1. Artificial intelligence in human resources – an introduction

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Artificial intelligence (AI) constitutes an important field of computer science that is additionally related to different further scientific disciplines such as philosophy, mathematics, statistics, anthropology, psychology, neurology, biology, or linguistics (e.g., Russell & Norvig, 2021). Starting in the 1950s, AI shows a long and volatile history of successes and setbacks (e.g., Delipetrev et al., 2020). Based on ever increasing ("big") data stocks and computing power, in the 2010s particularly machine learning, an important field of AI, took an upswing that led to intriguing improvements in a lot of domains such as machine translation, robotic vehicles, or game playing (e.g., Russell & Norvig, 2021). In the wake of these successes, AI induced growing attention, discussion, and also application in numerous domains, among them the human resource (HR) domain. In the HR domain it is expected that AI will massively expand augmentation and automation towards complex tasks such as communication and decision making and even entire management (e.g., Strohmeier, 2020; Strohmeier & Piazza, 2015). Following discussions and developments in practice, research also started to consider AI in HR. The current overall state of research, however, is that it is nascent and scattered over different disciplines, and is far from systematically accompanying and guiding practice. To trigger and support such research, the current handbook thus aims at providing a systematic introduction to research on AI in HR. To introduce readers to the handbook, the current chapter elaborates on the basics of AI in HR and subsequently delineates the objectives, structure, and contributions of the handbook.

BASICS OF AI IN HR

As AI in HR constitutes a multifaceted and complex phenomenon, it is frequently not well understood (e.g., Long & Magerko, 2020). The following section thus briefly introduces the basics of the field, by elaborating on the *definition*, *categorization*, and *history and state* of AI in HR.

Definition of AI in HR

Regarding a definition of AI, there is a large set of suggestions uncovering different understandings (see e.g. the review of definitions by Monett & Lewis, 2018, the discussion of definitions by Wang, 2019, and the versatile reactions to this in Monett et al., 2020). Existing AI definitions are often based on similarities between AI and natural intelligence (NI). That is, AI is defined as a technology that is "similar" to NI, while there are, however, differences in the ways in which NI and AI are seen as similar (Wang, 2019). Early definitions refer, for instance, to structural similarities of AI and NI ("AI is structured like the brain of a natural intelligent being") or behavioral similarities of NI and AI ("AI behaves like a natural intelligent being"). Since such similarities are narrow and restrictive, more frequently functional similarities ("AI provides functions like a natural intelligent being") are employed for defining AI (Wang, 2019). Aiming at researching and exploiting the *functions* that AI provides to HR, a functional definition approach thus seems adequate and the following working definition can be suggested: *AI designates the set of digital technologies that mimic certain functions of NI, such as perceiving, learning, knowing, or reasoning, to augment or automate human tasks, which conventionally require such functions of NI to be performed.*

This definition needs several clarifications: First, with the definition component of "*mimic* certain functions of NI" the above definition is premised on the idea that there is a similarity between NI and AI. This similarity of providing intelligent functions, however, is restricted and in need of concretization. A frequent metaphor for illustrating the restricted similarity refers to the comparison of natural flying with artificial flying (e.g., Russell & Norvig, 2021). Taking birds and helicopters as examples, both show the function of flying. However, both realize this function through very dissimilar procedures. A first clarification, thus, is that similarities of NI and AI refer to the results rather than to the procedure of gaining these results. Moreover, as helicopters for instance are able to fly backwards while birds are not, the results also differ. In this sense, AI uses procedures dissimilar to NI ones to produce results that are similar to NI results but are not identical. Second, with the definition component of "*function*s of NI" the scope of the AI concept sensitively depends on the understanding of the "NI functions" concept. A broad understanding that encompasses any cognitive activity as an NI function would imply that, for instance, "calculating" constitutes a function of NI. This, however, would in turn count spread-sheets, which augment and automate the human task of calculation, as AI, even though spread-sheets conventionally are *not* seen as AI. AI literature, thus, uses a conventional set of functions of NI such as sensing, reasoning, learning, or knowing (e.g., Russell & Norvig, 2021) to determine AI, rather than systematically determining the function concept and, based on this, determining AI. The definition is thus not fully selective in separating technologies conventionally understood as AI from further technologies. Third, the definition component of "*NI*" includes human intelligence as a core category, yet goes beyond by explicitly allowing for further categories such as general biological intelligence (Wang, 2019). Fourth, with the definition component "*set* of digital technologies" AI should be understood as a set of different technologies, rather than as one homogeneous technology.

Categorization of AI in HR

Recent attempts to categorize AI (e.g., Corea, 2019; Golstein, 2020) uncover the complexity and versatility of the field that evades any simple and neat internal and external delineation. Nevertheless, in order to create a basic understanding of the field, in the following the *strength*, *paradigm*, *convention*, and *function* of AI are employed as criteria to roughly categorize AI in HR.

Categorization by strength

Strength designates the overarching level of intelligence expected from AI, while in a rough categorization narrow, general, and super AI can be distinguished (e.g., Bostrom, 2014; Russell & Norvig, 2021; Searle, 1980). *Narrow AI* (also known as *weak AI*) aims at tackling a more or less defined, single human task. While narrow AI can even outperform humans in this specific task, it is not able to perform any other human task, even if more trivial. Narrow AI is frequently associated with the position that AI can only act *as if it would be* intelligent, that is, thinks, has a mind, and so on (Searle, 1980; Bunge, 1956a and 1956b). *General AI* (also known as *strong AI*, *artificial general intelligence* [*AGI*], *full AI*, or *human-level AI* [*HLAI*]) aims at tackling *any* task that humans can perform based on NI. General AI is frequently associated with the position that AI actually *is* intelligent – that is, actually thinks, actually has a mind, and so on – therewith raising issues such as machine consciousness, self-awareness, and intentionality, which on their part raise subsequent issues such as machine rights and responsibilities (Russell & Norvig, 2021; Searle, 1980). *Super AI* (also known as *artificial super intelligence*) aims at qualitatively and quantitatively outperforming humans in any task and beyond, allowing the performance of tasks that cannot be completed by humans due to their NI restrictions (e.g., Bostrom, 2014). Beyond the issues raised by general AI, super AI raises further issues such as self-triggered exponential growth ("explosion") of AI or machine dominance over humans (e.g., Bostrom, 2014). At the moment, only narrow AI can be realized, and there is ongoing dispute as to whether general (let alone super) AI *could be* or even *should be* realized (e.g., Russell & Norvig, 2021; Bostrom, 2014; Wang, 2019).

Based on this, *all* current applications of AI in HR necessarily are narrow AI. (For this reason, the above definition of AI shows an explicitly narrow understanding.) The current discussion on AI in HR, however, ignores this at times and (at least implicitly) assumes the existence of non-narrow varieties of AI, for instance in the popular discussion of whether "AI will take over HR" (e.g., Hmoud & Laszlo, 2019; Lin et al., 2018).

Categorization by paradigm

A paradigm designates the basic approach that AI takes to achieve results, while in a rough categorization symbolic and connectionist AI can be distinguished (e.g., Russell & Norvig, 2021). *Symbolic AI* (also known as *good old-fashioned AI* [*GOFAI*]) is a paradigm within which humans build a model of reality by using symbolic representations such as words or phrases and AI employs or manipulates this symbolic model to achieve results. Since such symbolic models are conventionally built by humans, they are "hand-crafted" and usually effortful. Symbolic AI was the dominant paradigm in earlier phases of AI research, thus explaining the designation of "good old-fashioned AI" (Haugeland, 1985). *Connectionist AI* (also known as *sub-symbolic AI* or *non-symbolic AI*) is a paradigm that uses representations of reality such as pixels or structured data to let AI itself learn a model of reality by connecting known inputs and outputs.

Both AI paradigms are discussed and applied in HR. Knowledge-based search and matching engines in recruiting, which use a symbolic knowledge base ("ontology") for improving search and matching results, constitute an example of current symbolic AI in HR (e.g., Martinez-Gil et al., 2016). HR analytics applications that use artificial neural networks to predict future employee absenteeism constitute an example of current connectionist AI in HR (e.g., Ali Shah et al., 2020). While systematic empirical studies on the adoption of AI paradigms in HR are missing, there are clear indications that applications in HR follow the general trend and a clear majority of HR applications refer to connectionist AI (see section "History and state of AI in HR").

Categorization by convention

Conventions are historically emerged agreements on categorizing AI, as for instance manifested in AI textbooks, journals, conferences, and departments. The background for this categorization thus is historical rather than theoretical (Wang, 2019). Conventional AI fields are rather distinct, are based on different foundations, and use different methods to solve different problems (Russell & Norvig, 2021; Wang, 2019). As a consequence, the different fields do not necessarily collaborate on a regular basis. This fragmentation evidently detracts from a unified discipline of AI (Wang, 2019). Moreover, as they have their own designations, such as "computer vision" or "natural language processing", these fields label themselves as "AI" only if the public opinion on AI happens to be positive (Russell & Norvig, 2021), as is the case at the time of writing this chapter. Though there are conventions of categorizing AI, it comes as no surprise that there is no complete consensus, and that existing categorizations somewhat differ. This brings about the question of which fields to consider. As this handbook aims at a comprehensive consideration of AI in HR, the following fields of AI that show actual or potential relevance in HR are considered: First, this of course includes the well-established "classic" AI fields of *computer vision*, *knowledge representation*, *reasoning*, *machine learning*, *robotics*, and *natural languages processing* (e.g., Russell & Norvig, 2021). Second, this includes three further fields of AI that show direct relevance for HR. A first additional field refers to *evolutionary computing* (e.g., Eiben & Smith, 2015). Occasionally, evolutionary computing is understood as a sub-category of machine learning (e.g., by Sammut & Webb, 2017); as it however differs from machine learning in its basic approach, it is counted as an AI category *sui generis* by this handbook. A second additional field refers to *affective computing* (e.g., Picard, 2000 and 2015). A third additional field refers to *robotic process automation* (e.g., Czarnecki & Fettke, 2021). By incorporating more and more AI functions, robotic process automation currently just establishes itself as field of AI. While other categorizations by convention are admittedly possible, these fields are seen as relevant and thus are briefly introduced in the following.

Computer vision constitutes a field of AI that aims at mimicking the visual perception of humans (e.g., Russell & Norvig, 2021). Computer vision learns patterns in existing digital images and videos as recorded by cameras and employs these patterns for sensing new digital images or videos. Core objectives refer to "seeing", "understanding" what is seen, and sensing complex visual information (e.g., Russell & Norvig, 2021).

Knowledge representation constitutes a field of AI that aims at mimicking the internal mapping of facts by humans (e.g., Russell & Norvig, 2021). Knowledge representation systematically ascertains intended knowledge and subsequently formally maps it in knowledge bases using knowledge representation techniques such as ontologies. The core objective is providing knowledge bases for reasoning and for solving problems (e.g., Russell & Norvig, 2021).

Reasoning constitutes a field of AI that aims at mimicking the internal thought processes of humans (e.g., Russell & Norvig, 2021). Reasoning employs *reasoners* (also *inference engines*), which infer logical consequences from a set of facts as for instance stored in a knowledge base. Core objectives are providing new information and solving problems (e.g., Russell & Norvig, 2021).

Machine learning constitutes a field of AI that aims at mimicking the acquisition of new knowledge by humans (Jordan & Mitchell, 2015). Machine learning employs existing data to "learn" knowledge inherent in these data and map this knowledge in a model. The overarching objective is improving human and machine performance in a certain application domain based on the provided knowledge (Jordan & Mitchell, 2015).

Robotics constitutes a field of AI that aims at mimicking the physical manipulation of (parts of) the world by humans (e.g., Russell & Norvig, 2021). Robotics employs physical *robots* that use sensors, such as cameras, radars, or lasers, to enable the perception of their environment, and effectors, such as wheels, legs, or grippers, to assert the intended physical forces. The overarching objective is purposefully changing the physical environment (e.g., Russell & Norvig, 2021).

Robotic process automation constitutes a field of AI that aims at mimicking the performance of operational work processes by humans (e.g., Czarnecki & Fettke, 2021). Robotic process automation employs non-physical (i.e., software) *robots* that first "learn" and subsequently automate human process performance, thereby autonomously interacting with operational software, further robots, and humans. The core objective refers to automating (and thus accelerating, improving, and cheapening) process execution (e.g., Czarnecki & Fettke, 2021).

Evolutionary computing constitutes a field of AI that aims at mimicking biological problem solving (and therewith general natural rather than specific human intelligence) for finding an acceptably good solution within a large set of alternatives. It therefore aims at providing heuristics for finding solutions for problems too complex for straightforward mathematical optimization (e.g., Eiben & Smith, 2015).

Natural language processing constitutes a field of AI that aims at mimicking the language-based communication of humans. Natural language processing employs speech recognition, natural language understanding, and natural language generation. Core objectives refer to a direct communication between machines and humans, and beyond to autonomous learning of machines from extensively available written human knowledge (Russell & Norvig, 2021).

Affective computing (also *emotion AI*) constitutes a field of AI that aims at mimicking the human perception and expression of emotion (Picard, 2000 and 2015). Affective computing thus recognizes, reacts to, and simulates human affects such as fear, anger, joy, surprise, or disgust. Core objectives refer to improving the interaction of machines and emotional humans, and thus the respective outcomes of the machine–human interaction (Picard, 2000 and 2015).

It is important to note that the above fields are not neatly separated, autonomous areas of AI research and application, but quite contrarily show complex overlaps and interactions. To give a rough impression of this, Figure 1.1 shows core *supporting* (an AI field supports another AI field by improving and/or expanding it) and core *enabling* (an AI field enables another AI field by transferring methods to a new application domain) *relationships.*

This uncovers the prominent position of machine learning that enables or at least supports diverse other fields (e.g., Jordan & Mitchell, 2015). Machine learning, for instance, enables affective computing by allowing for learning models of human affect based on voice, gesture, and other data, that can be used for automated affect recognition. Machine learning becomes even more prominent if evolutionary computing is categorized as a sub-field of machine learning (as e.g. by Sammut & Webb, 2017). Further supporting relationships refer for instance to reasoning and knowledge representation, since the former regularly employs knowledge bases of the latter as input. Moreover, relationships further uncover robotics process automation and robotics as "composite" AI fields that are based on the support of several other AI fields. As a consequence of such overlaps and interactions, existing applications of AI in HR are not necessarily unambiguously assignable to one field of AI. For instance, HR sentiment analysis (e.g., Costa & Veloso, 2015) can *be* and actually *is* assigned to machine learning, natural language processing, or affective computing. Beyond such categorization ambiguities, there are however true composite applications of AI in HR that rely on the functionalities of multiple AI fields. For instance, physical robots for conducting job interviews (e.g., Inoue et al., 2020) evidently rely on robotics *and* natural language processing.

Supporting *or* Enabling Category ↓ / Supported *or* Enabled Category →	Computer Vision	Knowledge Representation	Reasoning	Machine Learning	Robotics	Robotic Process Automation	Evolutionary Computing	Natural Language Processing	Affective Computing
Computer Vision					○	○			○
Knowledge Representation			○						
Reasoning									
Machine Learning	●	○			○	○		●	●
Robotics									
Robotic Process Automation									
Evolutionary Computing					○				
Natural Language Processing					○	○			○
Affective Computing					○	○			

○ *Supporting Relationship* ● *Enabling Relationship*

Figure 1.1 *Intertwining of conventional AI categories*

All the above AI fields show basic application potentials in HR. Even though systematic empirical insights on the adoption of AI in HR are missing, distinct differences regarding the application of different AI fields are to be expected. Machine learning, for instance, is by now already more broadly applied in HR, while robotics, for instance, is just beginning to be used (see section "History and state of AI in HR").

Categorization by function

Functions designate the categories of NI that AI intends to mimic. In the following, a pragmatic categorization based on different existing categorizations in NI literature (see e.g. the overview on NI theories by Kaufman et al., 2013) and AI literature (see e.g. the categorization by Russell & Norvig, 2021) is employed. As core NI functions mimicked by AI, *cognitive* (i.e., *perceiving*, *reasoning*, *knowing*, and *learning)*, *practical* (i.e., *deciding*, *acting*, and *solving*), and *social* (i.e., *communicating* and *empathizing*) *intelligence functions* can be distinguished.

Perceiving refers to the sensing and interpretation of external signals to represent and understand one's environment. *Reasoning* refers to the internal act of logical thinking to gain knowledge. *Knowing* refers to the internal representation and understanding of issues, such as facts (propositional knowledge) or skills (procedural knowledge). *Learning* refers to acquiring such new knowledge. As perceiving, reasoning, knowing, and learning are interrelated and refer to the acquisition, production, and representation of knowledge they can be categorized as core *cognitive* functions of NI (e.g., Brody, 2004).

Deciding refers to choosing between different alternative actions under uncertainty. *Acting* refers to performing a purposeful activity, be it by active doing or passive tolerating. *Solving* refers to finding the best – or at least an acceptably good – solution among a large set of different alternatives. As deciding, acting, and solving constitute three interrelated functions to realize humans' ideas and objectives to assert themselves, survive, and progress in their environment, they can be categorized as core *practical* functions of NI (e.g., Sternberg, 1985).

Communicating refers to transferring information and meaning in a verbal or non-verbal manner. *Empathizing* refers to recognizing, understanding, and reacting to the emotional states of humans. As communicating and empathizing constitute two important functions of starting, maintaining, and improving social relations they can be categorized as core *social* functions of NI (e.g., Kaufman et al., 2013).

The above functions can be used to categorize applications of AI in HR. However, because of the interrelations of the different functions, AI applications regularly mimic several interacting functions, rather than one isolated function. For instance, as the result of learning is knowing, an AI application that mimics learning necessarily also implies that it mimics knowing. Given the mentioned lack of empirical studies, insights on which functions are relevant in HR applications are missing, yet a broader relevance can be assumed based on existing application examples. For instance, expert systems mimic human knowing and reasoning (e.g., Lawler & Elliot, 1996), machine learning mimics human learning, knowing, deciding, and acting (e.g., Ali Shah et al., 2020), evolutionary scheduling mimics human solving and deciding (e.g., Apornak et al., 2021), robotic process automation mimics human learning, deciding, and acting (e.g., Papageorgiou, 2018), and conversational agents mimic human communicating (e.g., Sheth, 2018).

Integrated categorization

In order to provide an integrated overview, in the following the above criteria are employed together to allow for an integrated categorization – with the exception of the criterion of strength, which has only one existing category ("narrow AI") (see Figure 1.2).

This integrated categorization initially classifies the conventional AI fields according to the primary paradigm they mainly follow. With knowledge representation and reasoning, only two fields refer primarily to symbolic AI, while all other fields refer primarily to connectionist AI. Moreover, the integrated categorization uncovers the primary and secondary functions of NI that AI intends to mimic. The focus of the different fields is shown by their primary function. However, given the interrelations of NI functions, primary functions are regularly accompanied by secondary functions. For instance, machine learning shows the primary function of "learning" new knowledge from existing data. As the resulting knowledge however is mapped in a model, a first secondary function is "knowing". Moreover, as machine learning can learn how to decide based on data on past decisions or to solve a problem based on past solutions, “deciding” and “solving” constitute further secondary functions. Finally, if data contain solutions to problems or tasks, machine learning can learn these solutions, which if automated can be seen as autonomous “acting” as a further secondary function. In this way, different fields show different functional foci, which in sum add up to a broad set of relevant NI functions that can be mimicked by AI.

		by Paradigm		*by* Function								
				cognitive				*practical*			*social*	
		Symbolic	Connectionist	Perceiving	Knowing	Reasoning	Learning	Deciding	Acting	Solving	Communicating	Empathizing
by Convention	Computer Vision		●	●	○		○					
	Knowledge Representation	●			●							
	Reasoning	●				●						
	Machine Learning		●		○		●	○	○	○		
	Robotic Process Automation		●				○	○	●		○	
	Robotics		●	○	○		○	○	●	○	○	○
	Evolutionary Computing		●					○	○	●		
	Natural Language Processing		●	○	○						●	
	Affective Computing		●	○	○							●

● *Primary Paradigm or Function* ○ *Secondary Function*

Figure 1.2 *Integrated categorization of AI*

History and State of AI in HR

History

General AI shows a longer history that is characterized by cyclical ups and downs (e.g., Haenlein & Kaplan, 2019; Delipetrev et al., 2020). With the seasonal metaphors of “AI summer” (phase of positive expectations, attention, and investment) and “AI winter” (phase of negative expectations, disregard, and disinvestments), AI even has its own terminology to name the ups and downs of public opinion (e.g., Haenlein & Kaplan, 2019).

The beginning of AI is regularly dated back to the 1950s. In the subsequent *foundation phase* the basics of AI were researched and developed (e.g., Delipetrev et al., 2020). While there was a certain focus on symbolic AI in this phase, pioneering work in connectionist AI, particularly artificial neural networks, was also done. This led to a first AI summer. However, to the best of our knowledge HR research and practice did not participate and engage in AI in this first phase. By and by the – at times bold – expectations and promises of the foundation phase turned out to be exaggeratedly optimistic, thus bringing about the first AI winter in the 1970s (e.g., Delipetrev et al., 2020; Haenlein & Kaplan, 2019).

In the 1980s, a shift towards expert systems (also knowledge-based systems) induced a *symbolic phase* and led to a second upswing of AI (e.g., Delipetrev et al., 2020; Haenlein & Kaplan, 2019). Based on knowledge representation and reasoning, expert systems aim at mapping the expertise of a domain and use it for providing information and decision support to non-domain experts. Although with a certain delay, HR also participated in this second summer of AI, as diverse attempts to develop "HR expert systems" show (e.g., Chu, 1990; Extejt & Lynn, 1988; Hannon et al., 1990). Again, the high expectations of this second phase were finally not met. Being symbolic and thus "hand-crafted" AI, expert systems require high development effort, are dependent on experts and modellable expertise, and frequently have to be developed company-specific (e.g., Haenlein & Kaplan, 2019). In the wake of these difficulties, expert systems were not broadly adopted in HR and other domains. A new AI winter emerged.

A new upswing, the third by now, started with the dawning of the 2010s. Constantly growing ("big") data stocks and constantly increasing computing power enabled a massive shift to connectionist AI, especially machine learning (e.g., Delipetrev et al., 2020). This *connectionist phase* brought about intriguing improvements in a broad range of domains, such as machine translation, robotic vehicles, or game playing (e.g., Russell & Norvig, 2021), and led to a new AI summer. Like many other domains, HR is participating in this AI upturn, as manifested in broad discussions on and expectations of AI in HR (e.g., Ernst & Young, 2018; IBM, 2018; Oracle, 2019; PWC, 2017), in new AI-enabled HR conceptions such as "big HR data" (e.g., Garcia-Arroyo & Osca, 2021) or "HR analytics" (e.g., Madsen & Slåtten, 2017), and, of course, in practical applications of AI in HR such as natural language processing in recruiting or machine learning in selection.

State

To roughly delineate the current state of AI in HR, the paradigms, categories, and sub-categories of AI in HR are grouped into a life-cycle model of digital technologies (Gartner, 2021). The model assumes that digital technologies pass through ideal-typical phases over time, which are characterized by clearly different levels of expectations of the respective technology. These start with a trigger phase (a technological breakthrough triggers the respective technology), which is followed by a peak phase (overenthusiasm and unrealistic high expectations reinforced by media), a disillusionment phase (overexaggerated expectations cannot be met, expectations plunge again reinforced by media), and finally two recovery phases (ongoing elaboration of the technology allows for a more realistic assessment, improvement, and finally a productive application) (Gartner, 2021). Even though the model is not without critique (e.g., Dedehayir & Steinert, 2016), its application allows for deriving some interesting insights on the current state of AI in HR. As systematic empirical studies of expectations on and adoption of different paradigms, categories, and sub-categories of AI in HR are lacking, the grouping was realized based on expert estimates by the respective authors of this handbook (see Figure 1.3).

First, as already indicated by the above definition and categorization, AI is not a homogeneous block of technology, but decays into different paradigms, categories, and sub-categories. These imply different application potentials, different use cases, and different consequences in HR. A first insight thus refers to the heterogeneity of AI in HR. Consequently, the respective (sub-)categories should be carefully distinguished, rather than lumped together as "AI", therewith employing an attention-grabbing but heterogeneous and, thus, ambiguous concept.

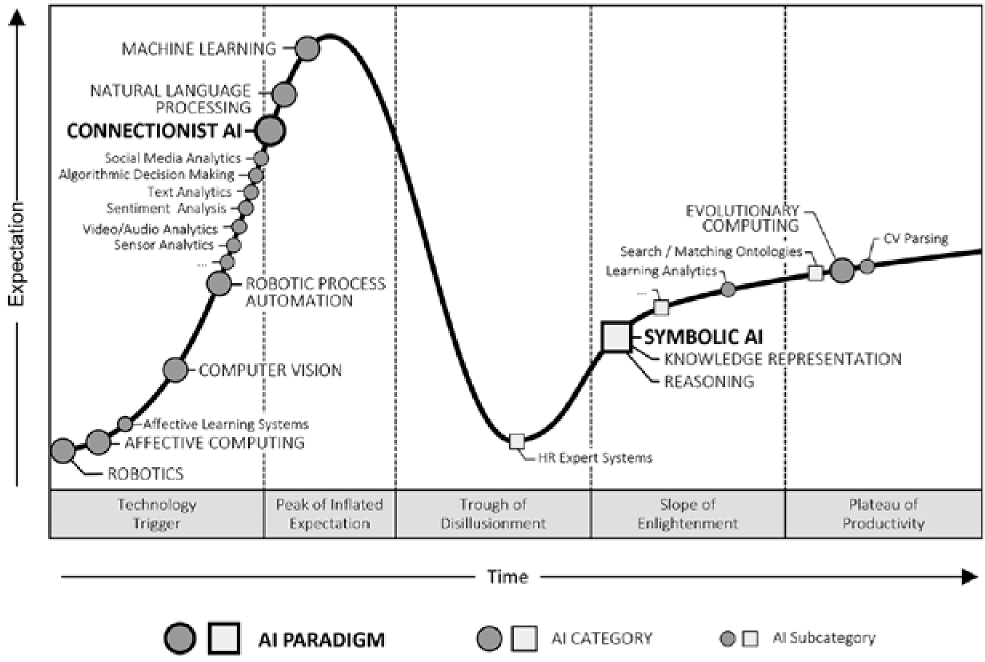

Figure 1.3 Current state of AI in HR

Second, on the paradigmatic level the model clearly predicts and maps the summer and winter phases of AI. The last AI winter referred to symbolic AI and its passage through the phase of disillusionment. Even though not all (sub-)categories of symbolic AI could be transferred into productive applications, there are nevertheless examples where this has been achieved, such as knowledge- (ontology-) based search and matching engines in recruiting (e.g., Martinez-Gil et al., 2016). This is evidence for the model assumption that continued development can lead to productive application of a technology after a disillusionment phase. The current AI summer and the high expectations of AI, contrarily are clearly driven by the connectionist paradigm and its versatile (sub-)categories. A second insight, thus, is that connectionist AI constitutes the dominant paradigm of current interest and expectation, while, however, applications of symbolic AI in HR also exist.

Third, the current high expectations do not apply equally to all categories of connectionist AI but refer mainly to three categories. Machine learning receives the most attention. Based on the current intensive discussion on "HR analytics" and related concepts, diverse forms of machine learning based analytics incur a lot of attention (e.g., Giermindl et al., 2021; Lengnick-Hall et al., 2018). Moreover, natural language processing, in particular in the form of conversational agents ("chat bots"), also gets a lot of attention in professional discussion. With a certain lag, and currently just emerging, robotic process automation is also attracting a growing amount of attention. A third insight, thus, is that the current high expectations of AI mostly refer to three connectionist AI categories.

Fourth, in HR, AI as a whole still constitutes an emerging rather than a mature technology. However, on a sub-category level there are AI applications that have already been adopted productively. This refers to sub-categories such as parsing of CVs in recruiting, knowledge-(ontology-) based search and matching in recruiting, or evolutionary computing in staff rostering. Although these applications are being more frequently adopted, they are not the focus of current attention and therefore constitute "stealth" applications of AI in HR, being mostly "beneath the radar" of current discussions. A fourth insight, thus, is that AI already has some established applications in HR and, thus, is more than just an academic mental exercise.

Fifth, the current discussion additionally largely overlooks potentially relevant AI categories that might become productively applicable in the future. This first refers to *robotics*, which has broad potentials for HR applications, be it as hybrid robots that beyond their primary manufacturing or service tasks (e.g., Steil & Maier, 2017) also perform secondary HR tasks such as performance appraisal, or as proprietary physical robots exclusively built for HR purposes such as job interviews (e.g., Inoue et al., 2020; Nørskov & Ulhøi, 2020). Moreover, as HR deals with humans and, thus, with human emotions, *affective computing* also promises obvious and broad potentials – for instance for identifying and managing employee stress (e.g., Richardson, 2020) or improving the performance of employees by considering and improving their emotional states (e.g., Lee, 2019). Perhaps even more mid-term opportunities (yet also threats) in HR will be offered by *computer vision*, which could be used not only for the prediction and prevention of work accidents (e.g., Liu et al., 2019) but also for the systematic surveillance of employee performance (e.g., Lebedeva et al., 2019) and even general employee behavior (e.g., Alom et al., 2014). A fifth insight, thus, is that there are more relevant categories of AI in HR than recognized and considered in the current discussion.

Sixth, as demonstrated by HR expert systems, there are also setbacks in applying AI in HR. In the wake of the second AI summer ("symbolic phase"), expert systems aimed at providing information and decision support in domains with rather qualitative procedures and expertise. HR, thus, initially seemed an ideal candidate for expert systems, and there were large expectations and promises. Consequently, there were practical attempts to develop and apply HR expert systems (e.g., Hannon et al., 1990). Only the practical attempt of developing HR expert systems uncovered the huge effort of "hand-crafting" knowledge bases and further problems such as the limited availability of experts and knowledge. While there still are current scholarly attempts to capitalize on the expert systems concept in HR (e.g., Angela et al., 2020; Bohlouli et al., 2017), expert systems have so far not been able to get rid of the negative image acquired in the second AI winter, and they currently show low expectations and adoption in HR. A sixth insight therefore is that applications of AI in HR have, of course, no guarantee of success and require the willingness to take certain risks.

Seventh, the model predicts that the current "hype" phase of connectionist AI in HR will be followed by a disillusionment phase, in which expectations literally plunge. As there are evident indicators of overenthusiasm in the current AI discussion, it is important to expect and accept coming disillusionment as a "normal" phase that can be followed by recovery and the productive application of AI (Gartner, 2021). Since it produces and increases *over*enthusiasm, the ongoing active "hyping" of AI in HR – as practiced by certain authors, consultants, and vendors at the time of writing this chapter – is clearly counter-productive. A seventh insight, thus, is that the current enthusiasm will expectedly be followed by disillusionment. The latter needs to be accepted and overcome through ongoing efforts to productively apply AI in HR, rather than precipitately giving up on it and therewith “throwing out the baby with the bathwater”.

HANDBOOK OF RESEARCH ON AI IN HR

With the above delineation of AI in HR, an intriguing, relevant, and manifold field of research appears in outline. The current section thus briefly and roughly provides an overview of current research on AI in HR to derive the objectives of this handbook and subsequently introduces its structure and chapters.

Existing Research and Objectives of the Handbook

So far, there is no established community of researchers (let alone established conferences or journals) that is specialized on AI (or one of its fields) in HR. Existing research is scattered over different disciplines and numerous outlets. While recently there have been some serious reviews of this research, these are restricted to specific disciplinary perspectives and boundaries, as well as to specific aspects of AI in HR. Existing reviews refer to:

- generic AI in general HR (Vrontis et al., 2021),
- generic “algorithms” in general HR (Cheng & Hackett, 2021),
- machine learning in
  - general HR (Berhil et al., 2020; Garg et al., 2021; Strohmeier & Piazza, 2013),
  - personality traits prediction (Azucar et al., 2018),
  - learning (e.g., Du et al., 2020; Romero & Ventura, 2020, among others),
  - recruiting (Siting et al., 2012; Freire & Castro, 2021), and
  - turnover prediction (Ekawati, 2019; Zhao et al., 2018),
- affective computing in learning (Yadegaridehkordi et al., 2019),
- computer vision in employee safety (Liu et al., 2019),
- fairness of AI in
  - general HR (Robert et al., 2020) and in
  - recruiting and development (Köchling & Wehner, 2020).

Gaining an overview of current research on AI in HR, thus, is complex and cumbersome. Scanning existing research nevertheless allows some initial insights on its state and allows deriving objectives for the current handbook.

First, existing research appears to be *multi-topical* in the sense that a broad range of topical issues are covered. Besides the technical issues of developing AI artifacts for HR (e.g., Pessach et al., 2020) and the managerial issues of applying AI artifacts in HR (e.g., Black & van Esch, 2020), diverse further topical areas such as the psychological (Hmoud & Várallyai, 2020), ethical (e.g., Loi, 2020), and legal (e.g., Barocas & Selbst, 2016) issues of applying AI in HR are addressed. Such multi-topical research is mandatory: While particularly the managerial issues of applying AI constitute a core domain aspect, it is clear that, first, application issues are dependent on the preceding technical issues of developing appropriate AI artifacts and, second, both development and application issues are inseparably superimposed by ethical, legal, and psychological issues, among others. The current handbook thus aims at an integrated consideration of the relevant issues of AI in HR.

Second, and related to the above, existing research appears to be *multi-disciplinary* in the sense that diverse disciplines participate. Relevant contributions stem for instance from computer science (e.g., Fernández-Martínez & Fernández, 2020), information systems (e.g., Ochmann et al., 2020), law (e.g., Barocas & Selbst, 2016), economics (e.g., Chalfin et al., 2016), ethics (e.g., Loi, 2020), industrial and organizational psychology (e.g., Langer et al., 2019), and human resource management (e.g., Charlwood, 2021), while the last – even though being the core domain discipline – seems not to lead the field. This research is *multi-* yet not *inter*disciplinary, as the different disciplines involved take little or no notice of each other, and do not regularly cooperate. This is particularly true for the two core categories of methodical-technical disciplines, which deal with the development of AI in HR, and managerial-behavioral disciplines, which deal with the subsequent application of AI in HR. While at first glance such a disciplinary division of labor seems obvious and promising, existing research shows that it is not. Methodical-technical disciplines often lack domain expertise. This yields AI artifacts that just do not fit domain opportunities and requirements (e.g., Strohmeier & Piazza, 2013). Vice versa, managerial-behavioral disciplines often lack technical expertise. This yields – at times blatant – misconceptions of AI, leading to both exaggerated hopes and promises and exaggerated concerns and caveats regarding AI in HR. To improve this situation, participating disciplines must close their respective gaps in expertise and/or cooperate with other relevant disciplines on an *inter*disciplinary basis (e.g., König et al., 2020). The current handbook thus aims at interdisciplinary research with the relevant disciplines considering and learning from each other.

Third, existing research appears to be *multi-functional* in the sense that it covers diverse HR functions. Relevant contributions refer for instance to recruiting (e.g., Johnson et al., 2021), selection (e.g., Liem et al., 2018), scheduling (e.g., Apornak et al., 2021), compensation and benefits (e.g., Petruzzellis et al., 2006), learning and development (e.g., Maity, 2019), performance management (e.g., Ahmed et al., 2013), or HR administration (e.g., Chichester & Giffen, 2019). However, following a general pattern of (applying and then) researching new digital technologies in HR (Strohmeier, 2007), recruiting and selection once again appear to constitute the pioneer and focus functions of current research. However, aiming at research that comprehensively and systematically maps the application domain of HR, future research should not only care for HR (sub-)functions that already show certain AI applications, but also and in particular for opening up HR (sub-)functions that so far do *not* show AI applications. The current handbook thus explicitly aims at covering all the (sub-)functions of HR.

Fourth, existing research appears to be *multi-technical* in the sense that it covers *all* conventional AI fields. Relevant contributions refer to reasoning (e.g., Kumar et al., 2014), knowledge representation (e.g., Martinez-Gil et al., 2016), machine learning (e.g., Ali Shah et al., 2020), evolutionary computing (e.g., Apornak et al., 2021), robotics (e.g., Inoue et al., 2020), robotic process automation (e.g., Papageorgiou, 2018), natural language processing (e.g., Sheikh et al., 2019), and affective computing (e.g., Lee, 2019) in HR. However, there appear to be striking differences regarding the intensity and frequency of research in these fields. A massive core focus refers to machine learning – thereby not seldom even *equating* machine learning with overall AI (e.g., Tambe et al., 2019). In comparison, research in other AI fields, such as robotics, computer vision, or reasoning, falls significantly behind. As research on digital technologies generally tends to follow trends in practice (e.g., O'Leary, 2008), current research on AI in HR echoes the current attention patterns of practice. However, as AI in HR is heterogeneous, and as diverse AI fields either show future application potentials or even current applications in HR, the current handbook explicitly aims at a systematic consideration of all AI fields in HR – whether or not they are currently "*en vogue*". Because connectionist AI in HR may be facing a phase of disillusionment and, beyond, connectionist AI as a whole may be facing a new "winter" (e.g., Floridi, 2020), it is necessary that research does *not* follow the volatile ups and downs of public opinion, but instead conducts constant and sober work on what AI can or cannot really do in HR.

Structure and Contributions of the Handbook

Structure

The current handbook consists of four parts:

Part I: Applications of Artificial Intelligence in Human Resources
  Part I.1: Applications of Machine Learning in Human Resources
  Part I.2: Further Applications of Artificial Intelligence in Human Resources

Part II: Consequences of Artificial Intelligence in Human Resources

Part III: Normative Issues of Artificial Intelligence in Human Resources

Part IV: Research Issues of Artificial Intelligence in Human Resources.

Part I deals with actual and potential *applications of AI in HR*. To this end, the above conventional categorization of AI fields is employed for structuring the different chapters. Doing justice to the distinct importance of machine learning (also) in HR, Part II is divided into two sub-parts. A first sub-part (Part I.1) deals with applications of machine learning in HR (Chapters 2–8), while chapters are oriented towards employing machine learning on core HR data types and in core HR functions. A second sub-part (Part I.2) maps further relevant AI fields ranging from HR knowledge representation and reasoning to HR affective computing (Chapters 9–13). This allows mastering the heterogeneity and scope of AI in HR and enables readers to selectively read chapters of individual interest, or else gain a comprehensive overview on AI in HR by working step by step through the different chapters. *Part II* deals with the *consequences of AI in HR*. As AI is seen as a trigger for the digital transformation of HR, a chapter elaborates on the direct transformations of HR to be expected from applying AI in HR and the indirect transformations of HR to be expected from applying AI for augmenting and substituting employees in their work (Chapter 14). *Part III* deals with *normative issues of AI in HR*. As ethical, social, and legal issues superimpose the development and the application of AI, four chapters deal with the explainability, fairness, accountability, and legitimacy of AI in HR (Chapters 15–18). *Part IV* deals with *research issues of AI in HR*. As this volume is research oriented, this part refers both to researching AI in HR and to employing AI for research in HR (Chapters 19 and 20).

Given the early state and manifoldness of research on AI in HR, this structure provides interested researchers and practitioners with a comprehensive overview of the field and, beyond, provides interested researchers with multiple starting points for their own work, in the hope that these will be taken up in the future.

Contributions

To provide a general orientation, the following section briefly introduces the chapters of the handbook.

Chapter 2 *"HR machine learning – an introduction"* written by me (Stefan Strohmeier) delineates the basics of machine learning by providing a definition and elaborating on the process, algorithms, and data of HR machine learning, as well as on its potentials and challenges. Based on this, the chapter examines research on HR machine learning and derives implications. In doing so, the chapter aims to act as an introduction to Part I.1 and lay the foundations for the following chapters on machine learning on different HR data types and in different HR functions.

Chapter 3 "*HR machine learning on text data*" written by Felix Gross deals with machine learning on the specific data category of unstructured HR texts. The chapter delineates basic machine learning technologies for text data and discusses their application possibilities in HR. Based on this, an overview on current research is given and an outlook for future research options and directions based on existing text data potentials is given. As the vast majority of existing data are unstructured and as comprehensive text data exist in HR, this constitutes a first important extension and specialization of HR machine learning.

Chapter 4 "*HR machine learning on audio and video data*" written by Carmen Fernández-Martinez and Alberto Fernández deals with machine learning on the specific data categories of unstructured audio and video data. The chapter delineates technologies for video, audio, and multimodal processing. Moreover, common HR use cases are outlined and open research issues and challenges are discussed. As audio and video data are increasingly available and employed, this constitutes a second important extension and specialization of HR machine learning. Since machine learning on video data largely overlaps with "computer vision" the chapter also addresses the latter AI field.

Chapter 5 "*HR machine learning on social media data*" written by Jake T. Harrison and Christopher J. Hartwell deals with machine learning on the specific data category of social media data. The chapter discusses the diverse data sources offered by different social media categories and uncovers how machine learning can be applied to capitalize on these data in different areas of HR, such as predicting personality. Based on this, core research directions are derived. As social media is widely adopted and is comprised of diverse data that are potentially valuable for HR, this constitutes a third important extension of machine learning.

Chapter 6 "*HR machine learning in recruiting*" written by Sven Laumer, Christian Maier, and Tim Weitzel deals with the opportunities for utilizing machine learning in recruiting, especially to automate the finding and evaluation of candidates. Following an introduction on machine learning and recruiting, the chapter offers a systematic literature review and develops a HR recruiting machine learning model. Based on the insights provided, various future research opportunities are put forward that would improve the usage of machine learning in recruiting, such as broadening the perspective of fit, using common recruiting data sets, and avoiding discrimination.

Chapter 7 "*Machine learning in HR staffing*" written by Florian J. Meier and Sven Laumer deals with using machine learning for predicting developments relevant to staffing – in particular for predicting future net employee requirements, reserve employee requirements, future hires, and future attrition of employees. After introducing the staffing function conceptually, the chapter systematically reviews existing research contributions regarding their orientation, objectives, data basis and algorithms employed, achievements, and challenges. Based on this, the consequences for practice and research are discussed.

Chapter 8 "*Machine learning in personnel selection*" written by Cornelius J. König and Markus Langer introduces machine learning in the field of selection – therewith tackling a current core HR application of machine learning. After initially introducing the approaches to using machine learning for selection purposes, the chapter reviews existing empirical research on the potentials and the challenges. Based on this, the chapter provides suggestions for future research, in particular research that will provide evidence for the validity of machine learning approaches to selection, explore the human–AI interface, and examine the reactions of users, applicants, and other stakeholders.

Chapter 9 "*HR knowledge representation and reasoning*" written by Jorge Martinez-Gil deals with current applications of symbolic AI in HR, thereby treating the interrelated AI fields of knowledge representation and reasoning together. The chapter uncovers how current knowledge bases and reasoners are employed in HR, with a particular focus on searching for candidates and matching them to positions in the process of recruitment. Besides introducing the technical realizations and applications, the chapter elaborates on future tasks such as automating the building of knowledge bases and using them beyond recruiting, for instance in HR development.

Chapter 10 "*HR robotic process automation*" written by Peter Fettke and me (Stefan Strohmeier) deals with the application of software robots to further automate the operation of already implemented digital applications in HR and therewith closing existing automation gaps. To this end, the problems that robotic process automation address and the solutions that it offers are described. Based on this application, potentials and challenges of robotic process automation in HR are derived along with the state of current research and implications for future research on the topic.

Chapter 11 "*HR evolutionary computing*" written by Lena Wolbeck and Charlotte Köhler deals with the application of algorithms inspired by biological evolution for solving HR problems that are too complex for straightforward optimization. To this end, the chapter gives an overview on the family of evolutionary algorithms. Based on this, various applications of evolutionary algorithms for solving HR problems, in particular in scheduling and re-scheduling employees, are highlighted. Finally, current and future developments in evolutionary computing within HR are reviewed.

Chapter 12 "*HR natural language processing – conceptual overview and state of the art on conversational agents in human resources management*" written by Sven Laumer and Stefan Morana deals with natural language processing, in particular conversational agents, as applied in HR. The chapter first introduces the technology of conversational agents. Subsequently, a conceptual overview on the application possibilities of conversational agents in HRM is elaborated. Based on this conceptualization, the chapter reviews relevant research contributions and derives perspectives for future applications and future research on natural language processing and conversational agents in HR.

Chapter 13 "*HR affective computing*" written by William J. Becker, Sarah E. Tuskey, and Constant D. Beugré deals with the recognition, stimulation, and expression of human emotion by AI. It elaborates how these functions can be applied to improve and transform HR. Based on an introduction to the current state and likely future of affective computing, the chapter explores several application areas of affective computing in HR, among others in personnel selection and performance management, and derives avenues for future research on affective computing in HR.

Chapter 14 "*Consequences of artificial intelligence in human resource management*" written by Maarten Renkema deals with the desired and undesired consequences of applying AI in HR. To this end, it develops a framework that offers a categorization of the effects of AI in HR and of the research on these effects. This allows for discussing the effects of AI and highlighting exemplary research. The chapter thus offers insights into (research on) how HRM can be transformed by achieving desirable consequences, while avoiding undesirable ones, when applying AI in HRM.

Chapter 15 "*Explainability of artificial intelligence in human resources*" written by Markus Langer and Cornelius König deals with the problem of the opacity of AI in HR both for humans applying AI in HR and for humans affected by it. The chapter introduces, discusses, and further develops the concept of eXplainable Artificial Intelligence ("XAI") as a means of overcoming the opacity of AI in HR. Based on this, suggestions for future research on XAI in HR are provided. As opacity and incomprehensibility undermine acceptance, and thus the adoption and success of AI in HR, XAI constitutes a crucial requirement of future applications.

Chapter 16 "*Fairness of artificial intelligence in human resources – held to a higher standard?"* written by Sandra L. Fisher and Garret N. Howardson deals with the problem of fairness of AI in HR decision making. While the biases of human HR decision makers are well known (and frequently more or less accepted), public opinion is highly sensitive regarding potential discrimination or errors in AI-based decisions. The chapter thus reviews different perspectives on the fairness of AI in HR decision making, discusses differences in judging the fairness of humans and machines, and derives implications for research and practice to contribute to a fairer AI in HR in the future.

Chapter 17 "*Accountability of artificial intelligence in human resources*" written by Katharina A. Zweig and Franziska Raudonat deals with the problem of the attributability of AI results in HR. If machines augment or even automate human tasks, in particular decisions, positive as well as negative consequences emerge, leading to the question of who is accountable for them. The chapter thus reviews different approaches to conceptualize accountability of AI in HR, and employs the "long chain of responsibilities" and the "five role model" to discuss responsibilities and uncover the complex accountability structures of developing and applying AI in HR.

Chapter 18 "*Legitimacy of artificial intelligence in human resources – the legal framework for using artificial intelligence in human resource management*" written by Kai von Lewinski and Raphael de Barros Fritz deals with the legal regulations of AI in HR. Given the large variety and diversity of relevant regulations worldwide, the chapter employs a three-times-three matrix to structure the field: on one axis, labor law, data protection law, and anti-discrimination law, on the other axis, the technological level, the implementation level, and the application level. This allows the systematic discussion of regulations based on concrete examples of different national regulations. In doing so the chapter offers a structured overview on central legal regulations.

Chapter 19 "*Design considerations for conducting artificial intelligence research in human resource management*" written by Richard D. Johnson and Dianna L. Stone deals with approaches to researching AI in HR and provides guidance to researchers regarding their choice of an adequate research design. To this end, quantitative non-experimental design, qualitative non-experimental design, experiments, and quasi-experiments are introduced and evaluated regarding their strengths and weaknesses for research on AI in HR based on illustrative current examples. The chapter thereby offers support for choosing adequate research designs in future research on AI in HR.

Chapter 20 "*Employing artificial intelligence in human resources research*" written by Chulin Chen and Richard Landers deals with the potential of AI for use in HR research. Given AI's improved capabilities to detect associations and relationships within data beyond traditional statistical tools, its scholarly applications are on the one hand obvious and promising yet on the other hand imply many challenges regarding validity, reliability, and ethics. Focusing on machine learning, the chapter provides guidance on how AI can be used to advance research on HR topics, reviews existing HR applications, and highlights research gaps and future research directions.

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