NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Computer Science

Master's thesis

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Artificial Intelligence for innovating recruitment and selection processes: evidence from Scandinavian companies

Master's thesis in Computer Science
Supervisor: Patrick Mikalef
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ABSTRACT

Artificial Intelligence (AI) has brought rapid innovations and is likely to substantially change the modus operandi for knowledge creation, coordination, and decision-making in organizations. AI has been extensively used for automating mundane tasks and for augmenting human abilities such as identifying imperceptible patterns. This might create new opportunities for gaining competitive advantage. However, it is not clear how AI affords innovation in human resources (HR) and how to actualize the action possibilities. Therefore, there is a lack of knowledge about AI affordances-actualization while recruiting and selecting potential candidates. This study investigated the interactions between AI technology such as androgynous robots, collaborative filtering models, AI-staffing assistants and key actors working in companies that offer HR services. Building on Grounded Theory, semi-structured interviews have been collected from seven case studies in Scandinavian countries. Affordance-Actualization theory guided the data analysis and extracted four specific affordances from selection and four affordances from recruitment processes. AI has the ability to automate repetitive actions such as conducting interviews using robots, collecting online behavioral information, and facilitating online job applications and to augment the legitimacy of hiring decisions and ranking candidates based on their competences and abilities. The results explain how AI innovated internal processes and contributed to unbiased and fair recruitment and selection processes. This study advanced the current understanding of the Affordance-Actualization theory in human resource management by explaining the second-order and first-order affordances and their actualization. Lastly, it provided guidance to practitioners to combine human and organizational capital with AI to stay competitive.

Keywords: *Artificial Intelligence, innovation, recruitment, selection, staffing, affordance actualization, human resources*

SAMMENDRAG

Kunstig Intelligens (KI) kan være en drivkraft for innovasjon og endring innen kunnskapsutvikling, koordinering og beslutningstaking for organisasjoner. KI-teknologi kan bli brukt til å automatisere repetitive arbeidsoppgaver og til å styrke menneskelige beslutninger gjennom for eksempel mønstergjenkjenning. Dette kan igjen bidra til å skape konkurransemessige fordeler for selskaper som klarer å utnytte potensialet som ligger i KI-teknologi. Derimot er det uklart hvordan KI muliggjør innovasjon innen HR (fra engelsk Human Resources, menneskelige ressurser) og hvordan disse handlingsmulighetene kan bli virkeliggjort. Følgelig finnes det en kunnskapsmangel om hvordan KI muliggjør ulike handlinger innen rekruttering og selektering av jobbkandidater. Denne studien tar for seg samhandlingen mellom KI-teknolog, som for eksempel androgyne intervjuroboter, maskinlæringsalgoritmer og bemanningsassistenter, og nøkkelaktører som jobber i selskaper som tilbyr HR-tjenester. Datainnsamlingen baserer seg på prinsippene fra forskningsmetoden Grounded Theory og består av semi-strukturerte intervjuer samlet inn fra syv forskjellige skandinaviske selskap. Affordance-acutalization teori har blitt brukt som veiledning for dataanalysen og har avdekket fire spesifikke affordanser i selektering og fire affordanser i rekruttering. KI kan bli brukt til å automatisere oppgaver som for eksempel gjennomføring av intervjuer, datainnsamling om adferdsmønster på nett og fasilitering av nettbaserte jobbsøkingsprosesser. Dette kan blant annet bidra til å legitimere ansettelsesbeslutninger ved å evaluere jobbkandidater basert på deres individuelle kompetanser og evner. Resultatet fra denne studien forklarer hvordan AI endret interne prosesser og bidro til mer rettferdige og objektive rekrutterings- og selekterings-prosesser. Studien bidrar til å øke forståelsen av Affordance-Actualization-teori innen HR gjennom å forklare førsteorden og andreorden affordanser og aktualiseringene av disse. Til slutt legges det frem en veiledning for hvordan aktører kan kombinere menneskelig og organisatorisk kapital med KI for å oppnå konkurransedyktighet.

PREFACE

This thesis is part of a master's degree in Computer Science at the Norwegian University of Technology (NTNU) in Trondheim and was written during the period of August to December in 2020.

I would like to thank my supervisor Patrick Mikalef and my co-supervisor Cristina Trocin for excellent guidance and support throughout the working process.

Ingrid Våge Hovland

Førde, 30th December 2020

Table of Contents

INTRODUCTION

Artificial Intelligence (AI) offers novel ways for innovation (Lehrer et al. 2018; Liu et al. 2020; Mikalef and Krogstie 2018) and for gaining competitive advantage (Campbell et al. 2012; Chadwick and Dabu 2009) due to its computational information processing capability for making predictions and supporting human experts in decision-making (Keller et al. 2019). Some authors have focused on how AI allowed firms to automate tasks as monitoring and controlling work (Tschang and Mezquita 2020). Other scholars highlighted AI as a tool that can augment human abilities such as decision-making (Brynjolfsson et al. 2017; Metcalf et al. 2019; Raisch and Krakowski 2020). Furthermore, more recent studies showed that the introduction of AI technologies enabled human experts to focus mainly on work in which they overcome machines, such as developing interpersonal relationships and attracting new customers as it required empathy and intuition. Taken as a whole, prior scholars - whether focused on input, process, or outcome - have generated important insights in Information Systems (IS) and Management by studying the role of AI for innovating.

However, many of these insights remained conceptual and difficult to implement. Artificial Intelligence has the potential to disrupt internal processes of organizations, but it is less clear how AI affords innovation in HR organizations. Therefore, it is necessary to understand how to actualize the action possibilities AI offered while recruiting and selecting potential candidates. While customized combinations of AI with human expertise might be beneficial to specific HR organizations, they may be inappropriate and detrimental to other HR organizations. Although, a number of commonalities in the process of implementing and using AI in HR organizations havs been identified (Cohen 2019; Davenport et al. 2020; Mikalef and Gupta 2021) there are almost as many ways to develop contextualized frameworks for combining AI with human expertise.

The purpose of this study is to explore the ways Artificial Intelligence enables innovation in recruitment and selection processes and how this contributes to organizations' competitive advantage. The guiding research questions are: how does Artificial Intelligence (AI) afford innovation in recruitment and selection processes? And how to actualize AI affordances for innovating in organizations offering HR services?

In order to respond to the research questions, I followed an inductive qualitative approach to explore multiple case studies that used AI technology to support recruitment and selection processes. Grounded theory (Strong et al. 2014a; Urquhart et al. 2010) guided the data collection and the Input-Process-Output framework (Espinosa et al. 2006) supported the analysis of semi-structured interviews. Additionally, I extracted potential actions performed with the support of AI in line with Affordance theory. Finally, Affordance-Actualization theory enabled an in-depth explanation of the first-order, second order affordances and their actualization.

This study does not present an algorithm for implementing AI in companies offering HR services but it helps to understand how to use AI technology to innovate internal processes and services in order to stay competitive. This study provides empirical evidence about how AI affordances are actualized in HR departments and staffing organizations. The findings present the affordances and their actualization in recruitment and selection processes. I identified four unique affordances in the first process such as *optimizing online recommendations* of potential candidates for HR managers, *conducting automated interviews* with an androgynous robot, *automatically assessing candidates' responses* based on the Big 5 model, and *data-driven legitimization for hiring decisions*. In the selection process, I extracted other four specific affordances, namely *fine-tuning algorithmic parameters* for online job advertisements, *collecting online users' behavior* while reading job advertisements, *recommending job listings* for HR managers, and *facilitating online job application* procedures.

The thesis is structured as follows. In the theoretical background, I presented core activities performed in recruitment and selection Then, I discussed the contribution of AI to innovation in HR. Lastly, I reviewed key contributions of Affordance and Affordance-Actualization theory in Information Systems (IS) when organizations implement new technologies. In the research method, I show the approaches followed to collect, analyze, and interpret the data. The findings describe the possibilities of actions and the combination of AI capabilities with human expertise to innovate internal procedures. In the last section, I discuss the contribution to theory and practice.

THEORETICAL BACKGROUND

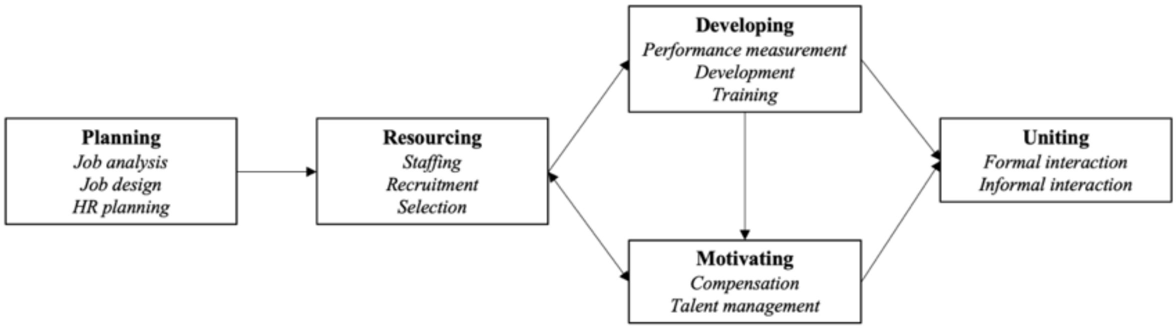
In order to understand the role of Artificial Intelligence technology in recruitment and selection processes, I provide an overview of Human Resource Management (HRM) core practices. First, I review most important HR activities to gain competitive advantage. Second, I discuss how Artificial Intelligence has been used in HRM. Then, I show the most recent AI applications in HRM as an enabler of innovation. Lastly, I present the Affordances-Actualization theory related to advanced technologies.

Strategic Human Resource Management for competitive advantage

Human Resource Management (HRM) plays a critical role for companies that want to gain competitive advantage because it adds business value and contributes to the creation of unique resources (Oehlhorn et al. 2020). Traditionally, HRM performed organizational and strategic functions to drive the business success by aligning employees' capabilities with organizational goals (Maier et al. 2013). However, technological progress, increasing complexity in HR tasks and competitiveness in the labor market transformed the conventional HR department into an interdisciplinary and cross-departmental function. Indeed, it is not considered anymore only as an administrative cost-center, on the contrary it oversees the managing of multiple functional tasks (Noe et al. 2017). For example, HRM is engaged with planning employees' skills to satisfy future operational requirements, selecting valid applicants with appropriate skills, developing employees' competences to improve their job performance, and administrating and supporting tasks. Thus, HRM can be considered an internal partner that adds value to organizations (Wirtky et al. 2011) and contributes to fostering advanced knowledge and competences.

To meet organization's needs for skills, HRM performs multiple functional practices that go from planning to uniting (Figure 1 - HRM functional tasks and practices) (Oehlhorn et al. 2020). For planning the nature of jobs and competencies, HR managers will need to decide which job positions, which skills and how many employees will be necessary in the future. Whereas the task of resourcing is concerned with three main activities, which are internal staffing, external recruitment, and selection of suitable candidates. Therefore, developing employees' competences for specific job positions has a direct impact on their job performance especially when they feel more aligned with organizational goals and more appreciated. After having identified valuable collaborators to different the organization from its competitors, motivation practices have been widely adopted to retain employees within the organization. Offering attractive career opportunities, providing talent management and offering rewards as form or compensation are most used strategies to retain valuable employees and make them feel appreciated and valuable. Lastly, uniting employees from different departments and units is a practice recently adopted to make the working processes more effective and harmonized.

Figure 1 - HRM functional tasks and practices



Source: Oehlhorn and colleagues (2020)

Recruitment and selection (R&S) are interrelated processes with the aim of attracting and choosing appropriate candidates in an organization. The effectiveness of recruitment and selection functions has a direct impact on the performance of the HR department in a firm (Gamage 2014), as the human capital is a crucial area for companies willing to “compete in a digital world” (Kane et al. 2017). Therefore, hiring inappropriate candidates because of lack of competences or lack of fit with culture of the company might be too expensive (Koch et al. 2018; Gamage, 2014).

In a digitized world, intangible assets such as human capital have become the biggest drivers for economic and productive growth (Rowe 2019). Aspects like flexibility, productivity, and innovation capabilities can be essential for a company’s competitive advantage and long-term development (Todericiu and Stăniţ 2015). With constant technological advancements, there will be an increasing demand for people who can effectively use these technologies such as AI, which might create a skills shortage in the future (Cohen 2019). Therefore, attracting, selecting, and retaining human capital is one of the top strategic priorities for a firm (van Esch and Black 2019).

The complexity of the recruitment process

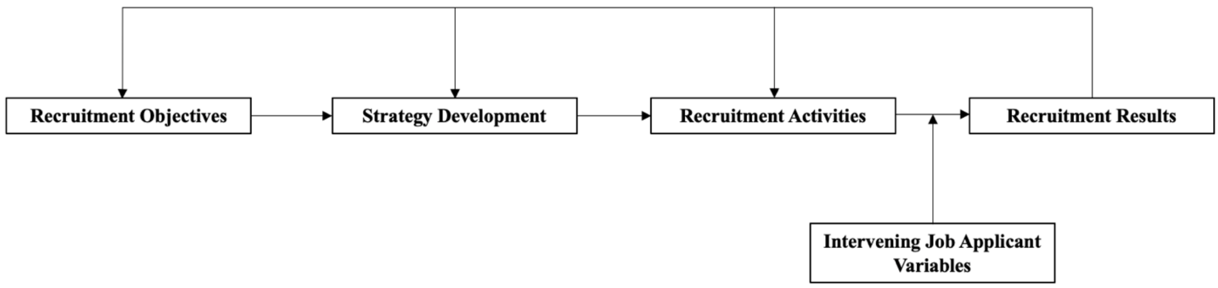
Several definitions have been developed to discuss the main activities and tasks performed in the recruitment process. Some scholars provided a broader perspective like (Asseburg et al. 2018), who defined recruitment as "*all organizational practices and decisions that affect either the number, or type, of individuals who are willing to apply for or accept a given vacancy*". A more detailed definition has been developed by Gamage (2014), who believed that *"recruitment is the process of finding and attracting suitably qualified people to apply for job vacancies in the organization*". Whereas other researchers focused on specific recruitment methods such as referral-based recruitment (González and Rivarés 2018) or recruitment by word-of-mouth (Van Hoye and Lievens 2009). Recent studies focused on the goals of recruitment process such as to locate and approach individuals who "possess the desired attributes" for a specific job opening (Acikgoz 2019). clearly stated that "*the process of searching the right talent and stimulating them to apply for jobs in the organization"* places a pivotal role to survive the market competition.

This study embraced the definition provided by (Breaugh 2013; Breaugh 2008), which described the activities conducted in order to find and attract job candidates external to an organization. The author said,

> *"an employer's actions that are intended to (1) bring a job opening to the attention of potential job candidates who do not currently work for the organization, (2) influence whether these individuals apply for the opening, (3) affect whether they maintain interest in the position until a job offer is extended, and (4) influence whether a job offer is accepted."*

From these perspectives, two typologies of recruitment processes emerged that are internal and external. The first type refers to those actions that are taken to select candidates from the already existing workforce in an organization (Sulich 2015) and is often related to specific cases such as career planning and development (Barber 1998; Holm 2012). Whereas the external recruitment is engaged with attracting candidates outside the organization to acquire new talents and competences. Prior studies suggested that the human capital acquired from other organizations can be more beneficial for meeting organizational knowledge needs because of access to new "*tacit knowledge and skills*" (Ge et al. 2020; Singh and Agrawal 2010). The recruitment process acquired more and more importance and the complexity of its tasks increased and multiple intermediate procedures have been created as shown in Figure 2.

Figure 2 - Model of the recruitment process



Source: (Breaugh 2009)

Four macro processes are performed in the recruitment process. One of the first activities is to decide recruitment objectives, which influence and determine the rest of the tasks. Indeed, they are strictly linked to firm's mission and this involve pre-hire objectives such as number of positions to be filled and types of applicants sought. Post-hire objectives are exemplified with retention rate of new hires and job satisfaction. Then, HR managers develop the recruitment strategy in line with recruitment objectives. Consequently, such decisions are concerned with who and where to recruit and what message to communicate in order to reach targeted candidates. For example, employer branding plays a central role in this segment (Gilani and Jamshed 2016). Another key factor for motivating job applicants is linked to their perception of the company's brand image and the organization itself (van Esch et al. 2019).

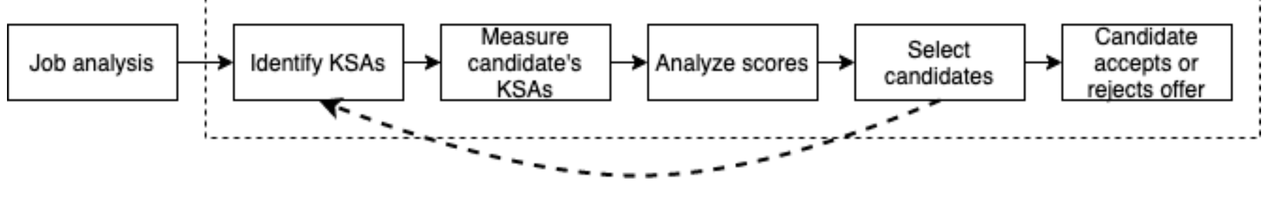
The core recruitment activities involve methods and techniques related to advertising the job openings, choosing what information to present about the job and how to present it. Hereunder (Breaugh 2009) also places the selection and filtering of candidates. The choice of recruitment methods (RMs) depends on several factors including the use of different technology and tools such as "job advertisement, online job and web portals, word-of-mouth, social media" (Muduli and Trivedi 2020). However, written job advertisements are still the most typical method of recruitment (Asseburg et al. 2018) and are often disseminated through websites and social media platforms to increase the number of applicants (Derous and De Fruyt 2016). Some intervening job application variables include applicant attention, message credibility and applicant interest which may influence the recruitment results. According to (Breaugh 2008) recruitment research tended to pay more attention to the position attractiveness compared to factors like attracting applicant attention and applicant self-insight. The latter is important when it comes to attracting passive job seekers and improve person-job/organization fit, respectively. Lastly, the HR manager measure the results achieved with metrics to check their work performance and whether they achieved their internal and organizational goals.

Prior studies also identified two main groups of candidates that apply to job positions. Some recruitment efforts were targeting active job seekers perceived as individuals who are actively looking for job opportunities. While passive job seekers referred to those applicants that were not actively looking for other job opportunities, but who could be interested in new career opportunities if receiving an interesting job offer (Acikgoz 2019).

The selection process

In contrast to recruitment, the definitions of selection as an activity are more unanimous amongst researchers. (Tambe et al. 2019) laid forward a general and broad definition of selection as the process of choosing among applicants those who should receive job offers. (van Esch et al. 2020) note that the selection process is also concerned with assessing the candidates who have applied. According to Bangerter and colleagues (2012) the selection of job candidates is the moment where the goals of the applicant and the organization are confronted, which is a "*competitive and cooperative endeavor*" as the employer and the applicant both seek to fulfill their own distinct objectives. Figure 3 shows the different stages of a selection process as depicted by Roberson and colleagues (2017). In their research, they followed the "dominant staffing model in USA and Europe" and broke down the selection process into distinct steps: (1) define work activities for the job position, (2) identify the knowledge, skills and abilities (KSAs) that are believed to predict individual-level performance in the job (3) measure the KSAs of each applicant based on job-performance indicators using assessment tools, (4) analyze scores to identify the best applicants, (5) select candidates and (6) candidate accepts or rejects the job offer.

Figure 3 – Job application selection process



Modified from source – (Roberson et al. 2017)

Selection of candidates generally happen in several phases. It starts with the screening on a surface-level followed by lengthier, more in-depth assessment procedures (Black and van Esch 2020). For this reason, Figure 3 has been modified with a stapled arrow to show how the four intermediate stages between KSA identification and selection of candidates can be repeated.

During the screening phase, the employer typically analyze and evaluate applicant job competencies based on their résumés (Derous et al. 2017) Candidates that pass the initial phase are then further assessed in one or more rounds to determine who should receive job offers (Black and van Esch 2020). Measuring enough KSAs to ensure a "holistic picture of candidate performance" while avoiding too lengthy and expensive processes is one of the major decisions that companies need to make before commencing the selection process (Roberson et al. 2017).

A vast amount of selection tools and instruments exist where the key purpose for the organization is to "*adequately estimate the quality of the future hires*" (Lievens et al. 2020). The employment interview is the most common form of selection method in the world according to Nikolaou and Gergiou (2018). Other evaluation methods used by companies include integrity tests, personality tests and cognitive ability tests (Klotz et al. 2013) which are shown to have varying correlations with work performance (Lievens et al. 2020). The payoff of a valid selection method also heavily depends on how many of the top-scoring applicants are retained during the process (Roberson et al. 2017) and who have kept their interest in employment at the organization (Pahos and Galanaki 2019). Specifically, the reactions of the job applicants during selection impact several factors including candidate performance during the selection procedures, job satisfaction and turnover (van Esch et al. 2020). In addition, it is becoming increasingly important for companies to construct selection processes that are considered as fair and engaging for the applicant because it can positively affect "the organization's image as an employer" (Lievens et al. 2020).

Many organizations strive towards hiring for a diverse workforce (Shaban 2016) in terms of ethnicity (Derous et al. 2017), age (Pahos and Galanaki 2019) and gender (Daugherty et al. 2019) as well as numerous other factors (Shaban 2016; Agrawal, 2012). Diversity was shown to be advantageous for companies because it might lead to "*greater creativity, better decision making, a broader pool of talent, improved company image, and increased access to various markets*" (Roberson et al. 2017). A typical effort that companies make in order to increase diversity involves removing or reducing human bias from affecting the selection process

(Roberson et al. 2017). In fact, from an economic, ethical and legal standpoint, employers need to ensure that selection procedures are free from bias that might negatively affect applicants (Derous et al. 2017). Nevertheless, many companies struggle to achieve diversity in their workforce (Pahos and Galanaki 2019). One reason may be that humans can be subconsciously bias and tend to favor people with similar traits to themselves (Cohen 2019). For instance, unstructured interviews, which is the most common form of selection interviews, often result in a "*variety of interviewer bias*" (Hudson et al. 2017). Similarly, it has been shown that recruiters tend to make biased decision and stereotypical categorizations during résumé screening (Derous et al. 2017)

Artificial Intelligence in Human Resource Management

Artificial Intelligence has attracted more and more attention in the last years due to its computational information processing capability for making predictions and supporting human experts in decision-making (Keller et al. 2019). This capability is constantly increasing and has the potential to provide more accurate results, which might contribute to firms' competitive advantage. Several studies in Information Systems investigated the role of AI on firm performance (Mikalef and Gupta 2021), on creating user value (Gregory et al. 2020), on dynamic decision making (Meyer et al. 2014) and on marketing strategies (Davenport et al. 2020). While describing AI capabilities, tools, techniques and tasks, scholars elaborated multiple definitions (Dwivedi et al. 2019; Haenlein and Kaplan 2019). Some focused on the concepts of *intelligence*, which was considered as the ability to make sense of the information collected from past experiences and to deal with uncertainty in the future (Ågerfalk 2020) and others focused on the concept of *artificial* referring to the emulation of human-like cognitive tasks (Benbya et al. 2020).

Researchers generally defined Artificial Intelligence (AI) as the ability of a computer to act intelligently or as a human would in a certain situation (Hovland, Ingrid 2020). The technology embodied into AI systems changes based on what we perceive it to be intelligent at a certain point in time (Haenlein and Kaplan 2019). Today the term AI encompasses different typologies of AI systems, which include machine learning (learns from datasets and identify patterns not evident to human eyes), natural language processing (understands written or oral human language), deep learning (data analysis can be supervised, semi-supervised, or unsupervised), robots and other automation technologies (Benbya et al. 2020; Faraj et al. 2018). A common element of AI systems is that they can apply rules, learn from new data and adapt to changes in a short time and with a high speed (Canhoto and Clear 2020). This study follows the definition provided by Mikalef and Gupta (2021) that is

> *"AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals."*

Advancements in computing power and Big Data during the recent years along with increased algorithmic effectiveness has put AI technology on the agenda for many businesses (Evry 2017). AI can now be used to deliver insight and streamline decision-making processes by analyzing and finding patterns in big volumes of data (Metcalf et al. 2019). In many areas AI-powered systems are capable of exceeding human capacities in terms of speed and efficiency, which has the potential to enable companies to "*enhance decision making, reinvent business models and ecosystems, and remake the customer experience*" (Duan et al. 2019).

More and more organizations, start-ups and societies are developing and implementing AI technologies to increase accuracy, sensitivity, and specificity when processing information (Tschang and Mezquita 2020). These technological developments have a substantial impact on organizations because AI can automate tasks that previously required human capabilities (e.g., reasoning, risk assessment). At the same time, AI can augment other human abilities (e.g., decision making, integrating information). AI applications are, as a result, edging closer to human capabilities and may gradually replace human experts, which might lead to worldwide knowledge work shortages (Brynjolfsson et al. 2017; Raisch and Krakowski 2020).

Therefore, AI is affecting organizations by automating tasks that previously were performed by human experts, by augmenting professional expertise when supporting experts' decision-making processes for example in the medical field and by changing the expertise necessary to be able to work with these machines. A combination of the tacit knowledge of humans and the explicit knowledge of machines should be leveraged in order to amplify intelligence and make better strategic decisions (Metcalf et al. 2019).

Relational and social tasks will become more important as AI disseminates our working lives and it is predicted that we are emerging into a "*feeling economy*" where total employment and wages to feeling tasks exceed those of thinking and mechanical tasks (Huang et al. 2019). Despite the rapid development of intelligent technology, AI systems possessing cognitive, social, and emotional intelligence does not exist yet (Kaplan and Haenlein 2019). Machines are superior to humans when it comes to processing and analyzing data but will have a hard time with making a joke (Daugherty et al. 2019). As AI-enabled tools can take over mechanical and analytical tasks to speed up tedious and repetitive work, companies can create more value by enabling employees to focus more on creative, high-level tasks (Hovland, Ingrid 2020).

Human Resource Management (HRM) recognized the potential value of AI in supporting HR managers for collecting information about the candidates and for evaluation (Woods et al. 2020). If HR is to take on a something more than just an operational role, the technological infrastructure must be up to date and be able to support efficient processes (Sivathanu and Pillai 2018). As a key domain of talent management and human resources, recruitment and selection practices are no exception to technological transformations (Derous and De Fruyt 2016), and in the next years only the companies that will be able to quickly sense and adapt to new opportunities will be able to "*seize the advantage in the AI-enabled landscape*" (Brynjolfsson E. and McAfee A. 2017). According to the literature, several application scenarios of AI-adaption for R&S activities can be considered, as depicted in Table 1.

Table 1 - Overview of AI technology application scenarios R&S

Tools	**Activity**
Resume screening	Analyse and filter résumés based on relevant skills, experiences, and competences.
Chatbots	Score candidate answers and help recruiters decide which candidates should be considered further in a process.
Video Interview Analysis	Scan and analyze video interviews to evaluate candidates' answers or expressions.
Games	Assessing candidates based on gamified tasks that measure cognitive and emotional attributes such as risk aversion and cooperation abilities.
Turnover prediction	Identify employees that are in the "danger zone" for quitting and point out the controlling factors that lead to a higher turnover rate.
Outreach methods	Optimizing methods for identifying and reaching out to specific types of candidates.
AI assistant for writing job advertisements	Design and review job descriptions e.g., to achieve more inclusive language.

Modified from source – (Hovland, Ingrid 2020)

The importance of human capital, digitization and the need for efficiency has changed AI-enabled recruitment from being *"nice-to-have"* to "*necessary-to-employ*" (Black and van Esch 2020). Despite these predictions, the application of AI in recruitment and selection is also stated to be "hugely underdeveloped" compared to its potential (Albert 2019). Tambe and colleagues (2019) claimed that "*the most complicated and challenging HR task to address with data* *science techniques is likely to be hiring*". Scholars further outlined four of the main challenging aspects of applying AI to HR decision making such as complexity of HR phenomena, constraints imposed by small data sets, accountability questions associated with fairness, ethical and legal constraints, possible adverse employee reactions to management decisions via data-based algorithms. Harris (2018) stated that the context of every job search is unique and changes over time along with the types of candidates available as well as recent hires and resignations, which poses as a challenging task for both humans and machines. This is supported by Tambe and colleagues (2019), who calimed that it is also difficult to define and measure the metrics of what makes a good employee. An experiment conducted by Harris (2018) found that a group of HR experts were not consistent when presented with the task of evaluating candidate features, suggesting that it would be very challenging to get an algorithm to replicate human expertise in that context. The complexity of activities in HR also raised issues about data management and control. For example, employers often use several different systems from different vendors, which again are based on different technology architectures, making them incompatible (Tambe et al. 2019).

When it comes to recruitment, van Esch and Black (2019) suggested that companies should take an experimental approach and should try implementing different tools to see which ones are working for them and adjust accordingly. In such cases, it will be crucial to hire and retain knowledgeable employees with reference to technology implementation and integration when companies apply AI into their operations (Cohen 2019; Daugherty et al. 2019). According to Cohen (2019) this will lead companies to experience an AI skills shortage in the future as it will be hard to keep up with the currently rapid evolvements in the field.

AI in HRM as enabler for innovation

Innovation has been investigated by recent studies (Kahn 2018; Merrian Webster 2017), who defined this concept in two. First, service innovation was defined as the introduction of "new services" where scholars distinguished between services that are new to the firm, new to the market and new to the world (Witell et al. 2016). For example, Lehrer and colleagues (2018) defined service innovation as a type of innovation that creates value propositions from firms' resources that improves also the value for customers. This might take place by adding new services or changing existing ones (Ye et al. 2018).

Second, (Fichman et al. 2014) defined business model innovation as "*a significantly new way of creating and capturing business value*". Consequently, this type of innovation results in changes to an industry, enterprise, or revenue model (Kahn 2018). According to (Fichman et al. 2014), creation of novel business models is a typical scenario for digital innovations. Third, process innovation pertains to changes in existing processes in a business or the introduction of new ones (Mikalef and Krogstie 2018).

More recent studies captured numerous fields, activities, and concepts that innovation may entail by defining innovation as "*a concept that describes both the process and the outcomes of attempts to develop and introduce new ways of doing things*" (Mamonov and Peterson 2020). Other researchers narrowed this definition by focusing on innovation enabled by digital tools, and I embraced the definition provided by Fichman and colleagues (2014) who described digital innovation as a "*product, process or business model that is perceived as new, requires significant changes on the part of adopters, and is embodied in or enabled by IT*". Additionally, Barret and colleagues (2015) suggested that IT can also be an enabler of service innovation. Therefore, there are several categories of innovation distinguishable by their possible outcomes including process innovation, service innovation, business model innovation and product innovation (Kahn 2018).

Furthermore, scholars distinguished between radical and incremental innovation (Mikalef and Krogstie 2018). Radical innovations are innovations that disrupt the industry and incremental innovation provides additions or changes to existing products or services (Mamonov and Peterson 2020). According to Kahn (2018) successful organizations recognize the value of all types of innovations and should view them as falling "*along a continuum, ranging from minor incremental changes to major radical innovations*".

Affordances and Affordance-Actualization theory

To study the ways Artificial Intelligence (AI) innovated recruitment and selection processes, we used Affordance theory. This approach provides powerful analytical tools for investigating technical and social aspects without privileging one at the expenses of the other when studying the relationship between digital artifacts, employees, and goals in organizations. Volkoff and Strong (2013) said that an actor, with a specific goal in mind, perceives an object in its environment in terms of how it can be used and of action possibilities for reaching that goals. The theory of affordance became increasingly popular Information Systems (IS) because it allows a better understanding about how technology affords different ways of reciprocal actions to achieve goals (Benbunan-Fich 2019; Chatterjee et al. 2019; Jónasdóttir and Müller 2020; Lehrer et al. 2018; Zeng et al. 2020).

Gibson (1986) was one of the first scholars to define affordances as a possibility of action offered by an object to an animal capable of executing those action in a specific context based on his studies about animals' visual perception of the surroundings. Later, this concept was applied in multiple disciplines such as psychology, sociology, computer science, human computer interaction and others due to its explanatory power for potential actions to perform with specific technologies (Anderson and Robey 2017; Chatterjee et al. 2019; Norman 2013). With the translation of the concepts elaborated by Gibson in the ecological psychology in non-native fields, several definitions and perspectives emerged. For example, Zammuto and colleagues (2007) argued that *"an affordance perspective recognizes how the materiality of an object favors, shapes, or invites, and at the same time constraints, a set of specific uses"* (p. 752). The authors identified five affordances for organizing wit ERP. This helped the authors to visualize the entire work processes and mass collaboration that emerged from the implementation of an ERP in an organization.

Other studies adopted a relational approach when they applied affordance theory (Leonardi 2011, 2013; 2019). The authors focused on the imbrication process between humans and material agencies. The aim was to explain how people reconfigured material and human agencies in their routines with the help of technology to achieve certain goals. Leonardi (2011, p. 154) sustained that "*depending on whether people perceive that a technology affords or constrains their goals, they make choices about how they will imbricate human and material agencies*". In line with this approach, Majchrzak and colleagues (2013) focused on the identification of patterns of the symbiotic relationships between the action to be taken in the context and the capability of the technology. The authors investigated the role of social media technology enactment in knowledge sharing processes without privileging specific components of a sociotechnical system at the expense of other components. They defined technology affordance as "*the mutuality of actor intentions and technology capabilities that provide the potential for a particular action*" (Majchrzak et al. 2013, p. 39).

These definitions have been slightly expanded to include complex artifacts and groups of actors engaged with organizational goals, as *"the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relation between an artifact and a goal-oriented actor or actors"* (Strong et al. 2014b, p. 69). Critical realist underpinnings of affordance theory have been discussed and scholars provided six principles for appropriately applying affordance lens in information Systems (IS) (Volkoff and Strong 2017). For example, scholars suggested to maintain a clear distinction between an affordance, which is a potential to achieve a goal and its actualization, which relates to the details of specific actions that an individual actor performed with the support of a digital artifact. Such distinction allowed many studies to separate potential action, goals, actors and consequences achieved (Dremel et al. 2020; Du et al. 2019). Principle five suggested to identify salient affordances and to explain how they interact based on first-order affordances. Lastly, scholars suggested to recognize social forces that affect affordance actualization, which have been influenced by the technology used such as social media (Chatterjee et al. 2019; Jónasdóttir and Müller 2020; Majchrzak et al. 2013).

A middle-range theory of effective use in the context of community-care Electronic Health Records (EHR) has been developed with the support of Grounded Theory (Burton-Jones and Volkoff 2017). Scholars explained how an affordance network supported the achievement of immediate concrete outcomes, which allowed to describe how larger outcomes were achieved in organizations and this contributed to broader organizational goals. Burton-Jones and Volkoff (2017) helped to understand how healthcare organizations could generate more value from EHR, how community clinicians use EHR and how managers defined and utilized community analytics. This contributed to broader organizational goals such as caring for the region, caring for each patient holistically, and meeting each patient's specific needs during one encounter.

Affordances stemmed from the properties of the environment, actor and from their relationship. They might change from context to context and from actor to actor. For example, a technology used by specific actors in a specific setting may achieve desired outcomes, instead the use of the same technology but in different settings may generate undesired outcomes or different actors but in the same context may experience unintended consequences. Affordances can be analyzed at individual and organizational level, which related to group level goals (Burton-Jones and Volkoff 2017; Volkoff and Strong 2013). In this study, we refer to organizational level action possibilities that are enabled from material properties of Artificial Intelligence (AI) technology, the socio-technical characteristics of the organizations included in this study and their recursive relationships (Strong et al. 2014b). AI technology enables actors to automate tasks such as collection of online behaviors and augments other tasks such rankings potential candidates, extracting patterns invisible to human eyes and augmenting decision making

(Mikalef and Gupta 2021). On this basis, we applied affordance theory on the task level such as recommending online job listings based on prior online behavior.

Du and colleagues (2019) used Affordance - Actualization theory to study the interactions of blockchain, the technology underlying bitcoin that is an emerging financial technology (FinTech) and a group of actors motivated by organizational goals such as secure loans from financial institutions, settle payment directly, automate transactions. Building on Strong and colleagues (Strong et al. 2014b, p. 53), scholars provided a new definition of affordance actualization as "*the goal-oriented actions taken by actors as they use a technology to achieve an outcome*" by removing terms like "concrete" and "immediate". This study embraced the updated definition as it better represents the use of AI technology in the context of Human Resources. Du and colleagues (2019) made a clear distinction between AI technology feature, uses, affordances, actualization and outcomes. They extended A-A theory with the experimentation phase, during which actors identified, developed new use cases but also tested their feasibility, thus created industrial best practices.

Dremel and colleagues (2020) identified four big data analytics (BDA) actualization mechanisms such as enhancing, constructing, coordinating and integrating. Scholars used affordance theoretic perspective to study the perceived value potential of BDA in an automotive manufacturing company. The actualization of four BDA affordances required the four mechanisms of orchestrated organizational actions. This discovery case study extended the current knowledge about development of BDA capability through two modes of organizational learning (i.e., incremental, and radical). Jónasdóttir and Müller (2020) theorized affordance actualization in digital innovation and identified four affordances (e.g., tool development, prototyping, user testing, and patching) and explained how they lead to innovation outcomes (e.g., new game functionality or new tools) and process innovation (ensuring stable and updated software). Four models discussed the technology as an enabler of product and process innovation.

RESEARCH METHODOLOGY

To respond to the research questions, I conducted semi-structured interviews in top-tier organizations that implemented Artificial Intelligence in HRM. Additionally, archival data was used to triangulate the information collected and ideas developed.

This study followed Grounded Theory (GT), an inductive research methodology (Urquhart et al. 2010). It is widely used in Information Systems (IS) because it encourages the researcher to "*engage with the data and participants in order to create theory*" (Walsh et al. 2015) .GT offers a suitable approach for exploring AI's role in recruitment and selection processes as an enabler for innovation. Additionally, this study is composed of six case studies represented by HR companies, which allowed me to investigate a phenomenon that is likely to be "*accurate, interesting and testable*" (Eisenhardt and Graebner 2007).

Birks and colleagues (2013) mentioned six characteristics necessary to conduct GT method studies in Information Systems (IS) that have been applied in this study. First, it allowed me to engage with theory development that is the most challenging and rewarding step. Second, I analyzed the data with a constant comparison between sources and analysis stages. Third and fourth, I proceeded with iterative coding until the theoretical sampling was not achieved. Fifth and sixth, I managed preconceptions and kept an unextractable link between data collection and data analysis. This was about avoiding the application of existing theories to drive the collection and analysis of data (Birks et al. 2013).

This section is structured as follows. First, I present the steps performed for collecting semi-structured interviews and archival data. Then, I present the research settings, referring to seven case studies of HR companies. I briefly present their background, the services they offer and their use of AI. Lastly, I conclude with the steps followed during the data analysis.

Data collection

Semi-structured interviews represent the primary data source for this study. suggested Conducting research with interviews is an efficient method of data collection and provides rich empirical data related to situations that are considered episodic and infrequent, thus unique as suggested by Eisenhardt and Graebner (2007). Due to the explorative nature of this study, I collected semi-structured interviews, which are flexible and interactive (Cachia and Millward 2011). Unlike unstructured interviews, the semi-structured one contains some structured elements as a fixed set of questions to keep the focus of the conversation within the topic of interest. Still, at the same time, it gives a level of freedom to capture new insights.

I collected data related to participants' thoughts, behaviors, beliefs, and feelings about the implementation of AI in HR companies. Before the interview collection, I outlined an interview protocol (Appendix). I provided a brief overview of the study's aim, how the interview would be conducted, and how the data would be analyzed and used. The questions were prepared in line with the research questions, but they were flexible and modifiable according to the interviewee's role as well as the specific case and context.

An important aspect of handling interview data refers to collect it with as few biases as possible and let the data talk. Eisenhardt and Graebner (2007) suggested two approaches to guide an unbiased data collection. First, the authors recommended using "*numerous and highly knowledgeable*" informants in order to get multiple perspectives about the same phenomenon. Second, they invited scholars to combine case studies that tell the occurrence of actions in real-time and cases that are retrospective in relation to the process of interest. For conducting an ethical research study, I followed these suggestions when deciding the companies to include and the employees to interview. Additionally, at the end of some interviews, I asked for suggestions about other potential employees to interview. With a snowball approach, I had the opportunity to get in contact with other employees and companies.

When deciding which companies to contact, I searched for various HR companies in Scandinavian countries that implemented AI technologies such as machine learning models, robots, collaborative filtering models, and others. I contacted fourteen HR companies to ask their availability to participate in this study, and seven companies were interested in sharing their experiences. A research journal tracked the activities followed during the data collection. Then, I asked to interview employees with different roles ranging from assistants of HR managers to CIOs. The respondents were HR practitioners, recruiters, and managers with first-hand experiences implementing or developing AI-tools for recruitment or selection processes. Some of the interviewees had past experiences with implementing advanced technological tools. I collected eleven interviews from seven HR companies from September till November 2020 (Table 2). A total number of 67 pages and 41929 words have been transcribed.

Table 2 – Interviews collection by role of employee, length, and period

Company	Role of interviewee	Total time	Period
A	Employee Branding and HR	1 h	September 2020
B	Product Manager	1 h 20 min	October 2020
B	Developer	30 min	October 2020
B	Product Manager	30 min	November 2020
C	Product Manager	30 min	October 2020
C	Recruiter	1 h	October 2020
D	CDO	45 min	October 2020
E	CEO	30 min	November 2020

E	Innovation Project Manager	1 h	October 2020
F	CIO	1 h	November 2020
G	CIO	30 min	November 2020

Interviews were recorded with the prior consent of the participants. As mentioned by (Mouratidou and Crowder 2018), audio recording has been successfully used in several GT studies and is especially encouraged in cases where a translation of the data is necessary. For this research project, recording the data was helpful in order to revisit the material and transcribe the interviews. The recordings also helped me to translate the interviews from Norwegian and Swedish to English. Indeed, all interviews were conducted in either Norwegian or Swedish and translated during the transcription. NVivo helped me to transcribe and translate the data. I found it necessary to complete the interviews in the participants' first languages in order to keep a certain level of detail and natural flow of the conversation.

Research setting

This study is composed of seven companies operating in Human Resources in Scandinavian countries (Table 3 – List of companies offering HR services included in this study).

Company A

Background and services

Company A is part of a leading Nordic corporate group providing financial services for retail customers and businesses. The group is present in several countries worldwide with thousands of employees. Company A is a division with approximately 500 workers providing services mainly in banking, asset management services and finance. Company A's HR department consists of a small team working mainly on an ad hoc basis to provide services from managerial coaching to employee branding and recruitment.

Use of AI

Due to the vast amounts of applications received for summer internship programs and the difficulty of differentiating similar profiles of young candidates during the selection process, Company A decided to use Artificial Intelligent technologies to support its staff. Through their collaboration with another recruitment company (Company C), company A used an interview

Table 3 – List of companies offering HR services included in this study

	Company A	**Company B**	**Company C**	**Company D & E**	**Company F**	**Company G**
Country	Sweden	Norway	Sweden	Norway	Sweden	Norway
Industry sector	Finance/banking	E-commerce	Recruitment and staffing	Recruitment and staffing	Staffing	Technology
Number of employees (estimated)	400	400	250	300 + 120	638	35
AI vision for HR activities	Deliver innovative solutions, attracting competent people and securing equality and diversity among employees	Provide recruiters with the best tools to reach the most competent candidates by continually developing and improving existing solutions	Provide customers with bias-free recruitment, selection and staffing in order to contribute to a diverse, sustainable, and innovative labor market	Creating value and meeting future needs by leveraging new technology and focusing on human development	Provide customers with qualified staff in the healthcare, social and educational sector at the best price	Empowering human potential by combining Scandinavian know-how with cutting-edge technology that considers the human factor in staffing (healthcare)
AI technologies	Interview robot	AI-powered job listing recommendations	Interview robot	AI staffing platform	AI staffing assistant	AI staffing assistant

robot to help recruiters and hiring managers during the evaluation of job candidates. Their goal was to select the top performing candidates from a large pool of applications while keeping the process as unbiased as possible, as explained by an HR advisor,

> *"We always think about how we can screen many applications in the best way because it is a challenge that everyone has, I think. How can we do it in a professional and rightful way? (...) Personally, I think it is extremely difficult when young candidates do not have any work experience due to their age to include in their CVs. After concluding the studies, they are very similar, which is totally normal and understandable, but it is more difficult to find out who to interview, and in those cases I think that the risks of biases are even greater than when we recruit and select candidates for the position of senior sales manager."*

The company also used a digital test supplier for evaluating job applicants through automated psychological personality tests and logical tests, which measured candidates' abilities based on a list of requirement specifications. These tests had usually been performed as the last step of selection activities. After the robot was implemented, the tests were moved to the beginning of the process and used to narrow the candidate pool from 400 to 40. The recruiters were then able to go on to the next round and use the AI-device for interviews. The combination of automated tests with an interview robot enabled the company to make the selection process more efficient as explained by the HR advisor,

> *"(...) the fact that we turned the process around made it more efficient. We did not have to go through 400 CVs in the beginning for example, which takes a lot of time. We solved this by doing tests and not only by using the robot."*

The robot conducted the interviews, recorded, transcribed candidates' responses and assessed their responses based on the Big 5 model. At the end of the process, the robot interview scoring, and the automated tests were combined to create a recommendation list with the most suitable candidates for the opening position. The changes made in the selection process allowed the company to increase its efficiency. However, this was not the main reason to include the robot in company A. Indeed, its primary goal was to achieve a process that was as unbiased as possible and to encourage discussions about this aspect both internally and externally, as stated by the HR advisor,

> *"As a traditional banking firm, we have and have had more males than females, so that is why it is an important question for us, to try to find more women for the finance business and for our company."*

With this innovation in the selection process, the company experienced an increased diversity in the newly hired personnel concerning ethnicity and gender. The participants also reported that they found the process more appropriate and fairer. The HR advisor said that due to these positive results, the threshold for experimenting with new technologies in Company A in the future has been drastically lowered.

Organizational goals	Advanced technology / AI features	Innovation
• To provide applicants with an unbiased selection process • To narrow down large candidate pools automatically	• Interview robot using NLP (Natural language processing) • Automated ability and psychological tests	• Anonymous competence-based candidate interviews • Automatic and anonymous candidates' evaluation based on their abilities and personality

Company B

Background and services

Company B is a Scandinavian company operating in the field of e-commerce. It offers an online marketplace for products and services, which attracts billions of visits each year. One of its core services is job listings, where companies can place advertisements for available positions. The site allows all users to search through job listings, which are also promoted and distributed via external channels.

Use of AI

Machine learning (ML) algorithms played a central role in Company B's distribution of all types of advertisings, including job listings. Two organizational goals encouraged the company to use machine learning algorithms. First, the company aims to increase the number of potential candidates that click on and apply for vacant positions. Second, it is trying to reach relevant job candidates among hard-to-hire segments or passive candidates. The company collects data about user behavior such as city preferences, job typology, length of employment contracts, and other related information. A collaborative filtering model creates clusters of ads based on users' online behavior, the model extracts patterns from the clusters of ads and make recommendations to users with similar preferences. Additionally, the company tries to personalize ad-content and the recommendations both on their own landing page and on other channels such as online newspapers and social media because this leads to higher rates of applications to opening positions and increase the revenues of Company B, as mentioned by a product manager,

> *"We have measured this. Totally, as much as 17% of all clicks into ads on our site comes from recommendations. That is very valuable. We want to be able to present you* (candidate) *with your dream job without you having to look for it."*

Innovation plays a vital role in Company B's vision, and they try to integrate it into multiple parts of their business. Employees are encouraged to experiment with emerging technologies and innovative trends. Indeed, several machine learning techniques are continually tested and implemented, and developers are always looking for new ways to optimize the company's current models.

The job listing segment represents a small part of company B's online services, but it brings substantial revenues. Specifically, the company provides empowered online job advertisements by increasing its visibility online and by sending it to more potential candidates with recommendations. These types of online services are more expensive than the standard ones. Company B noticed that the biggest user group of their job listing site were job candidates actively looking for new job opportunities. However, approximately half of the job listings on their site targeted job applicants with relevant working experience within certain fields, which often include workers who already have secure jobs. Thus, one of the firm's top strategic priorities in their job segment became centered around reaching passive work candidates, namely experienced workers who are already content with their current jobs, and not actively looking for other opportunities. User behavioral data are increasingly utilized for making personalized recommendations, and it will likely be even more critical in the future as pointed by another Product Manager,

> *"It is something we want to explore in the future. Which data we can collect in order to make more personal experiences and recommendations is definitely an important part of it. (...) active job seekers will find our site and look through almost all of the ads because they are so motivated, but these hard-to-hire passive candidates do not have the same motivation for looking at job listings, so it is more up to us to be able to get the ads out, showing them to the candidates."*

Organizational goals	Advanced technology/AI features	Innovation
• To increase the number of potential candidates that click on and apply for vacant positions • To reach relevant job candidates among hard-to-hire segments	• AI recommendation engine based on Collaborative Filtering Models • Neural network models for NLP	• Personalized recommendations for job seekers • Broader and more targeted reach of job ads for employers

Company C

Background and services

Company C is a recruitment and staffing agency in the Nordics with a special focus on competence-based evaluations and an unbiased recruitment process. The company offers services such as consulting, recruiting, and staffing for several fields of profession in private and public sectors.

Use of AI/advanced technology

An important part of Company C's strategy is to use digital tools for enabling efficient, scalable, and transparent processes. To achieve this, the company is constantly investing in new technologies. In fact, it has digitized a big part of the recruitment and selection processes with tools such as digital reference, background checks, digital applicant feedback systems, and automated evaluation tests. Personalized "test packages" are created to fit each specific recruitment need and job description as stated by a recruiter,

> *"We have personality tests, then we have logical tests, ability tests: verbal ability, numerical ability. For the personality test we have special tests for middle management and managers and then we have more general for customer support and sales and so on. There also exist some tools that can measure digital maturity and leadership qualities in a different way. We are going to start using them in about a month."*

Recently, the company's innovation lab launched its own AI-powered recruitment device, an interactive robot that can perform structured interviews, conduct personality tests and evaluate candidates. In a structured interview, the robot acts as an interviewer by asking competence-related questions (e.g., "how do you act in stressful situations?") and registers the applicant's answers. In these interviews, the robot listens to the candidate and acknowledges the answers through physical responses such as tilting its head and non-verbal responses such as saying "uh-huh" to indicate that the interviewee's responses are registered. For the personality test, the robot asks a set of pre-determined questions and provides a score about candidates' responses based on criteria from the big 5 model, a psychological trait theory.

Typically, the robot is used in the early phases of the selection, before an in-depth interview with HR managers. The idea is not to replace the recruiters' job, but to support their work by filtering candidate profiles from the beginning of the selection process by automating interview tasks. This innovation proved to be more efficient and reduced the pressure from candidates to make a perfect first impression. The assessment is based on personality traits and competence descriptions, and the robot only analyzes the language of the respondents without considering personal factors such as physical appearance, age, or gender. According to Company C's research, candidates interviewed by the robot experienced a high degree of trust, and 3 out of 4 candidates reported that they answered the questions more honestly compared to interviews with HR manager. Another important incentive to use the robot refers to the ability to legitimize the decisions for hiring specific candidates and providing evidence-based justifications, which is especially important in the public sector.

Having an innovative approach to recruitment has shown to be a strategically advantageous choice considering the recent economic and societal disruptions caused by the COVID-19 pandemic as stated by the product manager,

> *"(...) there is a constant development, now with corona it has slowed down, we are in a business where, the recruitment industry itself has many challenges these days, not many companies are growing, not many companies are recruiting. At the same time, we have one customer that started to use our robot because of corona, since it's able to ensure social distance."*

In conclusion, Company C combines its own digital solutions with external systems and tests in order to keep the selection process as streamlined and unbiased as possible. This allows recruiters to free up time from mundane tasks and dedicate it to build relationships with candidates and customers instead of administrative and repetitive activities.

Organizational goals	**Advanced technology/AI features**	**Innovation**
• To provide customers and candidates with efficient and unbiased recruitment processes	• Interview robot using NLP	• Anonymous competence-based candidate interviews

• To streamline internal HR processes • To legitimize hiring decisions based on data-driven documentation	(Natural language processing) • Automated ability and psychological tests	• Automatic and anonymous evaluation of candidates' abilities and personality

Company D & E

Background and services

Company D is a corporate group within the field of recruitment and staffing as well as organizational and managerial development. Company E is one of company D's many daughter companies and one of the Nordics. Because the two companies are so closely related in their field of work and innovative missions, I decided to merge them into one case. biggest recruitments and staffing agencies. Because the two companies are so closely related in their field of work and innovative missions, I decided to merge them into one case.

Use of AI/Advanced technology

One of Company D & E's main visions is to be the most leading innovative and sustainable company in human resources. Indeed, they use several digital systems for managing internal processes. By digitizing internal processes, company E was willing to free up time that they can spend to obtain new customers and further develop existing customer relationships. Earlier, all recruitment and selection activities were consolidated into one system, which created several challenges in the last year (2020). The old system did not allow Company E to make changes to internal procedures which made it difficult to integrate with other systems. In response to these challenges, and in line with company's innovative spirit, it adopted a new core system. It immediately experienced more value thanks to the possibility of systematizing internal processes and of integrating them with new solutions when available, as declared by the CEO of company E,

> *"we needed a core system (...) with open API's, making us able to connect to third-party systems because things happen so fast, maybe tomorrow there's something else that is better and that we need to use in order to stay competitive, so that we're not locked to one way of working. We need that flexibility."*

Like company C, Company E also used different test packages for automating psychological and ability tests for each job, which were often used in early phases of the selection process to filter candidate profiles. Company D's newly procured digital tool is a platform for handling job ads, screening, and communicating with job applicants. An AI-engine has also been implemented to recommend candidates for opening positions by matching the two parties. Additionally, this system has a feature that allows candidates to conduct automatic video interviews. Company E uses job tools according to specific job requirements, as stated by the innovation project manager in company E,

> *"We are looking at which candidate groups it would fit best with, we won't get a CEO in the age of 50 or 60 to register a video interview, so it's about targeting the candidate. There are a lot of nuances with the different processes, we don't want to lock down the processes to much, it should always be tailored to what we are working with and what we need, but we wish to make the functionalities available for everyone, so that they can choose to create their own processes."*

Bias-free recruitment is also a key priority for both companies D and E. In fact, they pay attention to how the new technology is understood and used in order to get the expected benefits. New technologies help streamline processes such as screening, sorting, and communicating with candidates, but for both companies it is important to keep "*humans in the loop*" to assure the quality of the processes.

Organizational goals	**Advanced technology/AI features**	**Innovation**
• To provide customers and candidates with efficient and unbiased recruitment processes • To streamline internal processes	• AI engine for matching candidates' profiles with job descriptions • Asynchronous video interviews • Automated ability tests and psychological tests	• Recommendation of candidate profiles based on matching candidates' descriptions with job requirements' description • Automatically narrowing candidate pool based on test scores • Evaluating candidates based on video interviews

Company F & G

Company F provides staffing and recruitment services for the healthcare sector. The main goal is to provide doctors, nurses, and other healthcare- and social workers with flexible working hours and locations while at the same time offering healthcare employers all over Scandinavia with competent and available workers. Company G is a Norwegian tech start-up called Globus AI that provides a virtual staffing assistant to help staffing bureaus with the deployment processes (placing people for available jobs) using Artificial Intelligence technology. Its focus is on healthcare staffing in both private and public sectors.

Use of AI/Advanced technology

Company F receives increasing demands for healthcare workers, who are considered as a scares resource. Indeed, hundreds of requests from hospitals and institutions are registered every day, and Company F had to find a way to match available and competent health workers with available jobs in an effective way, as stated by the CIO,

> *"The volumes are enormous, and each of the requests are specific and concrete, so we needed to get an agile and fast way of understanding the need, instead of reading through long e-mails with attachments and everything, because our customers are not very digitized. So, there was a need for understanding the request fast and to quickly communicate the right recipients for the different job requests."*

Recently, companies F and G initiated a collaboration for developing company G's staffing assistant. The tool kept track of open jobs and handled incoming job requests from customers. It automatically parsed unstructured data from customer orders (hospitals' requests for health workers) by using NLP algorithms to interpret the role, shift, and other relevant details. Furthermore, the system matched the job requests with information about available workers, as described by the CEO of company G,

> *"So, you rank them after how well they fit the job description based on competence, availability, location, all factors that are relevant for the specific customer. Then we either send the candidates that fit, or the staffing-coordinator can go in and choose who to send out. The system performs better when we have humans in the loop because they are out talking to the candidate and the customer, so they have a lot of information that is not registered anywhere in the system. If you suddenly get a very specific job then they can say "oh, I know who will be a good fit for this job" and then they can register that in the system."*

After the automatic matching, an HR coordinator chose the most suited candidate and the AI system continually learned how to rank the candidates better. Available workers received working requests on their phones and could register which options they will accept. Initially, all the mentioned tasks have been carried out by teams with up to 10 people using excel sheets, e-mails, and different candidate systems for coordinating and communicating their decisions. It was measured that the coordinators spent 6 hours on average each day to perform these manual processes. Thus, streamlining the registration, matching, and coordinating activities with AI systems allowed staffing coordinators to save time, which was used for other more critical tasks such as acquiring new customers, as expressed by the CEO of Company G,

> *"They want to do what they're good at, talking to candidates and customers, acquire new customers, all those things. I once talked to a woman who said 'ah, I feel like a robot! I only sit and punch in all of these requirements."*

Company F and G work closely to develop AI driven-services. The goal is to automate the process as much as possible and to make it easier for the job applicants and coordinators.

Organizational goals	**Advanced technology/AI features**	**Innovation**
• To provide HR employees with a flexible working environment • To match candidates with open positions efficiently	• AI assistant that registers and parses customer orders and matches them with candidate profiles	• Automatically registering and parsing structured and unstructured data • Recommendation of candidate profiles based on matching towards job requirement descriptions • Self-service registration for workers

Data analysis

In order to better understand how Artificial Intelligence enables innovation in recruitment and selection processes, semi-structured interviews and archival data have been collected and analyzed. Since focusing only on the agency of either the technology or human experts by themselves might limit our understanding too much (Leonardi 2011), this study focused on the interplay between social aspects and technical artifacts. Affordance theory guided the analysis of the interviews and archival data thanks to its strong analytical power (Dremel et al. 2020; Urquhart and Fernández 2016).

After concluding each interview, the audio was transcribed and translated in order to prepare it for analysis. The software Nvivo has been used for managing, transcribing, and coding the interviews. In order to securely record and store the sound-files, the web-based tool Nettskjema and the app Diktafon were used, which are developed by the University of Oslo for secure controlling of online data. Data analysis was performed by conducting the following activities: coding, memoing, sorting, and writing (Mouratidou and Crowder 2018). Memos were written in order to capture thoughts and ideas about the categories and concepts that emerged from the data. This activity is fundamental to GT as it helps to shape the development of theory (Mouratidou and Crowder 2018). Initial notes were made in a regular text editor program, then discussed with my co-supervisor. Sorting the memos was necessary in order to refine the emerging ideas and theories gradually. We went through three rounds of data analysis a method commonly used by prior studies (Burton-Jones and Volkoff 2017).

In the first round, we read the interviews to code the relevant information about AI, such as input, process, and output guided by the I-P-O framework (Espinosa et al. 2006). Additionally, we extracted other relevant information such as definitions provided by key actors about AI, challenges, goals, future suggestions, and surprises experienced by HR employees. The process of coding consisted of reading through the transcribed text and labelling words, sentences and sections that felt relevant to addressing our research question. The first interview was coded by me and the co-supervisor to find a common understanding of the process. Then, five interviews have been coded independently and the two researchers met once per week to compare the codes. The last interviews have been coded and discussed together. Lastly, we reviewed the codes elaborated and grouped some codes with similar meaning.

In the second round, we focused on the processes the interviews described. To do so, we followed six principles suggested by Volkoff and Strong (2017). First, we extracted potential actions performed with the support of Artificial Intelligence technology, thus the affordances arose from the relation between the users and the artifact. Then, we made a clear distinction between affordances and their actualization process. Therefore, we focused on the potential actions and not on their outcomes captured with the IPO framework. The granularity level we selected refers to the actions performed by each HR employee following the order necessary to perform recruitment and selection processes. Finally, we grouped first-order affordances into second-order affordances, which are also called salient. For example, the use of an androgynous robot for *conducting interviews with candidates* was composed of first-order affordances such as robot for *introducing* itself and informing the candidate about the time to prepare for the interview, *asking* questions about personality, competence, and work-experience to candidates, and *recording* and *transcribing* candidates' responses during interviews. We identified four salient affordances for recruitment and four salient affordances for selection processes (Tables 4 and 5).

In the third round, similar codes have been aggregated to create first-order and second-order themes with an iterative coding process. During this process, it was also necessary to look at previous interviews to examine and compare the associated codes and concepts with the new data. In this way, we could enrich existing concepts, form new relations between concepts or create new ones. The stages were not persistently conducted in a linear fashion, as they often overlapped each other and interplayed with the comparison of existing data, concepts, and theories.

FINDINGS

Based on the data analysis, in this section we present the results we extracted from semi-structured interviews and archival data. First, we discuss the affordance emerged in recruitment and selection processes while using Artificial Intelligence (AI). Then, we explain the actualization of the affordances we identified from our case studies. Finally, we present an AI-affordance-innovation framework to interpret the recruitment and selection processes.

Affordance-Actualization of Artificial Intelligence in recruitment and selection processes

In the recruitment process, we identified four second order affordances that can be performed only with AI technology. Then, we extracted first-order affordances that enabled HR employees to achieve organizational goals. Table 4 presents a summary of representative quotes.

Recruitment process

Matching appropriate candidates with specific job position has always been a challenging task, which required companies offering HR services to develop digital strategies. For broadening the pool of candidates, employers published job posts on HR specialized Websites, social media, and online professional networks. When employers filled out standardized digital forms to register job listings, they were asked to provide *relevant* information about the opening positions to better explain the competences and talents they were searching for. However, adjectives as competent and relevant are vague and leave a lot of freedom to interpret and realize them in online HR marketplaces but also, this increases the difficulty for structuring the communication between employers to potential candidates. In fact, one of the first activities in which the companies selected for this study were engaged was creating a common language between employers and candidates by structuring data in online job adds/posts and in online application templates.

Table 4 – Second-order and first-order affordances in recruitment process

Recruitment process		
Affordances		**Representative quotes**
2nd-order	**Fine-tuning algorithmic parameters for online job advertisements**	We collect models all the time and we have scraped a lot of different models that were not as good as those that we have today. We test them only on a certain percentage of users and those that provide better results are implemented in our company. The rest (of the models) are scraped or modified.
1st-order	AB-testing	We have started to make our own dashboards where we are able to make ab tests for different algorithms and tune different parameters so that we can see how it performs. We can lay out a different algorithms or new model in real time and then we just see how it works, if it's good enough we start using it.
	ranking candidates' profiles	In practice, the algorithm ranks all users from the most relevant to the least relevant and then you need to figure out where to set the limit (…)
	Setting a treshold value for online job advertisements	Where is the threshold value that is relevant enough, this decision will affect the size of the target group (…) we want to move closer to the goal of providing more applicants, not just people viewing and clicking on the ad.
2nd-order	**Collecting online behavioral information**	You construct a huge matrix and (...) we attach an id, a cookie, to each user as columns and then you have the codes for each job listing as rows (…) we try to find users that have a similar usage pattern as you (online user searching for job), and if these other users have clicked on an ad, then there is a big chance that you (online user searching for job) are also interested in that ad.
1st-order	collecting online behavioral metrics	(...) these machine learning models are very fond of new data, because that is what enables it to make recommendations (…) Until now we have been very focused on clicks, getting users to the landing page of the ad. It is a good proxy, but we will be working more on this. It is very probable that if we start to optimize for stronger signals (…) we want to show things (job listings) that you are more likely to apply for than those you think look cool.
	creating clusters of online job advertisements	The only information we need is your user ID and the job listing ID to fill out the matrix. It sounds kind of crazy, but we do not look at the content of the job listings. It's the users who create clusters of ads (…) We do not have to know and make all of these rules ourselves; it is the users who do that, indirectly based on what they click on, who decide these connections and correlations that we might not be aware of.

	ranking online users	
2nd-order	**Recommending online job listings**	Immediately when you open a listing, we will recommend listings that are similar, so if you click on the first ad (…) we then have a model that will get similar positions. That is the most important model that we have right now, because it targets the users in a good way and a lot of people will click on it (the job listing) and actually end up applying for the position.
1st-order	receiving suggestions for keywords selection	We will take the title of the listing and try to recommend which keywords you should register to the listing. That is also a machine learning model. When you have filled in a couple of keywords, we try to use both the title and the keywords to get other keywords, in order to make it (the recommendation) more targeted.
	creating connections and correlations	Then we have another (algorithm), for example if you have looked at three different positions, then you go out and get back in the day after.
	targeting job listings towards relevant users	
2nd order	**Facilitating online job application procedures**	You can register using LinkedIn or Vipps even, there is a CV parser engine from (a company specialized in AI software), which works really nice, you just input your CV and it makes a user based on that information.
1st-order	registering and parsing candidates' information	We try to not get this registration-mill that people resist towards when applying for a job, like "oh do I need to fill out all of this in order to apply for the job? I do not want to do that.
	matching online candidate profiles with online job listings	We are looking at making the process easier, and at the same time as we make it easier for the candidates it often comes along with better quality as well, because what they actually register is done better.

After the creation of a common language, HR companies performed multiple intermediate actions enabled by AI during recruitment and selection processes. From our data analysis, we identified four affordances per each process. In this section we describe the salient affordances or second-order affordances and their actualization.

Affordance 1 - Actualization: fine-tuning algorithmic parameters for online job advertisements

The goal of company B was not to attract as many applicants as possible, but to attract relevant candidates, who were not only interested in the specific job advertisement, but they were also likely to apply for that position. Companies were enabled with *fine-tuning algorithmic parameters for online job advertisements*. When a new model performed better than the existing ones, the company switched to the new action possibilities. A developer from company B explained how they tested AI models,

> *"We collect models all the time and we have scraped a lot of different models that were not as good as those that we have today. We test them only on a certain percentage of users and those that provide better results are implemented in our company. The rest (of the models) are scraped or modified."*

In order to actualize affordance 1, HR employees performed three first-order affordances. First, by using *AB-testing*, they could experiment different algorithms or new models in real time and check their performance, as a Product Manager mentioned,

> *"We have started to make our own dashboards where we are able to make ab tests for different algorithms and tune different parameters so that we can see how it performs. We can lay out a different algorithms or new model in real time and then we just see how it works, if it's good enough we start using it."*

Second, machine learning models enabled developers with the possibility of *ranking candidates' profiles from the most relevant to the least.* They provided a list of potential candidates that would be interested in a specific job advertisement. This was elicited from their own behavior and the behavior of similar users, who created clusters of ads as explained by a product manager of company B,

> *"In practice, the algorithm ranks all users from the most relevant to the least relevant and then you need to figure out where to set the limit (...)"*

Third, HR employees were enabled with *setting a threshold value* to limit the size of the ranked lists of users. By checking different parameters, the developers could identify the threshold that provided more value to the most relevant candidates, as the Product Manager of company B explained,

> *"Where is the threshold value that is relevant enough, this decision will affect the size of the target group (...) we want to move closer to the goal of providing more applicants, not just people viewing and clicking on the ad."*

A higher level of accuracy for recommendations of job listings led to increased number of generated clicks and a higher percentage of users applying directly for the positions. Through experimentations with different algorithms and incremental improvements to the parameters of existing machine learning models, developers could optimize the outreach towards job applicants and provide companies with increased, targeted exposure towards open positions.

Affordance 2 - Actualization: collecting online behavioral information

This second order affordance enabled HR employees with *collecting online behavioral information* when users were searching online job advertisements. Company B used several algorithms based on the information collected online. Collaborative filtering model was one of most used algorithms to make sense of the information collected from active users on company's B web page (Figure 4), as explained by product manager B,

> *"You construct a huge matrix and (...) we attach an id, a cookie, to each user as columns and then you have the codes for each job listing as rows (...) we try to find users that have a similar usage pattern as you* (online user searching for job)*, and if these other users have clicked on an ad, then there is a big chance that you* (online user searching for job) *are also interested in that ad."*

Consequently, the information collected about behavioral patterns of users could show how many clicks a job ad got and the percentage of users who applied for the position. For example, the project manager of company E expressed that a significant number of users initially interested in their ads were lost before applying,

> *"We saw (...) from statistics how many people have pressed on the "Apply here" button and how many of them actually got into our system. We noticed that we had an almost 30-40% loss of candidates."*

Developers at company B collected information about users' activity and behavior when visiting job listings. This helped the company to understand users' preferences for offering targeted job listings recommendations. Additionally, it provided companies with insights about the popularity and effectiveness of their job listings. Employees from company B specified that they only collected information from their websites, which was saved for up to one year. One of the product managers in company B pointed out that they did not collect any private or sensitive information, which is protected by GDPR,

> *"When it comes to what we gather internally, we store it for one year. Then it is deleted (...) You (the user) have the possibility to opt out of this (data gathering), and then we won't store anything, and we make sure to delete everything that is there or at least anonymize everything."*

Figure 4 – Collaborative filtering model: A movie recommendation illustrative example

Source: Google Developers (2020)

In order to see the number of visitors and their interest for specific positions, company B was enabled with *collecting online behavioral information* such as user clicks and time of stay on job listings as explained by the product manager in company B,

> *"(...) these machine learning models are very fond of new data, because that is what enables it to make recommendations (...) Until now we have been very focused on clicks, getting users to the landing page of the ad. It is a good proxy, but we will be working more on this. It is very probable that if we start to optimize for stronger signals (...) we want to show things* (job listings) *that you are more likely to apply for than those you think look cool."*

For actualizing affordance 2, HR employees from company B performed three first-order affordances. First, they had the possibility of *collecting online behavioral metrics* such as location, type of work and competences related to the job listings the users looked at online.

By connecting users' ID to behavioral online metrics, company B knew which users behaved similarly and thus were likely to be interested in job listings with similar content. Second, developers were enabled with *creating clusters of online job advertisements* by grouping users with similar online usage patterns.

> *"The only information we need is your user ID and the job listing ID to fill out the matrix. It sounds kind of crazy, but we do not look at the content of the job listings. It's the users who create clusters of ads (...) We do not have to know and make all of these rules ourselves; it is the users who do that, indirectly based on what they click on, who decide these connections and correlations that we might not be aware of."*

Finally, the developers were enabled with *ranking online users* from the most relevant to the least and group them, which helped to decide which users should receive recommendations about specific job listings. By analyzing online user behavior, companies could collect users' reactions to online job posts and could measure how many candidates were interested in specific job posts. This information was used to adjust the online job advertisements in order to attract more attention. Therefore, it was possible to manipulate factors like outreach methods, application processes, and job descriptions.

Affordance 3 - Actualization: recommending online job listings

This affordance enabled companies with *recommending online job listings* for candidates via platforms such as digital marketplaces, social media sites and digital newspapers. The recommendations were steered by machine learning algorithms that sought to target users with job listings that they were likely to be interested in, as developer in company B explained how the recommendations worked,

> *"Immediately when you open a listing, we will recommend listings that are similar, so if you click on the first ad (...) we then have a model that will get similar positions. That is the most important model that we have right now, because it targets the users in a good way and a lot of people will click on it (the job listing) and actually end up applying for the position."*

Job listings recommendations contributed also to increased revenues for company. Employers, who were searching for competent candidates, could pay a fee for getting a more targeted and broader reach when they posted job listings online. Based on this necessity, the developers of the Websites, where the job ads were published, started to use a machine learning models for suggesting potential candidates for specific job ads. Therefore, they created new services online for both employers and employees that were more expensive than the standard ones.

To achieve this, three first-order affordances were performed. First, HR employees were enabled with *receiving suggestions for keywords selection* to tag the job listing with. This was used to improve recommendation algorithms, as explained by a developer from company B,

> *"We will take the title of the listing and try to recommend which keywords you should register to the listing. That is also a machine learning model. When you have filled in a couple of keywords, we try to use both the title and the keywords to get other keywords, in order to make it* (the recommendation) *more targeted."*

Second, the machine learning models enabled the developers with *creating connections and correlations* based on users' online behavior and keywords selection.

> *"Then we have another* (algorithm), *for example if you have looked at three different positions, then you go out and get back in the day after."*

Finally, by leveraging users' online behavioral data and the information extracted from the job listings, companies were enabled with *targeting online job listings* towards relevant users on their Website as well as through other online channels with which the company collaborated.

> *"Many customers pay extra to get a broader reach (...) we use machine learning to give them the opportunity to distribute this into different platforms, but in order to make sure that not everyone who reads a specific online paper gets the recommendation we have few exposures, which are hopefully of high value, so it gives more clicks on the job listing and hopefully more people applying for the position."*

Company B used the recommendations to give employers a broad and targeted outreach towards possible job candidates while at the same time providing candidates with content tailored to the specifics of their user profiles. Recommendations of job listings through other platforms than the job listing Website itself may also enable the more passive candidates to discover jobs that they might find interesting.

Affordance 4 - Actualization: facilitating online job application procedures

This affordance was characterized by automating certain parts of the job application process, making it easier for users to create a candidate profile and registering necessary information in the staffing system. Company E allowed job candidates to register profiles automatically via other platforms and a CV parser, as explained by a project manager in company E,

> *"You can register using LinkedIn or Vipps even, there is a CV parser engine from (a company specialized in AI software), which works really nice, you just input your CV and it makes a user based on that information."*

To actualize affordance 4, HR employees performed two first-order affordances. First, they used a CV parser for *registering and parsing candidates' information* automatically into the company's Applicant Tracking System (ATS). As long as candidates followed a regular structure for their CVs, the parsing engine could register all necessary information without any extra effort from the candidates. This would contribute to diminish the frustration in candidates when they apply to many positions, as explained by a project manager in company E,

> *"We try to not get this registration-mill that people resist towards when applying for a job, like "oh do I need to fill out all of this in order to apply for the job? I do not want to do that."*

Second, company E, G and F were all enabled with *matching online candidate profiles with online job listings.* Through the use of AI-powered matching tools, candidate profiles were matched towards job descriptions and candidates could either be ranked from most to least relevant or displayed with an individual score based on how well their profile matched the job description. Consequently, the recruiters were able to quickly identify available and competent candidates for job openings.

> *"We are looking at making the process easier, and at the same time as we make it easier for the candidates it often comes along with better quality as well, because what they actually register is done better."*

Instead of asking for a complete application from all candidates from the first step, HR companies decided to just ask for the minimal amount of information needed in the initial stages and potential candidates would upload more information later on. This allowed time savings for candidates who did not need to fill out complete applications, which was time consuming and possibly intimidating, and for recruiters who did not have to review complete CVs but only look at specific information they required for the initial steps. This streamlined internal procedures. The information registration was quick and straightforward for the job candidates and ensured that staffing coordinators had necessary and updated information about candidates when matching them with jobs. Additionally, it could encourage more people to register for jobs, for example those who have holes in their CVs or less experience.

Selection process

In the selection process, we identified four affordances that can be performed only with AI technology and the relative first-order affordances that allowed the actualization process. Table 5 provides a summary of representative quotes.

Affordance 1 - Actualization: optimizing online recommendations for temporary job positions

This affordance facilitated work activities performed by HR coordinators when reviewing job descriptions and profiles of available candidates while trying to find an appropriate match based on their availability, location preference, experience, and competence. An AI supported staffing tool was used for parsing job requests and for matching them with candidate profiles in their database. This allowed staffing coordinators to view a ranked list of the most relevant candidates for each specific job position, as explained by the CIO of company F,

> *"We immediately get to see a pre-interpreted order, and we get a matching of the candidates including a weighting on how well they fit the position that is requested. And then the application learns better and better based on the choices that we make."*

In order to actualize the affordance of *optimizing recommendations for temporary jobs*, HR employees performed four first-order affordances that were strictly interconnected. This means that, if one of the first-order affordances were not actualized appropriately, it was not possible to proceed with the next actions. First, staffing coordinators used NLP algorithms for *parsing job requests* from the different employers, which was sent to the staffing bureau through e-mails, Word documents, Excel-sheets, or other formats. Coordinators received many requests for temporary jobs, especially in the healthcare sector, with long descriptions about job requirements, as a CIO explained,

> *"For us, (*the motivation for using the AI-assistant) *is to simplify a very time-consuming process, and especially from the big volume customers (...) the volumes are enormous, and each of the requests are specific and concrete, so we needed to get an agile and fast way of understanding the need, instead of sitting and reading through a long mail for example, with attachments and everything, since our customers are not very digitized.*

Parsing job requests was time consuming and involved many HR employees for processing the increasing amount of job requests. Instead, with the support of NLP algorithms the coordinators could automate and streamline this task. It especially added value to the interpretation of text from different digital formats, which many times did not follow any structure and challenged staffing coordinators' work even more.

Table 5 – Second-order and first-order affordances in selection process

Selection process		
Affordances		**Representative quotes**
2nd order	**Optimizing online recommendations for temporary job positions**	We immediately get to see a pre-interpreted order, and we get a matching of the candidates including a weighting on how well they fit the position that is requested. And then the application learns better and better based on the choices that we make.
1st-order	parsing job requests	For us, [the motivation for using the AI-assistant] is to simplify a very time-consuming process, and especially from the big volume customers (…) the volumes are enormous, and each of the requests are specific and concrete, so we needed to get an agile and fast way of understanding the need, instead of sitting and reading through a long mail for example, with attachments and everything, since our customers are not very digitized.
	reviewing the pool of available candidates	We do not do any other type of segmentation apart from certifications that need to be registered, (...) and then it is more about where do you (the candidate) want to work, when do you want to work and stuff like that (…) their name, address, phone and all of the personal information that needs to be registered (…) then it is of course their competence, what if you (the candidate) have a specialization for example, driver's license is an important element because if you are working as a nurse in a municipality for example, it is important that you can move around. We do some language evaluations (…) and then we map which systems they are used to work with, there are different journal systems for example.
	matching candidates' job profiles with open positions	
	ranking potential candidates with a decreasing order for each open position	They are ranked after how well they fit the job description based on (…) all factors that are relevant for the specific customer. Then we send, either we send the candidates that fit, or the staffing-coordinator can go in and choose who to send out. (…). When you introduce AI you must make them (staffing coordinators) trust the recommendations that the AI engine makes, not only continue to work the way that they did before. If they for example always choose Jon because they know him better, then the system won't have any effect.
2nd	**Androgynous robot for conducting interviews with candidates**	It (the robot) did not ask you any different follow-up questions than the other candidates, and I did not nod approvingly when you were on the right path and so on, so to be freed of that type of bias was the major point for us.

		Many thought that they became more honest when they talked to the robot than if they had been talking to a person. I think that they liked the concept, that they thought it was a righteous and fair process, it was my competence that was focused on, not that I have played golf or that I have gone to this and this school, so we got a lot of positive feedback on that.
1st-order	introducing itself and informing the candidate about the time to prepare for the interview	It (the robot) said for example "Hey (name of the candidate), come in and sit down, hope that you got here well" etc. So, it tried to imitate a normal interview situation (…) but one thing that I also thought was a good idea is that the device introduced itself and said that the candidate had 15 minutes in order to prepare for the interview, and then it said that it was going to pose questions from certain topics.
	asking questions about personality, competence, and work-experience of candidates	(...) we have looked at work performance, two parts in the Big 5 Model that correlates the most with someone who performs (at work) (…) So, the robot, with its personality indicator, asks questions, similar to the ones in the automatic online tests, which make it difficult to cheat (…) then we have the structured interviews, where the robot asks you to describe your competence; how you would act in a stressful situation and so on. A combination of the candidate answering the personality test and then describing their competence makes a really good foundation, because it is a personality part and a descriptive part.
	recording and transcribing candidates' responses	Many thought that they became more honest when they talked to the robot than if they had been talking to a person. I think that they liked the concept, that they thought it was a righteous and fair process, it was my competence that was focused on, not that I have played golf or that I have gone to this and this school, so we got a lot of positive feedback on that.
2nd order	**Automatically assessing candidates' responses**	This is the way that the robot identifies which individuals (…) have the best predicted possibility of scoring high at the workplace, of doing a good job. The big 5 builds on 5 different factors (...) and then we have chosen those who are the most interesting related to work performance, so this is what it (the robot) asks questions about and can judge a person's answers about those parts.
		Many would rule out candidates based on their looks, their age, sex, ethnicity and many would rule out candidates if they have tattoos, for example. But here they are judged based on their answers and what science tells us indicates good job performance, and after that you get to the subjective part which is moved as late in the process as possible in order to give the right people the right opportunity.
2nd		You will always be able to show why you gave a specific person the job, with our robot you get data driven documentation, and you are able to say, 'this is why we chose to go further with this candidate.

	Data-driven legitimization for hiring decisions	You also get time efficiency (…) you can plan better since the robot manages the interviews, and the fact that it is unbiased in its judgements, it only judges their answers, it does not focus on your appearance."

Second, staffing coordinators proceeded with *reviewing the pool of available candidates.* This was possible to do thanks to the information inserted by available workers in the AI system such as their interest in a position, qualifications, time availability and others. The amount of job requests was big and the time to review candidate profiles was limited, therefore the coordinators used machine learning algorithms to automate this task while reducing the time necessary to complete it. The CIO in company F explained the information needed to assess the candidates,

> *"We do not do any other type of segmentation apart from certifications that need to be registered, (...) and then it is more about where do you* (the candidate) *want to work, when do you want to work and stuff like that (...) their name, address, phone and all of the personal information that needs to be registered (...) then it is of course their competence, what if you* (the candidate) *have a specialization for example, driver's license is an important element because if you are working as a nurse in a municipality for example, it is important that you can move around. We do some language evaluations (...) and then we map which systems they are used to work with, there are different journal systems for example."*

Third, company F used an AI staffing assistant for automatically *matching candidates' job profiles with open positions* based on job requirements, candidates' competence, availability, location, and other factors. This played a pivotal role in company's work activities because it constituted the core of the services they provided to hospitals and other healthcare organizations. The increasing number of job requests and the scarcity of available workers challenged company F's ability to satisfy this need. Although up to ten HR employees were divided in four teams to accomplish these tasks, it was still challenging to process most of the job requests. One of the big advantages AI tools brought into the organizations was the automation of mundane tasks and the ability to process vast amount of structured and, especially, unstructured data. The CEO of company G describes how the staffing assistant automates the mechanical tasks,

> *"We combine that (information from job requirements) with the data that exists about candidates in the Applicant Tracking System (ATS) (...) and based on all of that data we manage to match the job and the candidates that exist in the database (...) "*

Lastly, the AI tool was used for *ranking potential candidates with a decreasing order for each open position* based on the information processed in the previous steps. Staffing coordinators opened the files automatically elaborated by AI tool and received a list of the most suitable candidates for that specific positions.

The automation of optimizing recommendations allowed staffing coordinators to achieve specific intended outcomes. For example, they speeded up the processes for analyzing vast amounts of information and they were able to better coordinate the work amongst each other since they did not have to use several systems for communicating decisions. Additionally, they could provide more transparent and competent-based recommendations for temporary jobs while avoiding personal judgements, as explained by the CEO of the company G,

> *"They are ranked after how well they fit the job description based on (...) all factors that are relevant for the specific customer. Then we send, either we send the candidates that fit, or the staffing-coordinator can go in and choose who to send out. (...). When you introduce AI, you must make them* (staffing coordinators) *trust the recommendations that the AI engine makes, not only continue to work the way that they did before. If they for example always choose Jon because they know him better, then the system won't have any effect."*

The goal of company F was to streamline the complex and time-consuming process for analyzing job requests as well as identifying and coordinating competent workers for available jobs. This enabled staffing coordinators to save time from mundane tasks. In fact, they dedicated this time for performing higher-level tasks and working with well-ordered processes.

Affordance 2 - Actualization: conducting interviews automatically with an androgynous robot

This affordance allowed HR employees to evaluate candidates with an unbiased approach by automating initial steps of the selection process and anonymizing candidates' responses with the support of an androgynous robot. Candidates conducted interviews with an androgynous robot based on predefined questions, as explained by company A's HR advisor,

> *"It (*the robot) *did not ask you any different follow-up questions than the other candidates, and I did not nod approvingly when you were on the right path and so on, so to be freed of that type of bias was the major point for us."*

In order to actualize the affordance 2 in the selection process, HR employees needed to perform a requirement and competence analysis in order to identify which skills and competences were relevant for a specific position. This was used to decide which questions the robot would ask the interviewees and helped candidates to provide more transparent responses, as the HR advisor explained,

> *"Many* (candidates) *thought that they became more honest when they talked to the robot than if they had been talking to a person. I think that they liked the concept, that they thought it was a righteous and fair*

> *process, it was my* (the candidates) *competence that was focused on, not that I have played golf or that I have gone to this and this school, so we got a lot of positive feedback on that."*

Then, the HR managers could filter out candidates based on automatic tests, which recruiters used to measure characteristics and abilities of candidates. For example, company A used automatic personality-tests in order to narrow down the candidate pool to interview with the robot, as explained by the HR advisor,

> *"Everyone who applied was anonymized directly, so we did not know who had applied. All candidates were able to conduct psychological personality tests and they received a score on those depending on a list of requirement specifications. This is how we gathered 40 people from a pool of 400, and they were then able to go on to the next round and use the robot for a second interview."*

Three first-order affordances were necessary to actualize affordance 2. First, before conducting a structured interview, the robot was used for *introducing itself and informing the candidate about the time to prepare for the interview.* The device was programmed so that it knew who it was supposed to interview and was also able to produce a few sentences of small talk. The candidates were informed about practicalities about the interview, as explained by company A's HR advisor,

> *"It* (the robot) *said for example "Hey* (name of the candidate), *come in and sit down, hope that you got here well" etc. So, it tried to imitate a normal interview situation (...) but one thing that I also thought was a good idea is that the device introduced itself and said that the candidate had 15 minutes in order to prepare for the interview, and then it said that it was going to pose questions from certain topics."*

Second, the robot was used for *asking questions about personality, competence, and work-experience of candidates.* Specifically, the robotic interview session consisted of two parts. The first one focused on personality evaluations and the second one engaged with competence-related questions. The personality evaluation was based on the Big 5 model about personality characteristics and traits, as explained by a recruiter from company C:

> *"(...) we have looked at work performance, two parts in the Big 5 Model that correlates the most with someone who performs (at work) (...) So, the robot, with its personality indicator, asks questions, similar to the ones in the automatic online tests, which make it difficult to cheat (...) then we have the structured interviews, where the robot asks you to describe your competence; how would you act in a stressful situation and so on. A combination of the candidate answering the personality test and then describing their competence makes a really good foundation, because it is a personality part and a descriptive part."*

Finally, the recruiters were enabled with the possibility of *recording and transcribing candidates' responses* during interviews conducted with the robot. This enabled the recruiters to review anonymously candidate's answers from the competence tests and to combine their scores with the results provided by the robot's personality indicator.

Thanks to robot-conducted interviews, the candidates experienced a fairer selection process as they were asked the same questions and evaluated mainly based on their answers to pre-determined questions. Candidates had more time to respond to questions and were less stressed about making a good impression on the HR manager,

> *"Many thought that they became more honest when they talked to the robot than if they had been talking to a person. I think that they liked the concept, that they thought it was a righteous and fair process, it was my competence that was focused on, not that I have played golf or that I have gone to this and this school, so we got a lot of positive feedback on that."*

This opportunity also brought important advantages to companies working in small municipalities, where there is a high risk of people knowing each other with private information. It also provided more privacy and respect for the candidates that were interviewed, as they could respond without perceiving any kind of feedback from the HR manager. Finally, the robot was advantageous for achieving the social distance necessary during pandemic times as human interactions were not necessary.

<u>Affordance 3 - Actualization: automatically assessing candidates' responses</u>

This second-order affordance was characterized by *automatically assessing candidates' responses* based on the psychological theory of the Big 5 personality model. The theory is based on five dimensions, which are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. The dimensions were used for understanding candidates' personality with a score assigned to each personality trait based on candidates' answers to specific questions. A product manager in company C explained how the AI-powered interview robot used the big 5 model,

> *"This is the way that the robot identifies which individuals (...) have the best predicted possibility of scoring high at the workplace, of doing a good job. The big 5 builds on 5 different factors (...) and then we have chosen those who are the most interesting related to work performance, so this is what it (the robot) asks questions about and can judge a person's answers about those parts."*

Job applicants' answers to specific questions were analyzed by HR recruiters, who provided scores on personality traits such as conscientiousness. Then, these psychological test scores were combined with other evaluations done by the robot for predicting which candidates will be the most relevant match for a certain position. A recruiter from company C explained how this led to better hiring decisions,

> *"Many would rule out candidates based on their looks, their age, sex, ethnicity and many would rule out candidates if they have tattoos, for example. But here they are judged based on their answers and what science tells us indicates good job performance, and after that you get to the subjective part which is moved as late in the process as possible in order to give the right people the right opportunity."*

Further, the androgenous robot created by company C has been validated by psychologists to conduct big 5 personality-evaluations based on participant's answers to pre-determined categorical questions. The goal was to enable HR employees with filtering out candidates based on factors linked to work performance instead of subjective judgements about personal letters and CVs.

<u>Affordance 4 - Actualization: data-driven legitimization for hiring decisions</u>

This affordance was characterized by using information created and analyzed by AI tools such as interviews transcriptions and automated test scores to legitimize the decisions taken when hiring a candidate. The product manager of company C explained how detailed documentation about each hire was used to legitimize his team's decisions,

> *"You will always be able to show why you gave a specific person the job, with our robot you get data driven documentation, and you are able to say, 'this is why we chose to go further with this candidate."*

The goal of using an androgynous robot for automating parts of the selection process was to select candidates with an unbiased approach in order to give similar opportunities to each candidate and to evaluate candidates' profiles based on their competences and abilities. To achieve this goal, HR companies inserted a robot for conducting interviews at the beginning of the selection, driven by the assumption that robot accomplished selection tasks with more objectivity and tracked the process. Instead, HR employees decided which candidates to hire at the end of the selection process by conducting personal interviews with the most suitable candidates suggested by the robot, thus re-ontologizing the decision making.

In order to actualize the second-order affordance *data-driven legitimization for hiring decisions*, HR employees performed two first-order affordances. First, all applicants for specific positions were enabled with *conducting automated tests* that were designed to measure different characteristics such as logical abilities and personality traits. Particularly, the metrics that the tests assessed were chosen based on the competence and requirement analysis made about the open job position. The results from the tests were then registered and the applicants that achieved satisfying scores were chosen to go further in the process.

Second, through conducting robot interviews, the HR employees were able with *evaluating candidates based on a pre-determined assessment matrix*. This was equal for all job applicants as the evaluations were made by reviewing the individual personality indicators produced by the robot and the transcribed versions of the structured interviews. HR employees were able with improving the legitimacy of hiring decisions, as expressed by a product manager in company C,

> *"You also get time efficiency (...) you can plan better since the robot manages the interviews, and the fact that it is unbiased in its judgements, it only judges their answers, it does not focus on your appearance."*

IMPLICATIONS

Implications for theory

This study had several implications for theory. First, it advanced our understanding of the Affordance-Actualization theory in human resource management by explaining the second-order and first-order affordances and their imbrication process while attracting and evaluating candidates. Additionally, this study explained how AI technology should be used in HR companies to innovate internal processes. Although this knowledge derived from HR field, I believe it can be applied also in other domains such as healthcare, law, and others. Additionally, the potential value of A-A theory is limited because prior studies did not distinguish affordances from the outcomes sufficiently (Du et al. 2019; Leidner et al. 2018). I addressed this gap, by making a clear distinction between actors involved, AI technologies used, affordances, their actualization and outcomes achieved guided by the I-P-O framework.

Second, this study contributed to the Artificial Intelligence (AI) literature by offering insights into how AI can be implemented and used in HR organizations for fostering innovation in recruitment and selection processes. As an emerging phenomenon, recently AI started to attract more attention by scholars after its first appearance in 1950s. However, the extant studies have mainly focused on hypothetical impacts and potential use, but little is known about how AI can be implemented in organizations, how it can contribute to innovation and competitive advantage (Ågerfalk 2020; Liu et al. 2020; Tschang and Mezquita 2020), and how key actors actualized technology affordances for innovating (Dremel et al. 2020; Du et al. 2019). This study addressed this issue by investigated seven cases studies that used AI tools to support internal procedures and to innovate them.

Third, this qualitative study explored the link between Artificial Intelligence as enabler for innovation and the development of competitive advantages (Campbell et al. 2012; Mikalef et al. 2020). By integrating HRM literature with nascent research studies about Artificial Intelligence and with the Affordance-Actualization theory, this study has addressed firm innovativeness and associated mechanisms to differentiate their selves from the competitors by conducting unbiased and fair recruitment and selection processes. The objective of this theoretical perspectives was to understand the actions HR companies should perform to realize competitive gains.

Implications for practice

This study also provided important practical contributions by guiding future HR practitioners to effectively implement Artificial Intelligence tools within their organizations and to extract value from their investment. First, I presented the possibilities of developers to use Artificial Intelligence technology for innovation purposes. The four affordances and their actualization processes identified in recruitment and selection process can help AI practitioners to understand how AI technology can support HR organizations and how this can complement its strategy for gaining competitive advantage. For example, robot can be used for conducting interviews with potential candidates and dimmish human biases as much as possible for offering similar job opportunities to the candidates applied to the same position.

Second, this study presented the actions (affordances) necessary during recruitment and selection processes and it clearly explained where AI technology can be used and how to perform these actions with the support of AI. Besides explaining how AI automates mundane tasks in HRM such as recording and transcribing interviews, this study explained also how AI augmented HR employees' abilities during the decision making. For example, AI provided a list of potential candidates among which HR managers could decide who to hire and it also provided the evidence to legitimize the recommendations.

Lastly, the HR companies involved in this study presented the challenges associated with competitive environments and innovation processes pushed by technological development. The contributions of this paper help practitioners to combine their resources such as human capital, organizational, and technological at their advantage to increase its capabilities to respond to these challenges.

LIMITATIONS AND FUTURE WORK

Although I carefully followed the procedures during the design phase, the data collection, analysis and interpretation, this study is subject to some limitations. The first limitation refers to the job role of the respondents. Even if I asked to interview employees with different working backgrounds in HR companies, there is an overrepresentation of employees in higher-level positions. I collected valuable insights from the HR managers, CEOs and CIOs about the implementation process and their reasons for implementing AI in HRM, however, this study lacks the perspective and voice of other types of HR employees that use AI tolls when recruiting, selecting, and hiring employees. Therefore, future studies might consider including more employees from all levels of an organization in order to broaden the perspective of how AI is influencing their work.

The second limitation refers to the focus on two specific processes of recruitment and selection. In order to understand how AI is used in HR, I asked questions that mainly considered recruitment and selection. Although these two processes play a critical role in HR, they are not sufficient to describe other human resources activities. Therefore, this limits our understanding about the other processes in the field such as job analysis, job design, HR planning and others. Future studies might consider investigating other processes besides those I discussed. Additionally, future scholars might consider designing their research project from the beginning by involving companies or start-ups that are specialized in these HR processes in order to better understand how the introduction of AI influences also other functions of this domain.

Third, the use of AI-technology was at an early and explorative stage in the companies involved in this study. Consequently, exaggerated expectations or prejudices about AI may have impacted this study. Additionally, most of the respondents felt almost uncomfortable to say they were using AI tools and preferred to specify they used robots, machine learning and collaborative filtering models to perform their work. Since AI is at the initial stages of implementation in HR companies or HR departments, this might limit our understanding about how it changes the work performed by HR employees. Before using AI across HR companies, AI developers make some experimentations and test the AI models and tools to check their performance, thus future studies might consider investigating the AI experimentation phase that anticipates AI implementation and use.

Fourth, this study focused mainly on Scandinavian HR companies that might present trends typical of a specific geographic area. Therefore, future studies might conduct studies in other countries that implemented AI in HRM, which could provide other perspectives and trends driven by the specific location, thus enriching our knowledge. The last limitation refers to the type of the companies included in this study. I interviewed respondents from mainly two types of companies, which are large companies with multiple branches across Scandinavian countries and start-ups offering AI technologies for HRM activities. Although, this allowed us to get a perspective from small and large companies, medium sized companies might provide additional insights as they might offer not only AI tools for HR companies but HRM services already combined with AI tools.

CONCLUSIONS

This paper explored how Artificial Intelligence afforded innovation in the recruitment and selection processes. Seven case studies composed by human resource (HR) companies presented how they engaged in innovation though the use of Artificial Intelligence (AI). Specifically, this study explained the procedures followed to actualize technology affordances to recruit and select candidates with an unbiased and fair approach. Grounded theory guided the data collection and data analysis. Based on the Input-Process-Output (IPO) framework, I analysed the entanglement of actions, AI technology and HR employees. By analyzing the processes followed by key HR actors, I identified four affordances for recruitment and four affordances for selection processes. Then, I described the associated actualization processes through Affordance-Actualization theory by explaining the strong link between first-order and second-order affordances.

By making a clear distinction between AI artifacts, affordances, their actualization, and outcomes achieved, I increased the awareness about the stimulating conditions of affordance actualization for fostering innovation in internal processes and for gaining competitive advantage. This study explained how to integrate AI technology in recruitment and selection processes for augmenting the automation of mundane tasks. Lastly, it provided suggestions for combining AI tools with HR expertise for innovating internal processes and gaining competitive advantage.

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APPENDIX

Interview protocol

Introduction

The purpose of this study is to identify how the use of Artificial Intelligence (AI) leads to innovation in recruitment and selection practices in organizations, in addition to understanding which new capabilities and knowledges are necessary to successfully work with AI in Human Resource (HR) practices. You will be asked about your experience with using AI-technology for recruitment and/or selection. The interview will be kept strictly confidential and it will be recorded to allow us to properly analyze the data.

- For the purpose of this interview, I need you to talk about the specifics of what you said, did, thought and/or felt during specific times.
- Normally when describing a situation, it is typical to use the term “we”. For the purpose of this interview, it is important for me to know what your specific roles in the situation was and your usage of technology.
- The interview will last approximately 40-60-90 minutes.
- Ask for permission to record the interview

Warm up and background

1. Can you introduce yourself and what you do?

[Start by asking for some basic information to establish rapport. Typical questions include the following name, current position, how long they have been with the company, key responsibilities, projects, or activities in the last years]

2. Can you describe your typical day (in details)?

[Ask interviewee about a recent experience. Ideally, within last 12 months]

3. What is your understanding of the term “Artificial Intelligence”?

First approach with digital devices

1. What type of technology and/or devices does [case organization] use that involves AI?
2. What [do you think] is the motivation of [case organization] to implement AI in the hiring process?
3. Can you tell me the first time you heard about AI in your organization/department or working group? How was the new digital device(s) introduced to your working team?
4. Can you tell me about your first impression and reaction regarding this technology?
    a. What was the impression of your working group?
    b. Did you already have the knowledge or capabilities to work with this type of t echnology?
    c. If not, how did you acquire the new requested competences and who were involved in this process?

AI in recruitment and/or selection processe

1. How exactly did you make use of AI in the hiring process? Can you make a detailed description of each step?
    a. How often, when, and why do you use them?
    b. What were your own expectations about using AI?
    c. Can you tell me your opinion on how these technologies are useful for improving your work in recruitment and/or selection practices?
2. Can you describe me a situation where the adoption of AI technology was successful and another where the outcome was unsuccessful?
    a. Who was involved?
    b. Did you expect these outcomes?
    c. Why yes or no?
    d. Can you remember what you did in that situation?

Organizational changes and innovation

1. What changes did you expect from the implementation of AI?
2. Are there any changes brought by AI that you did not anticipate?
3. How do these unexpected changes affect you and your team?
4. How do these unexpected changes affect quality and/or productivity of your work?
5. How would you work without the adoption of these digital technologies?
    a. Would it be worse or better? Why?
6. Are you satisfied with the adoption of AI technology at your workplace?
7. Do you have suggestions to improve the adoption of AI technology? Can you tell me a story or a real case that stimulated these suggestions?

Use of other digital tools

1. Do you use other digital tools or services for your daily working activities?
2. What do you use that for? When and why you use them?
3. Can you compare the different tools in terms of use and how they support your professional activities?
4. Do you have any stories that particularly highlight the changes coming from the adoption of technological devices? For which functions the change occurred?

Other perspectives

1. What do you know about AI in HR? How do you know this information?
2. Do you use AI in other areas?
    a. If yes, which tools exactly? How, when, why and for which purposes?
3. Can you describe the steps you followed while using AI technologies? How did you learn to do them?
4. Do you notice some changes in the HR department since you started to adopt AI techn ology?
5. Has the relation with your colleagues and/or customers changed as a result of using AI?
    a. If yes, how and when?
6. Can you give me your feedback about the utility and functionality of the digital device (s)? Do you have suggestions to further improve the digital device(s)?

— **Stop tape recorder** —

Close and summary

- Ask if there is anything else that he/she would like to discuss
- Thank interviewee
- Remind interviewee that the interview is confidential, it will be combined with the others in the study

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