Chapter 7
Artificial Intelligence Techniques in Human Resource Management—A Conceptual Exploration

Stefan Strohmeier and Franca Piazza

Abstract Artificial Intelligence Techniques and its subset, Computational Intelligence Techniques, are not new to Human Resource Management, and since their introduction, a heterogeneous set of suggestions on how to use Artificial Intelligence and Computational Intelligence in Human Resource Management has accumulated. While such contributions offer detailed insights into specific application possibilities, an overview of the general potential is missing. Therefore, this chapter offers a first exploration of the general potential of Artificial Intelligence Techniques in Human Resource Management. To this end, a brief foundation elaborates on the central functionalities of Artificial Intelligence Techniques and the central requirements of Human Resource Management based on the task-technology fit approach. Based on this, the potential of Artificial Intelligence in Human Resource Management is explored in six selected scenarios (turnover prediction with artificial neural networks, candidate search with knowledge-based search engines, staff rostering with genetic algorithms, HR sentiment analysis with text mining, résumé data acquisition with information extraction and employee self-service with interactive voice response). The insights gained based on the foundation and exploration are discussed and summarized.

Keywords Artificial intelligence · Computational intelligence · Human resource management · Artificial neural network · Genetic algorithm · Knowledge representation · Knowledge discovery · Data mining · Text mining · Sentiment analysis · Interactive voice response

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7.1 Introduction: AI Techniques in HR Management?

Human resources are widely perceived as one of the most important assets of any organization, and managing this asset successfully is, consequently, considered a crucial managerial duty (e.g., Devannah et al. 1984). Managing human resources comprises a broad range of different tasks, including staffing, management of employee performance, development of employee qualifications and careers, and compensation of employee efforts. In human resource management (HRM), as in any other domain, adequate techniques are crucial; proven techniques understood as systematic instructions for solving domain tasks enable humans to cope successfully with the multifarious requirements of a given domain. As a well-established and increasingly professionalized domain, HRM makes use of a broad and heterogeneous set of techniques. In addition to domain-specific techniques, this also refers to techniques that are "imported" from other domains, for instance, psychometric tests from organizational psychology (e.g., Wolf and Jenkins 2006), optimization from operations research (e.g., Ernst et al. 2004) or online analytical processing from information systems (e.g., Burgard and Piazza 2009). A further prominent discipline offering techniques that might be applied in HRM is artificial intelligence (AI) (e.g., Jantan et al. 2010). For AI, the literature offers a heterogeneous set of suggestions as to how specific AI techniques could be applied for specific HR tasks, for instance, how to use data mining techniques in employee selection (e.g., Chien and Chen 2008), intelligent agent techniques in employee development (e.g., Giotopoulos et al. 2007) or information extraction techniques in employee recruiting (e.g., Kaczmarek et al. 2005). Such contributions yield diverse and detailed insights into the potentials of individual AI techniques for individual HR tasks and, thus, are valuable. Yet, such contributions are not able to offer an overview of the general potential, i.e., which AI techniques generally exist, to which HR tasks these could be generally applied and which general conditions exist for a successful application. Thus, the current chapter aims to be the first exploration of the general potential of AI techniques in HR management. For this purpose, a brief foundation elaborates on the central functionalities of AI techniques and the central requirements of HR management based on the task-technology fit approach (Sect. 7.2). Based on this, the potential of AI techniques in HR management is explored in six selected application scenarios (Sect. 7.3). Finally, the insights gained based on the foundation and exploration are discussed and summarized (Sect. 7.4).

7.2 Foundation: "Fit" of AI Techniques and HR Management

7.2.1 Task-Technology Fit

Any general exploration of application potentials of specific techniques in a specific domain should be based on general insights into the overarching conditions and effects of an application. For this purpose, the task-technology fit approach (TTF) (Goodhue and Thompson 1995) offers a simple and useful foundation. Basically, the approach aims to explain the success of information technology and claims the task-technology fit ("correspondence between task requirements and the functionality of the technology") as the major criterion for success ("mix of improved efficiency, improved effectiveness and/or higher quality") (Goodhue and Thompson 1995, p. 218). The approach has been successfully applied to a broad set of application domains and technological categories (Furneaux 2012), and should be suitable for investigating the potential of AI techniques (which are interpretable as technologies because they are mandatorily implemented as technological applications) in HR management (which is interpretable as a set of interrelated tasks). As a basis for further exploration, the general requirements of HR tasks and the general functionalities of AI techniques are briefly elaborated on in the following.

7.2.2 Requirements of HR Tasks

As a prominent managerial domain, HRM is defined and categorized differently throughout the literature. Understanding the employees as the major source of organizational performance and competitive advantage and the systematic alignment of all employee related activities for business strategy constitute common characteristics of the concept since its beginnings (e.g., Devannah et al. 1984; Jackson et al. 2014). As a working definition, HRM thus can be generally described as a subset of management tasks that are related to potential or current employees to obtain contributions that directly or indirectly support the strategy and performance of an organization.

This implies a multitude of detailed tasks, which are categorized heterogeneously throughout the literature. Concentrating on major complexes of tasks with clear strategic relevance, staffing, performance management, development, and compensation, constitute commonly considered interrelated tasks of HRM (e.g., Devanna et al. 1984). Staffing in general refers to the provision of the quantity and quality of employees necessary for business. This implies numerous sub-tasks, such as requirements planning, recruiting, selection and onboarding of new employees, and, if needed, also relocations and dismissals of current employees. Moreover, assignment planning and day-to-day assignment of employees also constitute further sub-tasks of staffing. Performance management consists of the systematic planning, appraisal and attainment support of collective and individual objectives. Planning implies the downward cascading of (strategic) organizational objectives to individual objectives. Performance appraisal subsequently aims at a concomitant or periodical achievement evaluation of these objectives, while attainment support aims at diverse support measures that enable and facilitate individual goal achievement. Development aims at consequent advancement of individual employee qualifications as well as employee careers. Qualification development refers to the continuing training of employees to equip them with the qualifications necessary for the achievement of their goals, including the ability to cope with stress, work burdens, and conflicts, among others. Beyond the qualifications, career development aims at planning and realizing medium term positions/successions in a way that matches organizational needs as well as individual potentials and ambitions. Finally, compensation refers to remuneration of employees, including concepts of profit sharing and pension plans. Remuneration aims at a fair and motivating payment of employees corresponding with individual qualification requirements and performance contributions. Profit sharing aims at employee participation in the financial success of a company. Pension plans aim to extend the financial funding of employees in the retention phase.

Each of these HR task categories can be supported by intelligent techniques in two basic interrelated ways that are automation and information (Zuboff 1985). Automation of an HR task aims at the (partial) task performance transfer from humans to machines. Human qualification and effort thereby are replaced by machines, while the same tasks can usually be performed quicker and at less cost (Zuboff 1985). Thus, in the past, significant efforts were made to constantly push the automation of HRM. Information of an HR task is based on its preceding automation and aims at producing valuable insights about the task that was automated. This enhanced knowledge offers decision support for human deciders and, therefore, should improve the overall decision quality (Zuboff 1985). Thus, there have also been diverse endeavors to utilize the inherent information potential for HR decision support.

In summary, the automation and information of staffing, performance management, development and compensation constitute major task requirement categories, as depicted in Fig. 7.1.

Staffing		Performance Management		Development		Compensation	
Automation	Information	Automation	Information	Automation	Information	Automation	Information

Fig. 7.1 Categorization of major HR task requirements

7.2.3 Functionalities of AI Techniques

Based on the problems of defining general intelligence properly, AI constitutes a multifarious and fragmented area of computer science, and there is heterogeneity and even certain confusion regarding the proper definition and categorization of AI techniques (e.g., Duch 2007; Kahraman et al. 2010; Wang 2008). Narrow definitions focus on structural or behavioral analogies with natural intelligence, i.e., an intelligent technique is structured and/or behaves as a natural intelligent system (Wang 2008). This allows for a clear determination of relevant techniques (which are usually in the categories of neural, fuzzy and evolutionary techniques, as well as hybrids of them) and also a clear demarcation to general computer sciences, while this narrow understanding is increasingly termed as "computational intelligence" (e.g., Duch 2007; Kahraman et al. 2010). Broader definitions focus on functional or capability-oriented analogies with natural intelligence, i.e., the technique performs certain functions and/or has certain capabilities of natural intelligent systems (Wang 2008). This expands the set of incorporated techniques and allows the consideration of "classic" AI techniques, such as knowledge representation; yet, this also aggravates a clear demarcation of "intelligent techniques" from further computational techniques and therewith a proper demarcation of AI from general computer science. To cover the range of existing intelligent techniques, the current chapter adopts a broad understanding and defines AI techniques as machine-processable instructions to solve tasks that would require clear cognitive capabilities if solved by humans. Based on this definition, it becomes possible to categorize AI techniques based on the cognitive capability they refer to. In this respect, knowledge, thought and language constitute major cognitive functions that comprise different categories of related AI techniques, which are briefly introduced in the following.

Understanding *knowledge* as awareness and understanding certain relevant facts, the generation, preservation and processing of knowledge constitute clear cognitive capabilities. Major AI techniques that are related to knowledge can be categorized into knowledge discovery, knowledge representation and knowledge processing. Knowledge discovery (also "machine learning", "pattern recognition" or "data mining") refers to the process of identifying novel, potentially useful and valid information in data (Fayyad et al. 1996). For this purpose, a broad range of knowledge discovery techniques is available, with classification, association, segmentation and prognosis techniques constituting prominent categories (e.g., Wu et al. 2008). Knowledge representation refers to the mapping of a set of relevant propositions ("knowledge") to formal symbols in a way that allows computers to use these formal symbols when solving tasks (e.g., Brachman and Levesque 2004; Davis et al. 1993). Major varieties are declarative (representation of mere facts) and procedural (representation of procedures to utilize knowledge) knowledge representation. For knowledge representation, there is a larger set of techniques, with frames, semantic nets and ontologies constituting prominent example categories (e.g., Tanwar et al. 2010). Knowledge processing (also "reasoning" or "inferencing") aims at utilizing knowledge represented in a computer to produce new knowledge.

Knowledge processing therewith is dependent on existing knowledge representations as a basis and input for reasoning (e.g., Brachman and Levesque 2004). There are different techniques for reasoning, while deductive, inductive and abductive reasoning constitute major categories (e.g., Brachman and Levesque 2004).

Understanding *thought* as the purposeful internal processing of existing knowledge to produce new knowledge and solve problems, thought constitutes a further clearly cognitive capability relevant in AI. As is explicitly defined here, thought is related to knowledge in a twofold manner because it utilizes existing knowledge as input and aims at producing new knowledge as output. For this reason, particularly techniques that process knowledge have to be additionally classified as thought-related as well. Moreover, techniques for searching solutions (also "solving optimization problems") constitute a second crucial category of thought-related techniques. Basically, these techniques aim at formalizing "hard problems" and solving them based on intelligently searching a search space for an optimal, or at least a feasible, solution (Kahraman et al. 2010). For this purpose, a broader set of intelligent techniques, such as the A* search algorithm, hill climbing algorithms, particle swarm optimization and genetic algorithms, is suggested (e.g., Kahraman et al. 2010; Luger 2005).

Finally, understanding *language* as the use of a complex system of spoken or encoded elements for communication, language usage constitutes a further clearly cognitive capability. Referring to language, text processing and speech processing constitute major categories of intelligent language-related techniques (also subsumed as "natural language processing [NLP]"). Text processing techniques aim at supporting tasks related to written language, such as topic extraction, text summarization, text translation, or text classification, among others. For this purpose, a set of text processing techniques, such as tokenization, lemmatization, and part of speech tagging, are available (e.g., Jurafsky and Martin 2008). Speech processing techniques aim at supporting tasks related to spoken language, in particular automatic speech recognition and automatic speech synthesis but also further tasks, such as speaker recognition and verification or hearing aid provision, among others. A broader set of different techniques is available, with Hidden Markov Models constituting a prominent example in the area of speech recognition (e.g., Benesty et al. 2008).

In summary, the discovery, representation and processing of knowledge, the search for solutions, and the processing of text and speech constitute major categories of AI functionality, as depicted in Fig. 7.2.

As it is possible to realize an AI application based on only one technique from one category, several techniques are increasingly combined and therefore constitute hybrid techniques (e.g., Kahraman et al. 2010).

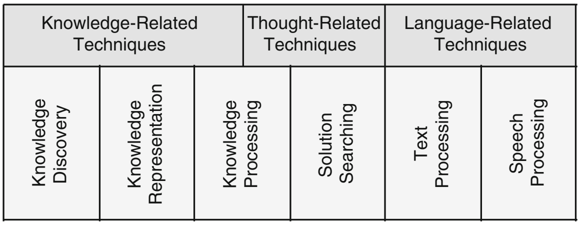

Fig. 7.2 Categorization of major functionalities of AI techniques

7.3 Exemplification: Scenarios of AI Techniques in HR Management

7.3.1 Overview

Against the backdrop of the task-technology fit approach, the intended conceptual exploration of potentials implies the investigation of technological functionalities, task characteristics, the potential fit of both and the resulting consequences. Any exploration, however, is confronted with the multifariousness of individual AI techniques, of individual HR tasks and, consequently, of imaginable task technique-combinations. The resulting exploration task, thus, is huge and far beyond the scope of a single contribution. On this account, a conscious selection of six different application scenarios of AI techniques in HR is discussed below (see Fig. 7.3).

While this does not allow any final tackling of the topic, it enables various first explorative insights. The scenarios were selected based on two criteria: Firstly, the portfolio of application scenarios should cover the range of AI techniques as well as the range of HR tasks rather than concentrate on one or a few techniques and/or one or a few tasks. Secondly, the examples should constitute "mature" application scenarios, i.e., applications of AI in HR that are already elaborated, tested and, at least occasionally, also adopted in practice, rather than "futuristic" scenarios with uncertain practical feasibility. In the following, it is briefly discussed for each scenario which functionalities the respective AI technique offers and whether and how these fit with requirements of the respective HR task.

7.3.2 Turnover Prediction with Artificial Neural Networks

Artificial Neural Networks (ANNs) are information processing systems that comprise a certain number of information processing units (also "cells," "neurons") that incorporate mathematical functions and are connected by directed weighted links (e.g., Rojas 1996). ANNs constitute a category of knowledge discovery that is able to solve clustering, classification, estimation and prediction tasks. The information processing units are usually organized in layers, with an input layer to provide the

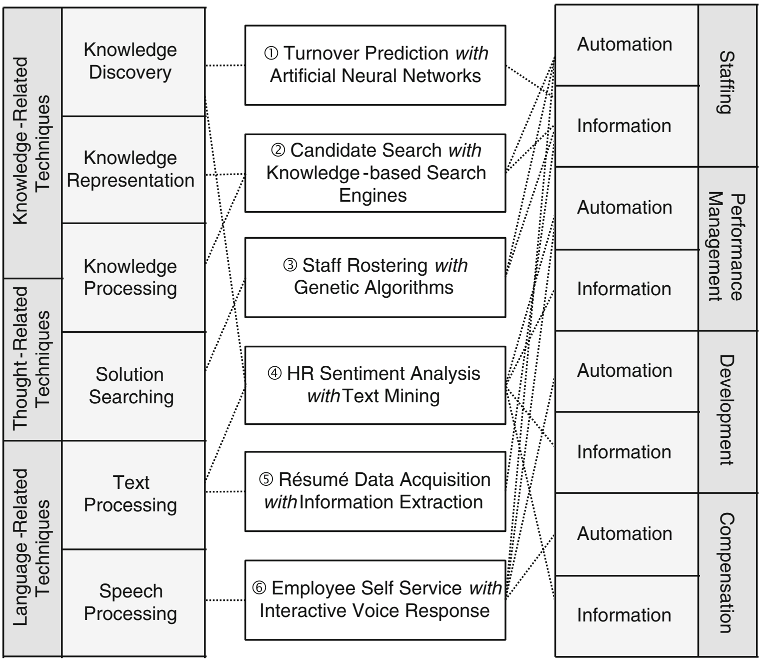

Fig. 7.3 Selected scenarios of AI techniques in HR management

input data, one or more hidden layers to process the data through the neural network and an output layer to provide the result. ANNs are inspired by an analogy to the brain, where information processing is based on neurons that are connected to each other and transmit the degree of activation through nerve fibers to other neurons (e.g., Rojas 1996). They learn from training examples and reorganize their internal structure (architecture) comprising the units, layers and directed weighted links to generate good outputs. When the output meets a certain quality criterion, the architecture of the ANN is fixed and can be used for prediction tasks. Further intelligent techniques are occasionally used to realize ANNs, for instance, genetic algorithms are applied to adapt the weights of the links during the learning process (e.g., Sexton et al. 2005). Due to their internal structure, ANNs are able to approximate any mathematical function (e.g., Hornik et al. 1990; Leshno et al. 1993) and, thus, to discover complex patterns within data. However, the ANNs themselves are complex and nontransparent and work as “black boxes”, delivering good outputs but few explanations.

An application scenario of ANNs in HRM is the prediction of employee turnover. Employee turnover refers to the voluntary resignation of employees based on their own reasons and explicitly excludes dismissals based on employer reasons or unavoidable separations, such as retirement, death or permanent disability. This phenomenon, especially dysfunctional turnover (good performing employees leave, while poor performing employees stay), is of crucial interest for organizations because of the decreased productivity associated with it (e.g., Sexton et al. 2005). Moreover, dysfunctional turnover leads to increasing staffing costs because new employees have to be searched for, hired and trained to fill vacant positions. Against this background, turnover prediction offers the potential to identify the employees that are likely to leave and therewith enables the development of individual employee retention measures. The turnover prediction task can be modeled as a classification task where the output variable realizes the two discrete classes "yes" and "no" relating to turnover. To apply the ANN, a training dataset is required that contains historic employee data concerning turnover as well as other potentially relevant data influencing turnover, such as age, seniority, salary, qualifications, position, gender, family status, etc. In a first step, the ANN is trained on a training set, i.e., a partition of the available employee data, to reveal systematic associations between the input variables influencing turnover and the respective output variable representing turnover. As they can approximate any function, ANNs are also able to discover highly complex patterns of employee turnover. The quality of the generated ANN can be assessed by using a test set, a partition of the employee dataset left out from the training process, which can reveal insights into the error, such as the percentage of employees wrongly classified as "leavers." A sensitivity analysis can further show the importance of the influence factors and allows for identification of the factors that most influence the employee turnover. The generated ANN hence can be applied to predict which employees are likely to leave and also can deliver information about the relevant factors influencing turnover (e.g., Sexton et al. 2005).

ANNs obviously fit with the task of turnover prediction as they address the nature of the underlying classification and prediction task. An ANN can predict which concrete employees are likely to leave as well as uncover unknown factors that influence turnover. Therewith, valuable predictive information for staffing that enables proactive management of the turnover of employees is offered and that cannot be offered by conventional techniques, such as merely querying employee databases. Predicting and proactively managing turnover can avoid, or at least alleviate, the severe downsides of "dysfunctional turnover," including drops in organizational productivity and the costs of recruiting and introducing new employees. In summary, turnover prediction with ANNs supports the information of staffing and allows for a proactive HRM. While the factual practical application of ANNs in turnover prediction is not revealed in the literature, several evaluations and prototypes reveal "application maturity" of the scenario in applying a knowledge discovery technique in HRM (e.g., Fan et al. 2012; Quinn et al. 2002; Sexton et al. 2005; Somers 1999).

7.3.3 Candidate Search with Knowledge-Based Search Engines

Knowledge-based search engines (also frequently called "semantic search engines") basically offer functionality for searching the web for content. Compared to conventional search, however, not only the search string entered but also semantically related concepts, such as synonyms, hypernyms and hyponyms, are automatically considered (e.g., Mangold 2007). Thus, a knowledge-based search functions as if it would understand the semantic meaning of the searched content and, thus, improves the search result quality. Therewith it also reduces the often complex and time consuming search process. The basic AI techniques that are used to enable knowledge-based search are ontologies as a technique of knowledge representation and related reasoners as a technique of knowledge processing. Ontologies represent knowledge of a certain domain in the form of concepts, relations, instances and rules (e.g., Guarino et al. 2009). Concepts refer to classes of objects that are relevant for the domain. Relations refer to associations between concepts. Depending on the domain, any desired relation can be mapped, while specific types of relations between concepts refer to superiority and subordination of concepts, allowing for the distinguishing of sub-concepts, concepts and super-concepts. Instances are concrete individual members of a certain object class described by a certain concept. Rules, finally, represent causal relationships between concepts and/or instances that can be used for inferring new knowledge. Usually, ontologies also comprise synonyms for concepts and instances. In this way, knowledge of a certain domain can be represented, and ontologies thus constitute a particular knowledge representation technique (e.g., Guarino et al. 2009). Reasoners use knowledge of the ontology and, dependent on the basic application objective, also external case-dependent data to generate new knowledge (e.g., Abburu 2012; Bock et al. 2008). For instance, applying a rule ($A \Rightarrow B$) from the ontology on an object that meets the premise "A" allows concluding that it also meets the conclusion "B"; in this way, new knowledge can be created. The combination of ontologies and reasoners allows for a knowledge-based search that yields results comparable to that of intelligent humans with deep domain knowledge (e.g., Guha et al. 2003).

An application scenario of knowledge-based search-engines in HRM is searching for candidates (e.g., Mochol et al. 2007). Due to labor market shortages, many organizations actively search for suitable candidates on the web, e.g., on web-based job boards. Due to the redundancy and heterogeneity of human language, searching for suitable candidates based on conventional search engines frequently turns out to be both incomplete and effortful. Problems of conventional search arise, in particular, if the relevant terminology of the organization and the candidate deviate from each other—which is a regular occurrence in e-recruiting. The searching organization has to then employ an abundance of search terms, yet it still cannot know with certainty that suitable candidates are not being overlooked. A knowledge-based search engine utilizing a domain-ontology and a reasoner can improve candidate search processes, as rendered in Fig. 7.4.

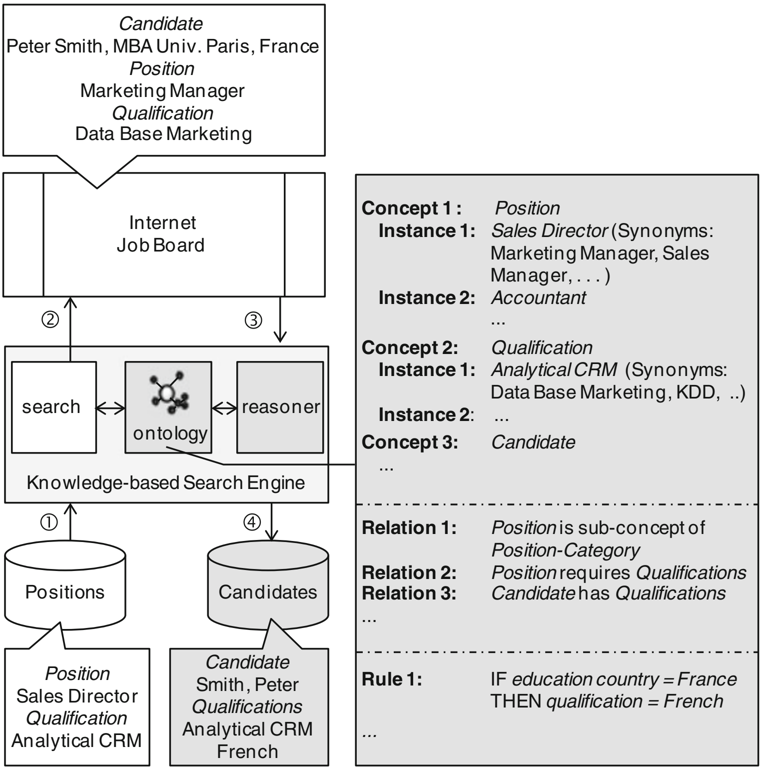

Fig. 7.4 Candidate search with knowledge-based search engines

Organization and candidate use a deviating terminology to describe relevant aspects, such as offered and desired positions, required and offered qualifications, etc. The recourse on a domain ontology allows the search engine to “recognize” that the vacant position “sales director” semantically corresponds with a searched position “marketing manager” among others, and it offers a suitable search result that a conventional search engine would not be able to. If a reasoner is used in addition, this might offer additional information, such as deducing French language qualifications from the fact the candidate was educated in France.

Knowledge-based search engines therewith visibly fit with the task of searching for candidates who describe their desired position and offered qualifications in natural language and, thus, in a heterogeneous and multifarious terminology that can be handled by knowledge-based search. Knowledge-based search engines are able to automate parts of the search task and also offer valuable information for supporting pre-selection decisions; thus, the automation and information of staffing is supported. Compared to conventional search, central improvements relate to efficiency (increased speed and decreased effort) and quality (increased accuracy of results) of candidate search (e.g., Strohmeier et al. 2011). Knowledge-based search is a mature technology that is at least occasionally applied in HRM, for instance, several web-based job boards offer semantic search of jobs and candidates.

7.3.4 Staff Rostering with Genetic Algorithms

Genetic algorithms are problem-solving techniques inspired by biological processes comprising variation and selection to optimize "survival of the fittest". As a major application realm, parameter optimization problems are those in which the variables representing the parameters are typically encoded by bit strings (e.g., Sivanandam and Deepa 2008; Whitley 1994). Genetic algorithms generate solutions according to a specified objective function and problem specific constraints. In the first step, an initial population is generated (randomly, for example) where each member of the population is represented by a bit string (also referred to as a "genotype" or "chromosome"). Algorithms further perform the phases of selection, crossover and mutation (e.g., Linoff and Berry 2011; Sivanandam and Deepa 2008; Whitley 1994). Within the *selection* phase, only the fittest members in a population survive to pass their genetic material on to the next generation. A fitness value for each member is calculated based on the objective function of the optimization problem. The better the fitness value relative to other members, the more copies survive to the next generation. The size of the population remains constant from one generation to the next. Therefore, the fittest members are selected and copied, while those with the lowest fitness value do not survive. The subsequent phase, *crossover*, is the phase analogous to reproduction in nature and aims at creating new members of the population from existing ones by combining pieces of them. There are several crossover strategies, such as single-point, two-point, n-point or uniform crossover. The new members are different from the existing ones but do not necessarily fit better. However, when a new combination turns out to have a high fitness value, it is likely to be replicated in future generations. *Mutation* aims at realizing changes that cannot result from selection and crossover alone, for example, by flipping a randomly selected bit. Selection and crossover depend on initial conditions and randomness that might prevent potential successful combinations from being generated and considered in succeeding generations. Like in nature, mutations are likely to be harmful and destructive; therefore, mutation should be rarely applied. If the initial population provides a good coverage of the solution space, selection and crossover are sufficient. Selection, crossover (and mutation) form a new generation, which will be evaluated again, leading to an iterative process. Common stop criteria for genetic algorithms are a fixed number of generations, a time limit or the absence of improvements. Genetic algorithms are stochastic heuristic search methods that simultaneously consider many points in the search space, and therefore the probability of finding only local optima is reduced (e.g., Kahraman et al. 2011). Genetic algorithms can therefore be categorized as a thought-related intelligent technique.

An application scenario of genetic algorithms in HRM is staff rostering (also "employee scheduling"). Staff rostering addresses the generation of optimal assignments of employees to shifts matching the qualitative and quantitative requirements of the tasks with the qualitative and quantitative disposability of the employees (e.g., Ernst et al. 2004). In many branches, such as manufacturing, service or health care, a flexible and efficient generation of valid staff rosters is a crucial task. The resulting optimization problem refers to multiple criteria, such as costs, job-person fit and employee preferences, and is characterized by multiple constraints regarding domain specific aspects, such as maximum working time, recreation times and qualification requirements, among others. For example, each employee works at most one shift per day, while the overall monthly working time should meet a particular tolerance limit around the target working time. Further examples for constraints are that a maximum number of consecutive working days should not be exceeded, that the night and weekend shifts should be distributed among the employees according to their contracts and in respect to a fair distribution and that employee preferences should be considered as much as possible. Constraints can be incorporated in the calculation of the fitness value as penalty costs by lowering the fitness value if a higher fitness value indicates a better member and vice versa. Rosters can be encoded as strings representing the individual members of the population. Performing the genetic algorithm, i.e., selection, crossover and mutation, leads then to generations of improved rosters, and the roster with the best fitness value can be finally selected (e.g., Aickelin and Dowsland 2000).

Genetic algorithms obviously fit with the task of staff rostering as they address its very nature as an optimization problem and provide feasible rosters considering a multitude of constraints. They are able to automate the rostering task and to informate regarding valid rosters. Genetic algorithms clearly outperform any manual scheduling. Given that various publications indicate the successful application of genetic algorithms in staff rostering (e.g., Aickelin and Dowsland 2000; Gonçalves et al. 2005; Kim et al. 2014; Moz and Vaz Pato 2007; Souai and Teghem 2009), and given that genetic algorithms are actually integrated in commercial staff rostering software (e.g., Ernst et al. 2004), a mature scenario of applying an intelligent solution search technique in HRM can be presented.

7.3.5 Sentiment Analysis with Text Mining

Text mining (also "text analytics") offers different functionalities related to unstructured text documents (e.g., Aggarwal and Zhai 2012): Topic detection and tracking identifies topics in documents, lists text documents that are related to the same topic, and assigns new documents to already identified topics. Text summarization summarizes the content of a text document in a brief summary. Text classification classifies text documents into predefined categories. An application example of text classification is sentiment analysis: Sentiment analysis (also "opinion mining") aims at the automatic extraction of sentiments and opinions that are expressed in unstructured text documents and, thus, classifies text documents into the categories "positive sentiments" and "negative sentiments" (e.g., Liu and Zhang 2012; Pang and Lee 2008). In this way, it becomes possible to condense sentiments expressed in numerous texts, such as employer reviews on employer rating web sites. The basic intelligent techniques used to realize sentiment analysis is a combination of text preprocessing and subsequent text classification. Text preprocessing refers to the decomposition of the text into single terms ("tokenization"), the linguistic categorization of these terms ("tagging"), their reduction to the root form ("lemmatization"), and their transformation into a vector that renders the relative frequency of all identified terms ("vector space model"). These vector models can then be used as input for text classification, while support vector machines are algorithms that are frequently employed for classification. As is usual in knowledge discovery, the classification algorithm has to first be "trained" based on training documents. Thus, these training documents are first preprocessed to obtain a vector space model of each document that can be used by the algorithm to induce rules for documents expressing positive or negative sentiments or opinions (e.g., Liu and Zhang 2012). After the classification algorithm training, the documents that need to be analyzed also have to be transferred into vector space models via preprocessing before the rules are used to classify the analysis documents as expressing either positive or negative sentiments. The combination of preprocessing as an intelligent text processing technique and classification as an intelligent knowledge discovery technique allows for analyzing and summarizing sentiments expressed in documents, while text mining therewith can be uncovered as an inherently hybrid technique.

An application scenario of text mining in HRM is sentiment analysis (e.g., Strohmeier et al. 2015). Knowing sentiments of employees, managers, applicants and further HR stakeholders relating to numerous HR-relevant aspects, such as compensation ratios, career possibilities, quality of training, leadership style, work climate, etc., constitutes valuable information on the strengths and weaknesses of HRM as perceived by the major stakeholders. Such opinions and sentiments are increasingly expressed in numerous web-based documents on employer rating websites, social networks, blogs, etc. Text mining can realize the task of analyzing sentiments, as rendered in Fig. 7.5.

Initially, suitable training documents must be crawled, preprocessed and transferred into vectors that a classification algorithm can use as input to learn classification rules that render typical vectors for the respective sentiment classes, such as "sentiments staffing: negative" or "sentiments compensation: positive". These rules are then applied on preprocessed analysis documents to classify them into a specific class. These individual results can be aggregated in a bar diagram that shows positive and negative ratings. If text documents for several companies c1, c2, … are analyzed, results can also be compared. Moreover, depending on existing text documents, more detailed and refined information can be gained. For instance, the refined knowledge on how the compensation policy (i.e., types, amount and structure of compensation) is judged by employees and applicants will offer valuable insights into strengths and weaknesses and thus support strategic compensation decisions.

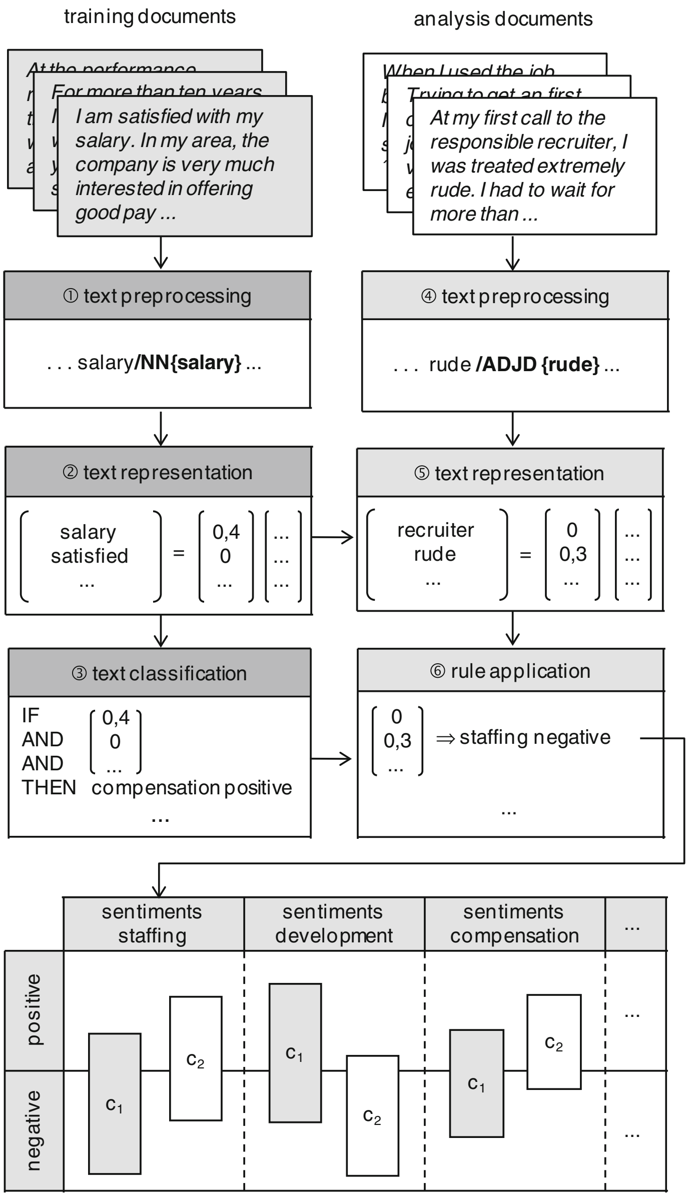

Fig. 7.5 Sentiment analysis with text mining (adopted from Strohmeier et al. 2015)

Text mining therewith fits with the task of the analysis of HR-related sentiments expressed in unstructured text data. Compared to a manual realization, central improvements relate to efficiency because even a very large number of texts that are beyond manual processing can be easily analyzed; however, the individual training of the system also implies initial effort before any application. Visibly, the scenario therewith aims at supporting the information in all HR functions. Currently, there are diverse concepts and prototypes of HR sentiment analysis (e.g., Aqel and Vadera 2010; Brindha and Santhi 2012) and also pioneering commercial offers of HR software vendors. Text mining thus constitutes an intelligent technique that is on the verge of application in HRM.

7.3.6 Résumé Data Acquisition with Information Extraction

Information extraction aims at automatically finding and extracting, structured information from unstructured or semi-structured text (e.g., Jiang 2012; Sarawagi 2008). The fundamental tasks of information extraction are named entity recognition and relation extraction. A named entity is a token (i.e., a character or a group of characters) or a sequence of tokens that denotes a real world entity, such as a certain person, organization or qualification. Relations span two or more entities related in a specific way, such as "is employee of." Information extraction requires several text preprocessing steps, such as tokenization, part of speech tagging and lemmatization (see Sect. 3.5). There are several methods to perform information extraction that can be roughly categorized into rule-based and statistical methods (e.g., Jiang 2012; Sarawagi 2008). Rule-based extraction methods rely on a (manually defined or automatically learnt) set of rules with hard predicates, while statistical methods are based on a weighted sum of predicates to identify and extract entities and entity relationships. Information extraction enables the automatic identification and extraction of named entities and entity relations in a text and therewith constitutes a particular category of intelligent language technique focusing on text processing.

An application scenario in HRM is résumé data acquisition (also "CV parsing"). Within the recruiting process, organizations regularly receive a plethora of résumés in terms of text documents. These text documents then have to be processed by humans, i.e., the relevant information has to be manually extracted and entered into HR information systems to continue the recruiting process. Information extraction aims at automating this process by an automatic identification and extraction of relevant information from the résumés of job applicants, such as name, address, job titles, work periods, names of previous organizations, qualifications, etc., to provide and process this information in HR information systems (e.g., Kaczmarek et al. 2005; Karamatli and Akyokus 2010; Sen et al. 2012; Yu et al. 2005). Résumés are usually semi-structured text documents providing information in different blocks, such as personal information, educational information, work experience, etc. Hence, instead of searching the whole text, structuring the document into the respective blocks of information eases the automatic identification and extraction of the respective entities (e.g., Sen et al. 2012; Yu et al. 2005). For example, the entity "candidate name" can be found within the personal information block, whereas entities of qualifications can be found within the educational information block. Because résumés are provided in diverse text data formats, such as pdf, txt, etc., résumé information extraction should be able to handle different formats. The identification of a specific single entity can then be performed, for example, with rule-based methods where the rule optionally captures the context before the start and after the end of an entity and matches the tokens in the entity. Identifying a person's degree from university can hence be based, for example, on rules capturing the string "university" around "master" or "bachelor" within the educational information block. Résumé information extraction might also incorporate knowledge representation techniques, such as ontologies (see Sect. 3.3), to consider semantic aspects in information extraction (e.g., Çelik and Elçi 2013), therewith constituting an improved hybrid approach. Résumé information extraction usually provides the extracted information in diverse conventional formats, such as HR-XML, XML or JSON, which can be easily imported into HR information systems, such as recruiting systems.

Résumé data acquisition with information extraction evidently fits with the HR task of ascertaining résumé data from text documents and entering them into HR information systems. It automates the time consuming manual ascertainment by humans, including reading résumés, extracting relevant data and entering them into respective HR information systems. Therefore, résumé processing with information extraction evidently aims at automating staffing. Central improvements are the increased speed of further processing of applicant data, offering the potential to decrease respective costs. Résumé data acquisition with information extraction shows a high level of maturity because diverse domain specific systems have been offered by various vendors for several years.

7.3.7 Employee Self-service with Interactive Voice Response

Interactive voice response (IVR) aims at the interaction of humans and computers via voice. Such voice-based interactions can be realized via direct voice contact of the human and the computer or mediated voice contact via telephone or networks, such as the web. Basic intelligent technologies that underlie IVR are automated speech recognition and automated speech synthesis (e.g., Benesty et al. 2008). Automated speech recognition (also "speech to text [STT]") aims at the conversion of spoken language into machine-readable strings. The speech recognition process comprises different steps (Deng and Li 2013; Gulzar et al. 2014): Initially the human speech signal has to be received and stored in an audio file. Using differing extraction algorithms, typical features of speech signals are extracted and transformed into mathematical models of the signal in the form of a vector. These vectors are used as input for recognition algorithms that associate the vector to text; as an example, Hidden Markov Models are frequently used for recognition (for an overview of different extraction and recognition techniques, see Gulzar et al. 2014). As a result of automated speech recognition, the speech utterance of the human user is transformed into its textual correlation, which is machine-readable and, thus, can be used by the computer for further action. To transform computer output into voice, automated speech synthesis (also "text to speech [TTS]") is employed. Automated speech synthesis is realized in different steps (Schroeter 2008): Initially, the input text document has to be preprocessed, which includes tasks such as text structure identification (e.g., number and type of sentences) or text normalization (e.g., handling of abbreviations and acronyms). A subsequent phonetic analysis prepares the speech by grapheme-to-phoneme conversion, i.e., determining the pronunciation of each word. Based on this, a prosodic analysis determines the adequate intonation, duration, and loudness, among other aspects. The still symbolic output of these analyses steps is used by speech synthesizers that actually perform the articulation. Major types of synthesizers are articulatory (the synthesizer uses a computer model of the human vocal tract and its parts to simulated articulation), formant (the synthesizer computes the waveform of the intended acoustic output) and concatenating (the synthesizer concatenates units of recorded sounds from a database).

An application scenario of interactive voice response in HRM is employee self-service (ESS). ESS aims at the technology-based shifting of HR tasks from HR professionals to employees. Basically, ESS is perceived as a concept that transfers operational tasks, such as updating personal data, changing benefits, or registering for training measures, etc., to employees, with the major objective of efficiency gains (e.g., Marler et al. 2009). Major technologies used to realize ESS are telephony- and web-based systems. Telephony-based ESS enables employees to carry out tasks remotely using mobile and fixed-net telephones. A typical application example is time bookings of employees that work outside the company within the frame of attendance management. It becomes immediately clear that IVR constitutes the basic enabling technology of telephony-based ESS. IVR enables the employee to interact with diverse HR backend systems, such as time and attendance management systems, to fulfill the respective task. Inputs, such as requests, data input, etc., can be directly made by voice, and respective outputs of the system can again be offered by voice. While telephony-based ESS arguably constitutes the main application scenario, IVR might be well used also in web-based ESS, for instance, for speech-based search of content on an HR portal or for realizing chatbots that answer HR related questions.

As an intelligent speech processing technique, IVR therewith visibly fits with the task of enabling the voice-based interaction of employees with a broader set of HR backend systems. For simpler operational HR tasks throughout the respective HR functions, it becomes possible to automate the interaction tasks of human HR professionals and, thus, to realize ESS concepts. Major improvements relate to efficiency gains, in particular cost and time savings in the HR department (e.g., Marler et al. 2009). Moreover, the permanent availability of HR services "around the clock" also constitutes an improvement. IVR has been a mature technology in HR for some time and is—with some international differences—also broadly applied.

7.4 Discussion: Potential of AI Techniques in HR Management

Against the backdrop of the task-technology fit approach, an application of AI techniques is successful if the AI techniques offer functionalities that correspond with the requirements of the HR task. The discussion of mature application scenarios could uncover that, across different technique and task categories, fitting combinations could be found. This basically underscores the assumption of the broad application potential of AI techniques in all categories of HR tasks. However, it also became very clear that these application potentials are far from being explored and, all the more, far from being practically exploited; also, not each AI technique is suitable in HR management, and not each HR task can be solved by an AI technique. While, ultimately, the fit of technique and task has to be laboriously elaborated on an individual basis, some concretizations can be made on the categorical level in the following.

Starting with knowledge discovery techniques, the above scenario of using artificial neural networks for turnover prediction reveals that this category mainly fits with the requirement of informating HR throughout the respective tasks. In particular, knowledge discovery techniques can be used to complement conventional querying approaches that yield historic-descriptive information (that describes existing phenomena) with explanative information (that gives reasons for existing phenomena) and predictive information (that predicts future phenomena) (Strohmeier and Piazza 2010). This potential of complementing existing HR information techniques is also underscored by the growing research on knowledge discovery techniques in HRM that refers to a remarkably broad portfolio of individual technique task-combinations (Strohmeier and Piazza 2013).

Combining knowledge representation and knowledge processing techniques, in the last decade of the last century, there were expectations towards establishing knowledge-based "expert systems" in HRM (e.g., Inoue 1993; Lawler and Elliot 1996). However, these expectations could not be met in practice given that expert system technology was not more broadly developed and applied. Yet, within the framework of semantic (web) technologies, knowledge-based techniques experienced a phase of revival in HRM, as also demonstrated with the application scenario of knowledge-based candidate search. The scattered research on semantic technologies in HRM mostly refers to semantic search, retrieval and matching in recruiting (mostly candidates and jobs) or development (mostly learners and courses), while explicit research reviews are missing (e.g., Ontology Outreach Advisory 2007; Janev and Vraneš 2010). Given this, the potential of knowledge discovery and processing techniques has to be determined more abstractly as fitting the task of establishing interoperability between humans and machines or between different machines that use deviating designations, therewith enabling further communication and "understanding". Evidently, this abstract potential might apply to a broad set of concrete automation as well as information tasks across all HR functions.

Solution searching techniques refer to quantifiable optimization tasks, while in HR different assignment tasks can be subsumed under this category. As exemplified with the scenario of staff rostering, assignment tasks exist mainly in staffing (assignment of employees to tasks, projects, shifts, position, units, etc.). Moreover, career and succession planning as a subcategory of development comprises the related task of assigning employees to different career positions over time. Further HR-related assignment tasks, for instance, assignment of instructors, rooms and learners in employee development, are imaginable yet not investigated thus far. For several decades, such tasks have been already addressed by optimization techniques from operations research. Yet, given that that these problems often qualify as NP-hard, they are not solvable by optimization. Solution searching techniques from AI thus constitute an important heuristic alternative for HR assignment problems (Ernst et al. 2004).

Text processing techniques correspond with the existence of a broad variety of HR-relevant text documents, such as employee mailings, application documents, references, written memos, or performance appraisals, among others, and related HR tasks. A first general potential is the automation of a broad variety of document-related operational tasks, such as searching, ranking, categorizing, extracting, comparing or summarizing text documents, among others. The scenario of automatically extracting CV data constitutes an example for this automation potential. A second general potential is in providing decision-supporting information by analyzing text documents. The scenario of sentiment analysis in web documents constitutes an example of this potential. Following a general trend in business intelligence, in this way, information based on structured data can be complemented with information based on unstructured data also in HR management (e.g., Strohmeier et al. 2015).

Finally, speech processing techniques offer the basic potential of speech-based human machine interaction as elaborated on in the scenario of interactive voice response for employee self-service. Basically, the potential of speech processing exists in situations where keyboard-operated computing is uncomfortable or difficult, such as in mobile computing.

Aiming at harnessing these potentials in the future mandatorily implies the tasks of evaluating the success potentials and developing a domain-driven application of AI techniques in HRM. Evaluating the success potential does firstly imply a thorough estimation of whether the providable functionality actually fits with HR tasks that are practically relevant. Moreover, given that HRM already disposes of a broader set of well-established techniques for a broader set of HR tasks, the intended application of an AI technique has to be compared with already existing HR techniques. Any AI technique needs to be more effective (improved results) and/or more efficient (less implementation effort) than the already established HR techniques; otherwise, an application is useless. For example, the application of neural networks to predict employee turnover might achieve valid results in predicting the probability of employees leaving the organization. If, however, established techniques, such as simple interviews of employees and line managers, deliver the same or even improved results, an application of an ANN is not useful. In this way, AI techniques not only need to fit with HR task requirements but also have to outperform the existing techniques. Developing a domain-driven application constitutes a second necessary step. Just providing the "pure" AI technique and expecting that HR professionals adjust the technique to their needs and then utilize it does not usually work. The adaption of any AI technique to a practical HR task constitutes a voluminous and challenging task sui generis that requires both deep HR knowledge and deep AI knowledge. An excellent possibility to realize this is to directly embed AI functionality in domain-specific HR information systems (Strohmeier and Piazza 2013). This allows HR professionals to apply the AI technique within their familiar domain context without having sophisticated technical and/or methodical AI skills. Providing such "custom-fit" HR applications constitutes a prominent method of harnessing thus far unexploited potentials of AI techniques in a way that is actually accepted and, therefore, actually creates value for HRM.

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