-Designing Worker Tools with Gig Workers through Data Probes (Zhang et al., 2023)		Workers communicated their patterns & mentioned own ideas of what this could imply for design of AI Involve workers as experts	Data probes as a way to “support stakeholders in co-designing AI” (p.2) → can help stakeholders reflect → should be designed in forms familiar to workers → Probes as a way to communicate work patterns and contexts & come up with own implications for AI	Workers own expertise should not be undermined, could lead to them not using the system “Treating workers as experts can also help AI practitioners [..] recognize challenges to consider” (p. 14)	Feedback being implemented → redefining features	

			→ Can bring up important context			
Employee experience –the missing link for engaging employees: Insights from an MNE's AI-based HR ecosystem (Khakurel & Blomqvist, 2022)	Technological maturity, size of workforce, or nature of workers crucial to consider when deciding which AI etc. HR managers should be ready to change their ways	Employees were involved in "co-creating the meaning of rewards" (p.107) which was then integrated into the AI (Staff surveys, EX reactions / responses were used to inform the corporate values created) Involving through persona of employees who would typically use these Ais HR team and business teams were involved in co-designing (with also technical experts) Must co-create with "direct involvement of a diverse group of stakeholders" (p.111)	HR managers codesign AI applications by "drawing team insights" (p. 106) PeopleXp framework (platform to engage w employees) was "designed collaboratively by business and HR teams" (p.107) HR professional and business lead "co-owned" (p.107) elements of each framework (AI) Senior leadership and HR teams co-created corporate values Collaboration requires new skills with "working with cross-functional teams" (p.111)	Employee experience (EX) informed and enabled the program development (reward one) HR managers need digital and data science skills to implement the AI "Managers can leverage employees' skills by encouraging collaboration and knowledge sharing through traditional and AI-mediated social exchanges" (p.111)	Consistently and iteratively engaged with employees (HR managers creating their AI framework / strategy)	Important to note that this is about an IT company
From coexistence to co-creation: Blurring boundaries in the age of AI (Waardenburg & Huysman, 2022)	"Self-learning"(p.4) characteristic of AI Users' involvement in further development (due to self-learning AI) is overlooked → often "disconnect between the developers and users" (p.7) after deployment	The field consists of practices from actors from "multiple, different communities" (p.8) Organization holds role in data construction	Propose "blurred boundaries" (p.1) bw development & use Developers and users "perform shared practices to co-create" (p.8) Developers & users unbox AI together (explainability & interpretability of AI) AI deployment: "sustained collaboration between developer and user, even when the tool is fully deployed" (p.7)		Consequences of AI deployment applies both to user context and feeds "back into the further development of tool itself" (p.8)	Also insights into data
Managing Collaborative Development of Artificial Intelligence: Lessons from the	AI could fail if its not developed through collaborating with the experts its supposed to "bypass" (p.6139) Case 1:	Developers designing HR managers being consulted → Coming together to discuss New role of intermediary (e.g. UX researcher) created further distance	Case 1: Introduced intermediaries to aid collaboration: "in-house user experience (UX) researchers and business analysts" (p.6141)	Case 1: HR consultants didn't mention important part of their practice cause they took it "for granted" (p.6140) Case 2:	Case 1: First iteration failed bc of failed collaboration, second one organization gave up and switched to simpler technology	Two of the three cases are HR (recruitment) Specifically really good

Field (Mayer et al., 2023)	HR didn't use and started distrusting after first failed iteration Introduced intermediaries but this only created further distance bw developers and users → no direct interaction anymore General challenges to collaboration: AI was introduced to outperform experts and therefore seen as a threat for them → user resistance Gap / Blackbox / language barrier → both actors had inaccessible language of their own domain and gap of understanding of the others' "AI systems have difficulties incorporating rich, domain-specific, and practice-based knowledge" (p.6144) Developers assumed at beginning that they didn't have to involve the domain experts (in the 2 HR cases)	Managers hold crucial role in supporting the projects and collaboration	(had to also work with someone who had a bad experience with AI now) Case 2: developers didn't want to include experts bc they feared adding subjectivity but had to learn that including experts was quite helpful and needed "Model discussions also united developers and experts in their shared goal of improving the hiring process" (p.6142) → began viewing it as a "collaborative effort" (p.6142) Bi-weekly meetings discussing challenges and outputs Strategies for managers of these projects: "(1) Creating a shared vision, (2) building a common understanding, and (3) developing complementary abilities" (p.6144) 1. Create shared vision (Clear vision of what AI can bring to the table) (Involve domain experts in figuring out how AI can help in their day-to-day; be realistic with expectations (can be done via meetings and workshops exploring possible value of AI) 3. Complementary abilities (don't involve selectively but throughout and from beginning)	Expert knowledge was helpful for process; Groups knowledge as "complementary insights" (p.6142); Developer present what AI uncovered; recruiter revealed about their process "experts to understand the system's technical abilities and for developers to understand the procedures and reasoning of experts" (p.6142) General: important to bridge language barrier between developers and domain experts "tacit knowledge patterns of domain experts' decisions were not accessible to developers" (p.6144) → led to irrelevant AI Managers have to figure out how to "bridge the gap between developers and domain experts" (p.6144) 2. Build common understanding ("Common ground and mutual reflection" (p.6145)) (Transparency of AI → involve domain experts in decisions around the design (builds trust)) Training for domain experts Discussions around trade-offs with developers and experts		for collaboration
Key elements in transferring knowledge of the	There is not enough "employee data, no clear vision, a limited understanding" (p.81) of how	HR managers also in role to manage and include their employees	Manager should include employees and make them	"Intensive training programs" (p.91) can help transfer knowledge (teach HR		Knowledge focus

AI implementation process for HRM in COVID-19 times: AI consultants' perspective (Tuffaha et al., 2022)	AI makes decisions, managers want to bypass decisions made by AI "Mistrust between AI and managers" (p.89) Employees already have idea that AI cannot understand human perspective well	Can appoint role of AI specialist to take care of data processes and ensuring AI contributes well (organization-wide consultant)	aware also to minimize resistance	managers) of how to implement AI Managers don't understand how AI makes decisions or assumes stuff → need explanation tools		(especially for HR managers) More focused on organization side
Can HR adapt to the paradoxes of artificial intelligence? (Charlwood & Guenole, 2020)	AI developers don't care about solving ethical problems related to AI in HR AI developers prefer automating decisions instead of augmenting, put the AI over "traditional decision-making by domain experts" (p.733)	HR managers responsible of centering ethics in the design "dangerous cases of AI use are likely to occur where domain experts are excluded from the design and development of AI tools" (p.733) "AI can only be ethical if it is based on consultation with and the involvement of stakeholders […] who will be effected by the AI at the design, development and deployment stages" (p.736)	Experts should work closely with developers and make sure everything from building and using it is informed by their expertise (Ethical) standards should "include processes for stakeholder consultation and engagement" (p.737)	Domain knowledge is "essential for the development of AI tools that work as intended, are fair and which do not reproduce existing organisational biases" (p.736) AI should be questioned and understood to avoid de-skilling HR practitioners need upskilling (big data literacy)		Focuses also on views regarding AI's value or effect
An interdisciplinary review of AI and HRM: Challenges and future directions (Pan & Froese, 2023)	Vague definition of AI also makes it hard for non-AI-experts to understand it and gain knowledge for it Many AI tools "lack support of management knowledge" (p.16)	All kinds of stakeholders are involved or effected: HR managers, developers, employees,….	"companies could jointly develop AI tools, ideally in cooperation with AI and HRM experts" (p.16), instead of buying e.g. off-the shelf AI that is not yet fully validated or useful	"developers' insufficient HRM knowledge incurs significant shortcomings of AI tools" (p.13)		More general but still relevant overview of a lot of literature on AI right now
Using AI to predict service agent stress from emotion patterns in service interactions	Privacy constraints of emotion recognition algorithm → had to have everything anonymized Staged data for emotion recognition technology is not sufficient since it lacks context	Call centers were involved already in the first step of data collection Professional service agents coded/ labelled / annotated their calls	Deployed model in call center to have it trained through further collected data Expert coding	Only the service agents themselves could know what stress they experienced which means their knowledge / perception was unavoidable		

(Bromuri et al., 2021)	of emotions and is often unnatural		Consent about sensitive data is needed from both service agents and customers recorded			
Agent-based simulation for computational experimentation: Developing an artificial labor market (Chaturvedi et al., 2005)		Recruiters are actively modelled into the labor market model as agents since their decisions would influence developments	Multiple steps gathered user input and then modelled it into the model Used a war simulation environment exercise with workshops etc. with military stakeholders as further input and to have the model evaluated by users (e.g. are the outcomes believable?) Got user feedback through this and implemented it to refine some and add new features to their model	Conceptual model should be represented in a way that is "intelligible to both end users and analysts" (p.700) → used a double helix DNA model	Had to "fine tune" (p.712) after war simulation trial	Developed a detailed model of a labor market to e.g. help test out policies Highly complex tech. Related to HR practice through their case
Smart Work Injury Management (SWIM) System: Artificial Intelligence in Work Disability Management (Cheng et al., 2020)		RTW stakeholders identified "human factors" (p.356) to complement data with context Focus group discussions as method to "involve all RTW stakeholders" (p.356) Stakeholders: "injured workers, trade unions, employers, healthcare providers, and insurers" (p.356)	Held interviews and focus group discussions with different stakeholders to gain insight into different perspectives → goal to have common understanding / definition of elements Field testing at 8 companies End users verify and accept system → feedback used to finetune	/	Prepared to fine-tune according to feedback	RTW = Return to work Focused also on benefits of ML in context
On-line consistent ranking on e-recruitment: seeking the truth behind a well-formed CV (Faliagka et al., 2014)	More complex job roles had a lower accuracy of the model (senior positions)	Domain experts used to label	Expert came in to score 100 blogs of possible candidates for extraversion to be tested against the machine Model is built to allow recruiters to assign own relevance score as well, which then can help the AI improve over time	Domain knowledge was used in the semantic matching step where domain experts created this knowledge for the system	Plan to make improvements and expand, paper talks about improving and refining an older version	

			Tested it in recruitment scenario, where they had recruiters assign scores and compared those w the model ones			
Designing fair AI for managing employees in organizations: a review, critique, and design agenda (Robert et al., 2020)	"lack of consideration for the organizational or social context surrounding the use of the AI system" (p.554) "not always clear how to make sense of these data for individual employees" (p.557) Employees might be unable to understand information bc of lack of expertise	Some considered stakeholders' perspectives in their design for fairness Organizations should make their processes fair (or define the fairness there) before they go into AI development Employee should be able to directly tell the AI about sth being unfair	AI affordances: Transparency (make "underlying AI mechanics visible and known to the employee" (p.555)), Explainability (describe AI "to employee in human terms" (p.555)), Visualization ("Representing information to employees via images, diagrams, or animations" (p.555)), Voice ("Providing employees with an opportunity to communicate and provide feedback to the AI" (p.555)); voice only effective if "employees believe their feedback […] can influence the AI actions and decisions" (p.558)	Have to first decide what fairness is relevant for the case & then operationalize it		Design agenda, fairness, ethics
Explaining Decision-Making Algorithms through UI: Strategies to Help Non-Expert Stakeholders (Cheng et al., 2019)		"goal of positioning participants as experts in their own right" (p.559) Invited students to "represent the stakeholders who are affected, directly or indirectly, by the algorithmic decisions" (p.559)	Design workshops to create diff. explanation prototypes → already feedback through design workshops User online experiments for evaluation	Stakeholders / experts coming together to create first sketches / concept	Improving after feedback (first sketches, then low-fidelity prototype, then high-fidelity prototype)	
Questioning the AI: Informing Design Practices for Explainable AI User Experiences	Trade-offs regarding explainability have to be considered → "inherent tension often exists between explainability and other system and business goals" (p.7)		"Explanations as an integral part of a 'feedback loop'" (p.6) "realization [of explainability] requires teamwork with data	Users want explainability to be able to "evaluate the capability of the AI" (p.5), e.g. to see if it "aligns with domain knowledge" (p.5)		

(Liao et al., 2020)	Challenge of "skill gaps" (p.7) needed to be engaged; Challenge of "cost of time and resource" (p.7) "research still struggles with a lack of understanding of real-world user needs for AI transparency" (p.9)		scientists, developers and other stakeholders" (p.7) Method of question bank to make it conversational and be able to have specific questions asked by users	"Several informants attempted to mimic how people, especially domain experts, explain in their design work" (p.7)		
Bargaining with the Black-Box: Designing and Deploying Worker-Centric Tools to Audit Algorithmic Management (Calacci & Pentland, 2022)	Workers had trouble understanding the raw data (was then simplified)	Workers and organizers were involved in co-designing the tool Workers were involved in the design through organizers → Organizers collected "informal feedback" (p.10) from workers by showing them the bot as well	"Collective action through data" (p.19) The researchers worked with organizers to find a way to scale the current system and find further possibilities to develop → suggested two options, had organizers pick "open discussions" (p.9) with organizers Organizers had conversations with workers, Decided together on design goals, Collaborated on user flow through shared google slides deck	Researchers talked about what would be feasible and "computable" (p.9) based on the data, organizers brought knowledge about the context and workers' (users) needs Organizers had conversations with workers and brought the topics discussed there to the discussions with researchers	1st: Prototype 2nd: proof-of-concept prototype 3rd: decide design goals 4th: researchers created user flow and then organizers gave feedback and edited "made several other iterative changes to the bot" (p.11) → informed by feedback	
Hiring Algorithms – An Ethnography of Fairness in Practice (van den Broek et al., 2019)	Diff. stakeholders had different understandings of fairness in their work Candidates felt unfairly treated and misrepresented by the results from the gaming AI Some gamed the system HR managers didn't accept AI decisions but overruled Concern that only one kind of employee would end up being hired / recommended by AI	Three involved stakeholder groups: Recruiters, HR managers, AI team, managers New role of PA for the project "HR team started to actively enroll stakeholders into their project" (p.5)	HR managers collected data; AI team made pilot First HR had human in the loop for every step Involved stakeholders "by communicating and educating them about the use of AI for enhancing fairness" (p.5)	"forced both teams to consider new notions of fairness" (p.5)		