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Exploring the Black Box of Machine Learning in Human Resource Management

An HR Perspective on the Consequences for HR professionals

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Abstract

From a theoretic point of view, it can be argued that machine learning applications can do the same things as HR professionals can but only better and faster. This paper uses a Delphi study to investigate how machine learning could influence the function of HR professionals. Consequences for HR professionals in terms of responsibilities, tasks, value creation and competencies are identified. It was found that machine learning, alone, does not face HR professionals with an existential threat. The interaction between HR professionals and line and top management holds that the HR professional still has a surplus over machine learning applications. Machine learning, alone, thus supports HR professionals to become a true business partner and provides them with accurate and reliable advice. However, predicting the future is hard and technological developments and possibilities are unprecedented. Therefore, this paper must be seen as a starting point for further research.

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Keywords
HR Function, HR Professional, Machine Learning, HRML, Human Resource Machine Learning, Human-Automation Interaction, Human Resource Management, Delphi Study, HRA, HR Analytics

Introduction

The main goal of Human Resource Management (HRM) is to increase the organizational performance by influencing employee behaviours and attitudes while taking into account contextual and situational factors (Beer, Spector, Lawrence, Mills & Walton, 1984; Strohmeier & Piazza, 2015; Looise, 2016). Attention for the contextual factors has grown since research could not provide universal laws that are effective under any given circumstance (Wall & Wood, 2005; Beer, Boselie & Brewster, 2015; Looise, 2016). A universalistic approach in HRM does not provide solid answers regarding the strength and direction of correlations since different "organizations are confronted with different environmental constraints" (Paauwe & Boselie, 2003, p. 59). HR professionals add value to organizations when they incorporate those environmental constraints and "bring it into everything they do" (Ulrich, Brockbank, Younger & Ulrich, 2012, p. 7).

HR professionals are struggling with creating value for the organization and every now and then an article with a harsh title such as "Why we hate HR" is being published. Marchington (2015) states that it seems as if HRM is in a constant search of legitimacy. Nevertheless, not only HR professionals are responsible for their – alleged – lack of value creation as line and top management are also important actors. Valverde (2001, as cited in Valverde, Ryan & Soler, 2006) defines the HR function as "all managerial actions carried out at any level regarding the organisation of work and the entry, development and exit of people in the organisation so that their competencies are used at their best in order to achieve corporate objectives" (p. 19). HR are professionals are faced with considerable ambiguity because of this shared responsibility between themselves, top and line management (Legge, 1995); HR professionals have HRM responsibilities but do not hold the hierarchical authority. This implies that HR professionals can be seen as internal consultants for workforce related topics who add value by advising line and top management.

By advising line and top management, HR professionals aim to "better justify, prioritize and [eventually] improve HR decisions" in organizations (Ulrich & Dulebohn, 2015, p. 202). Organizations have started to use HR analytics to make business decisions based on or supported by data. Modern day organization can use enormous amounts of data to their advantage. Exemplary is that ninety percent of all available data has been created in the past two years and "large amounts of data exist on virtually any topic of interest to a business" (Baesens, 2014; McAfee & Brynjolfsson, 2012, p. 63). This type of data is referred to as big data. Big data is big in volume, high in velocity, diverse in variety, exhaustive in scope, finegrained in resolution, relational in nature, and flexible (McAfee & Brynjolfsson, 2012; Kitchin, 2014, as cited in Strong, 2015). Big data is, thus, more deep and broad than 'regular' data (Strong, 2015; Yeomans, 2015). Furthermore, new technology allows for digitalization of traditionally offline sources like sentiments and emotions, speech, and interactions and relationships (Strong, 2015). Businesses possess rich information about customers and employees but also about their environment, competitors and the labour market. Exploring and utilizing all this data in HRM can help HR advice to go from whims to science (Ulrich & Dulebohn, 2015).

Using data to make organizational decisions is referred to as data-driven decision-making and can lead to better organizational performance. While there has not been a lot of research done to data-driven decision-making, Brynjolfsson, Hitt and Kim (2011) claim to have found a positive causal relationship between data-driven decision-making and organizational output and productivity. This positive relationship can be explained by the fact that humans have difficulty to cope with complexity, huge amounts of information, high time pressure and simultaneous choices (Milkman, Chugh & Bazerman, 2009). To reduce the complexity, humans are inclined to take short cuts – and fall back on old behaviour and assumptions – which leads to bias and error (Miller, 1956; Kahneman & Frederick, 2005; Maule, 2010). Computers have the upper hand over humans here, since computers have almost unlimited processing power and are, in essence, not prone to bias and subjectivity (Frey & Osborne, 2013) which means that they have no reason to reduce complexity. Moreover, Frey and Osborne (2013) describe how machine learning algorithms not only allows computers to perform routine tasks, but how the algorithms can also substitute for non-routine cognitive tasks. Until recently humans were needed to perform those tasks (Frey & Osborne, 2013), machine learning algorithms could thus take over work from humans.

Machine learning is seen as the process of performing tasks by looking at historic data and from that draw generalized conclusions to respond to new situations. At the very core, machine learning is a "branch of artificial intelligence employing pattern recognition software that analyses vast amounts of data to predict … behaviour" (Mena, 2011, p. 1). The ultimate goal of machine learning is to transform apparently dissimilar problems to a set of relatively similar sorts of problems after which the problem can be solved using various algorithms and to – ultimately – generalize the algorithm to examples beyond those in the training set (Smola & Vishwanathan, 2008; Domingos, 2012; Frey & Osborn, 2013). In other words, machine learning algorithms continuously learn from context specific historical data and make future predictions with high internal validity and can autonomously perform routine and non-routine tasks. In many ways then, machine learning is not that dissimilar from human learning, in fact

Carbonell, Michalski and Mitchell (1983) argue that it shows remarkable similarities. Simon (1983) elaborates on learning – be it machine or human – by pointing out that it is “any change in a system that allows it [the system] to perform better the second time on repetition of the same task or on other tasks drawn from the same population” (p. 28). Computers do this by generalizing from examples and figure out how to perform tasks by learning from the huge amount of data available (Mena, 2011; Domingos, 2012). Without machine learning algorithms these tasks could not be performed, as manual programming those tasks would prove inefficient (Simon, 1983). Simultaneously, machine learning applications have benefitted from the rise of big data making them accessible to more organizations (Frey & Osborne, 2013).

The science of machine learning is translated to business applications in numerous ways which influences business models and employees. Marketing, risk management, logistics, legal departments, finance departments, health care and even education have started to use machine learning applications (Baesens, 2014; Frey & Osborne, 2013). Big data and machine learning have the potential to transform virtually any business (McAfee & Brynjolfsson, 2012; Yeomans, 2015) and machine learning is “likely to change the nature of work across a wide range of industries and occupations” (Frey & Osborne, 2013, p. 17). However, unlike in other business domains, Human Resource Machine Learning (HRML) is not – yet – commercially ready.

Machine learning can, in theory, help us moving further away from the universalistic paradigm in HR. When HR and business data is combined with big data (e.g. information on competitors, the labour market, etc.) it allows for the creation of context specific HR models that have a high internal validity. In plain language, HRML gives better, individualized and tailor-made HR advice than HR professionals ever could give. Several researchers have already investigated HRML. Examples include, among others, (1) how to reduce selection criteria for hiring managers, (2) to predict turnover intentions of employees, (3) extract information from resumes and motivation letters, or (4) to improve employee selection (Wang, Li & Hu, 2014; Fan, Fan, Chan & Chang, 2012; Kaczmarek, Kowalkiewicz & Piskorski, 2005; Chien & Chen, 2008). These examples show how HRML can be used to improve HR outcomes. Therefore, it is the working proposition of this paper that HRML increases the quality of HR advice.

The question then of course arises if we still need HR professionals when HRML can perform routine and non-routine tasks and can give context specific HR advice with high internal validity. Will HRML empower line and top management to do HR without HR professionals? Or will HR professionals remain to play an important role within HRM? To investigate this, the current research will not investigate the broad HR function as defined by Valverde. Instead, this paper exclusively focusses on HR professionals in the HR department who are in direct contact with line management. Until now, machine learning research in an HR context has been done from a technological feasibility point of view (for an overview see Strohmeier & Piazza, 2015). Consequences of HRML for the function of HR professionals have not been thoroughly investigated, in many ways machine learning is still a black box to HRM. This paper aims to explore that black box. More specifically, the research question in this paper is: How could machine learning influence the function of HR professionals?

Theoretical framework

It is important to understand the history of HRM before predictions about the future can be made. Therefore, the first part of this chapter will start of by delineating the history of HRM and indicate how these developments have influenced the function of HR professionals. The second part of this chapter will provide insights on how the function of todays effective HR professionals looks like. Finally, this chapter concludes by diving deeper into the machine learning literature and discuss how these developments influence jobs in general and by extension the function of HR professionals.

Broad developments in HR: a historical perspective

The genesis of HR can be traced back to the American labour problems when working conditions were extremely poor which resulted in strikes, high job turnover en poor work efforts (Kaufman, 2014). In the beginning of the twentieth century personnel departments first appeared (Kaufman, 2014; DeNisi, Wilson & Biterman, 2014) that aimed to improve “worker relations by properly handling employee grievances, discharges, safety and other employee issues” (DeNisi et al., 2014, p. 219). DeNisi et al. (2014) describe how personnel management was mostly an administrative function “to keep out the unions” (p. 219). Scientific management at that time was the dominant management paradigm which implies: standardized tasks and motivation through performance pay, but little attention to the cognitive or physical quality of a job (Weisbord, 2004; Grant & Parker, 2009; Kaufman, 2014; DeNisi et al., 2014). Mayo’s Hawthorn studies changed this as companies started to link happy and satisfied employees to increased productivity (Kaufman, 2014; DeNisi, 2014) and organizational performance (Kaufman, 2014). Despite this, personnel management was still seen “as a necessary evil rather than as valued contributor” (DeNisi, 2014, p. 220). The rebrand into HRM gave the field “an updated, broader and more progressive image” which illustrated the newfound believe that human resources can make all the difference in achieving competitive advantage, consequently, academic and managerial attention for HR grew (Kaufman, 2014, p. 207; Storey, 1995; Legge, 1995).

The evolving HR professional: HR roles and competencies

HR professionals had to change to deliver the promise of HR as source of competitive advantage. To grasp these changes, it is useful to look at competencies that HR professionals have. Boselie and Paauwe (2005) detect a shift from focussing on "different HR roles and subsequent shifts in it… [towards] a more empirically based trend, which tries to establish the necessary competencies on the basis of the demands of the main stakeholders" (p. 551).

Brief historical overview of HR roles

The majority of the earlier empirical work, however, did focus on shifts in HR roles. These studies show an evolution towards a more general business manager role that happens to have HR knowledge and responsibilities. Tyson (1987) observed the changing nature of HR as one of the first and distinguishes between the clerk of works model, the contract manager model and the architect model. HR professionals, here, are mainly focussed on administrative and trade union issues, however HR professionals were also expected to add to business success through HR interventions (Tyson, 1987). Schuler (1990) explicitly stressed that the HR professional should be seen more as a general manager. He believed that strategy formulation, consultancy skills, and change management competencies were important next to the administrative work (Schuler, 1990). Carroll (1991) builds upon Schuler's notion and argues that much of the operational HR tasks should be distributed to line management so that HR can focus on becoming an HR expert, provider of personnel services, policy formulators and innovators for business problems. This shift towards decentralization of the HR function – which still characterizes the HR function today and faces HR professionals with considerable ambiguity (Legge, 1995) – provided HR professionals with more time to contribute to business success. In practice, however, HR professionals were and are mostly busy with operational tasks and providing service to line management while strategic decision making is reserved for top management (Valverde et al., 2006; Woering & Van Dartel, 2014).

The first round of Ulrich's Human Resource Competency Studies (1997)

Despite the extra time and the considerable attention for Strategic HRM (Paauwe & Boselie, 2003), it remained unclear how HR professionals could or were allowed to add value. Ulrich's seminal work offered four "templates to guide its focus, roles and structure so that HR professionals could become 'HR champions'", consequently, many HR functions were realigned according Ulrich's typology of effective HR professionals (Guest & Bos-Nehles, 2013, p. 93). Ulrich (1997) advocates for four HR roles: the administrative expert, who seeks to deliver the most efficient possible processes throughout the HR value chain, the employee champion, who primarily is focused on increasing employee commitment, the change agent, who makes sure the organization is capable of going through changes needed to face business challenges, and the strategic partner who seeks to align the HR strategy with the organization's strategy. HR can add value to stakeholders when all four roles are being addressed in an organization and when HR professionals understand what delivers value to customers and align HR practices to these value drivers (i.e. adopting an outside-in approach) (Ulrich, 1997).

In later years the work of Ulrich continued to develop incrementally and delivered more granular information about HR competencies and roles, however the underlying assumptions (the outside-in value delivery) have not changed fundamentally (Pol, 2011). In the following paragraph, the state of the art insights in the function of HR professionals are given.

The seventh round of Ulrich's Human Resource Competency Studies (2015)

Two fundamental roles of Ulrich's work are the strategic positioner and the credible activist (The RBL Group, 2015), these roles can be seen as the most important roles – together with the newly added paradox navigator – of effective HR professionals as they appear in the last five rounds of the HRCS. Ulrich and his colleagues found three roles that are labelled as strategic enablers and three roles that are seen as foundational enablers (The RBL Group, 2015).

HR role: The Strategic Positioner

HR professionals who act as strategic positioner must understand the basics of finance, marketing, strategy and operations. HR professionals must also understand how contextual trends (e.g. technology, economy and politics) influence the organizational strategy. Furthermore, they must be able to link the contextual trends with stakeholders' interests and internal processes. In addition to all this, HR professionals must know to position in HR and the HR strategy in this spectrum. This has been referred to, for many years already, as the outside-in perspective by Ulrich and colleagues.

HR role: The Credible Activist

The credible activist is an HR professional that builds trustful relationships with business partners in the organization. However, the word activist also implies something else. Ulrich argues that HR professionals must have an opinion or a point of view about business challenges and opportunities (The RBL Group, 2015). HR professionals must simultaneously build trusted relationships with the people they work with in order to have an influence on these business challenges and opportunities. This also implies that when HR professionals see irrational, emotional, greedy or vindictive behaviour in organizations they must act upon this – after all he or she is an activist. They will be able to do so because they have invested in building trusted relationships, and acting upon such behaviour then benefits the organization as a whole.

HR role: The Paradox Navigator

In the latest version of the HRCS Ulrich and his colleagues add an important role: the paradox navigator. Organizations have a constant need for agility and change. This, however, creates a tension from which HR professionals must be able to create value (The RBL Group, 2015). This paradox can refer to the tension between strategic vs. operational goals, local vs. global orientation, or internal vs. external focus. Ulrich argues that both parts of the apparent paradox are necessary for organisations that want to be successful (The RBL Group, 2015). HR professionals must be able to create value from this paradox by navigating line and top management through both sides of the paradox (The RBL Group, 2015). For instance, most organizations have strategic plans that are partly aligned with the goals that individual departments pursue. HR professionals must make sure that both the short-term goals of the individual department and the long-term goals of the organization are being managed simultaneously. Another example: why would a local manager in a random country put effort in educating a management trainee from the Chinese department of the organization? HR professionals, as consultants, must manage this constant paradox and to do this effectively they must use their abilities as a strategic partner and as credible activist. It is the first time that Ulrich and his colleagues make the explicit connection between HR professionals as strategic positioners (direction) and HR professionals as credible activists (individual action). And this makes sense, because “if you have individual actions without direction it is random, if you have direction without action its fantasy” (The RBL Group, 2015, n.p.).

Three HR roles: Strategic Enablers

Ulrich and his colleagues identified three HR-roles that they refer to as strategic enablers (The RBL Group, 2015). Firstly, there is the culture & change champion. HR professionals must simultaneously manage change and culture within organizations. Ulrich argues that management of change without culture management is not sustainable, he foresees an important role for HR professionals here (The RBL Group, 2015). Secondly, HR professionals must act as human capital curators. HR professionals must not only make sure that technical talent in marketing, finance, strategy and operation is attracted and developed, they must also develop leadership in the organization and have to make sure to give talent challenging expectation goals (The RBL Group, 2015). Ulrich states that you have to care for talent much like a museum curator cares for the art. Talent management is thus an important task for HR professionals. Finally, as total rewards stewards HR professionals have to build a reward system that builds positive accountability in such a way that it linked to a fair economic and non-economic consequence that drive the organization in the 'right' direction (The RBL Group, 2015). With this he means that not only monetary rewards are important, HR professionals must also ensure that line management has true attention for their employees and praise them when possible. Again developing leadership in the organizations appears to be important.

Three HR roles: Foundational Enablers

The latest round of the HRCS also contains three foundational enablers. As compliance managers, HR professionals make sure that the day-to-day activities in HR are being done appropriately. Both from the perspective of the employer as from the perspective of the employees. The basic things have to be done well which grants HR the permission to work more strategically and to seize a spot in the boardroom (The RBL Group, 2015). Second, HR professionals must now know about statistics. As analytics designer and interpreter is a newly added role to the framework. HR professionals must be able to link workforce data to business data in order to make decisions that have an impact (The RBL Group, 2015; Ulrich & Dulebohn, 2015). Technology can be applied to all major HR topics. The outside technology (e.g. LinkedIn or Facebook) is as important as the HRIT systems. HR professionals must, as technology & media integrators, know what is possible from a technological point of view. Technology changes the way that work is being done in or outside the company, managing the out- and inside technology secure that employees can work how, when and where they want to (The RBL Group, 2015).

Thirty years of research to the function of the HR professional: where are we now and where will we go?

Research has identified competencies and roles of HR professionals. Over the years HR professionals have partially moved away from their highly administrative role (i.e. being a necessary evil) towards being a more strategic contributor. Ulrich states that their data shows that the bar has been raised for HR professionals throughout the consecutive rounds of the HRCS (The RBL Group, 2015a); this points out the fact that HR professionals today have more knowledge and skills than their colleagues thirty years ago. Undoubtedly, this can be linked back towards HR professionals' development towards a more general business manager role (e.g. see Tyson, 1987; Schuler, 1991). This business manager role is still important today (e.g. see Ulrich and colleagues) as HR professionals must understand the basics of the business, (e.g. marketing, finance and operations), however Ulrich's work also shows that specific HR responsibilities have gained importance again emphasizing the unique position that HR has as an internal consultant for both the employer and the employees. HR professionals still have administrative and operational tasks but there is also considerably more attention for strategic decision making, delivering services and support to line management, organization development, and high level HRM (speciality) tasks (Valverde et al., 2006; Woering & Van Dartel, 2014). HR professionals who act with their customers (both internal as external) as starting point can deliver true value to organizations. This is what Ulrich and colleagues call the outside-in approach and what has been the underlying research principle for investigating what effective HR professionals do, how they add value and what competencies they need in order to do so.

Unfortunately, in today's fast changing world, what was right yesterday will not be right tomorrow. The biggest macroeconomic trend that will influence the function of HR professionals in the future will undoubtedly be technology. As discussed earlier, there has been little research done to how machine learning will influence the function of HR professionals – or technology in general for that matter. In the remainder of the theoretical framework, the concept of machine learning will be elaborated on and it is explored how machine learning influence jobs in general (as no specific HR research exists on this matter).

Machine learning and the consequences it holds for jobs

Machine learning as a subfield of artificial intelligence

Earlier, machine learning was conceptualized as algorithms that autonomously learns from context specific historical data and based on that make future predictions with high internal validity and autonomously perform routine and non-routine tasks. Machine learning can be seen as a branch of artificial intelligence (AI) which at the core uses advanced pattern recognition software to "adapt to new circumstances and to detect and extrapolate patterns" (Mena, 2011, Strohmeier & Piazza, 2015; Russell & Norvig, 2014, p. 2). In theory, machine learning could detect and extrapolate patterns in HR and business data and then provide line and top management with real-time and reliable HR advice without interference of an HR professional. In a future where machine learning algorithms enter the arena, the tasks that HR professionals, then, perform, how they create value and what competencies they need might change considerably. Moreover, a valid question indeed is: Can we do HR without HR professionals in the future? And who will be responsible for HR?

The prospects of AI in HR

AI is a relatively new field of science with a lot of different subfields. The general potential of AI in HR was nicely described by Strohmeier and Piazza (2015), who link task requirements to AI functionality in six HR tasks. Figure 1 shows which AI techniques can be used to perform the six selected HR tasks (i.e. strategic workforce planning or staff rostering). The presented AI techniques are operationally ready rather than uncertain futuristic scenarios (Strohmeier & Piazza, 2015). The synergy of the combined AI subfields – and other non-AI techniques – is likely to have the greatest impact on HR professionals' jobs. Especially if AI techniques can directly communicate with and respond to employee and line or top management questions autonomously. And while the individual AI techniques might be technically ready, a full AIHR-system is nowhere near from being commercially ready.

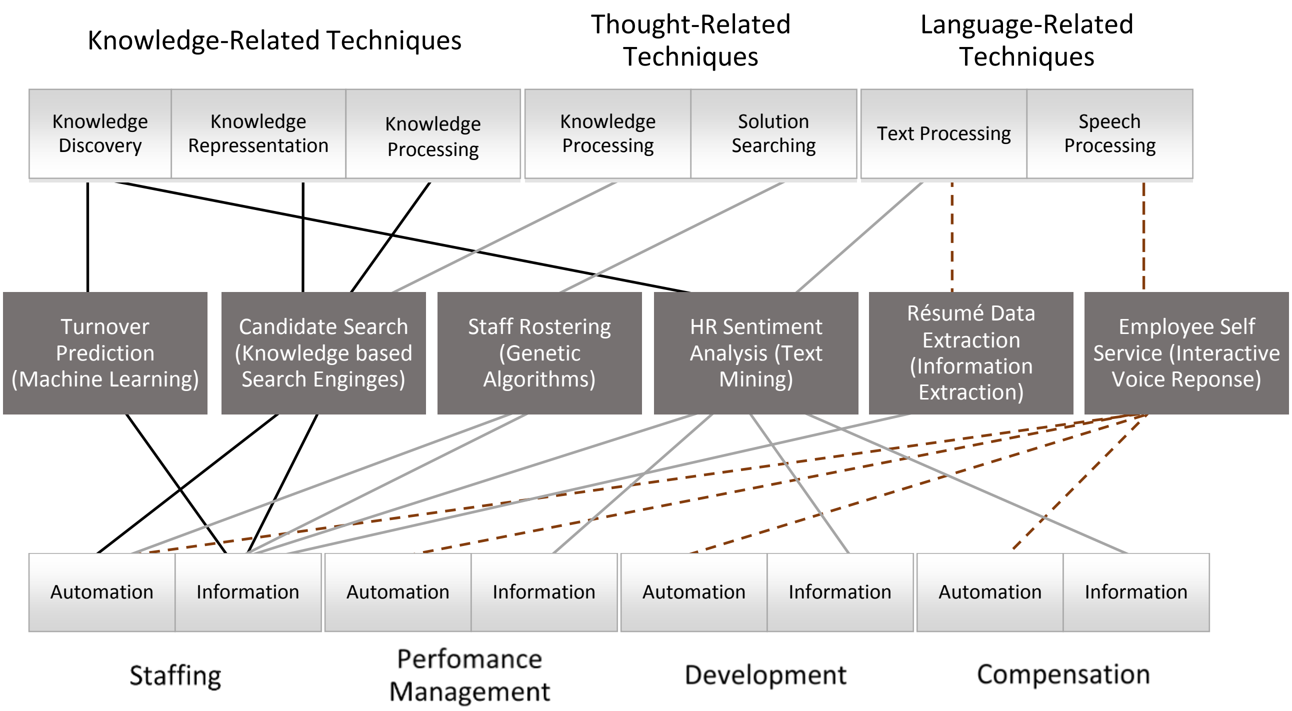

***Figure 1** - Application of AI techniques in HR Management (Retrieved from Strohmeier & Piazza, 2015)*

Machine Learning and its influence on jobs

Machine learning is the most developed branch of AI, or as technology journalist Kosner (2013) coins it: machine learning is the part of AI that actually works. With this he means that machine learning applications are already being applied in organizations. This is because machine learning algorithms are "extraordinarily good at pattern recognition within their frames" – their programmed purpose (Brynjolfsson & McAfee, 2014, p. 193). This particular attribute was used by Frey and Osborn (2013) to determine the susceptibility of 702 professions to computerisation. Senior HR professionals here scored low on the susceptibility index and HR professionals responsible for operational tasks scored average on that index. Frey and Osborne, however, investigated how susceptible entire occupations are to computerisation. Arntz, Gregory and Zierahn (2016) argue that it makes much more sense to look at individual tasks. So while the function of HR professionals as a whole might not be susceptible to computerisation, various individual tasks could be highly susceptible to computerisation. Strohmeier and Piazza (2015) explain that fitting combinations of machine learning and other AI techniques can be found for all categories of HR tasks (e.g. the categorization that Valverde, Ryan & Soler (2006) use). However, as already concluded by Frey and Osborne (2013), not all tasks within those categories can be fully computerized (Strohmeire & Piazza, 2015).

Criticism on the macro perspective of ‘threat to computerization’ occupation studies

Frey and Osborne’s prediction that 47% of all American jobs are at risk of being computerized is an overestimation according to Arntz et al. (2016). Instead of taking the Frey and Osborn occupation-based approached, Arntz et al. (2016) take a task-based approach because it cannot be assumed that jobs and task structures between and even within countries are the same. Consequently, they find that only nine percent of all jobs in the OECD countries is at risk of being computerized. What can we learn from both studies? The Frey and Osborne study gives a prediction – overestimated or not – whether a complete occupation can be computerized. It provides us with no insights if and to what extent parts of an occupation can be computerized. Occupations that scored low on the Frey and Osborne-index might be more prone to computerization than one would expect. Despite taking a task-based approach, the Arntz et al. study also does not elaborate on which parts of occupations can be computerized as they still give a susceptibility to computerization prediction for entire occupations. However, computerization “is not only a matter of either automating a task entirely or not, but to decide on the extent of automating it” (Save & Feuerberg, 2012, p. 43). Therefore, it makes more sense to investigate occupations in-depth instead of taking a macro perspective.

Human-automation interaction – humans will remain valuable

Ten levels of automation were distinguished in the seminal work of Sheridan and Verplank (1978) suggesting that a big variety of human-automation interactions are possible. Parasuraman, Sheridan and Wickens (2000) argue that this human-automation interaction varies depending on the automation function (information acquisition, information analysis, decision selection and action implementation). In later taxonomies (e.g. Save & Feuerberg, 2012), the different human-automation interactions were specified further and updated to new technological possibilities. Striking to see is that, in these taxonomies, humans are only rarely completely removed from a task. So, it is likely that in the near future, some occupations might disappear, but most will probably not disappear completely.

This view is supported by Brynjolfsson and McAfee (2014) who state that humans will still play an important role in a machine learning future since the collaborations between man and machines are likely to yield the best results – or at least better than humans and machines both acting independently. While machine learning algorithms “are terrible outside their programmed purpose” (Brynjolfsson & McAfee, 2014, p. 193) the human brain, on the contrary, is exceptionally good in recognizing patterns regardless of context or situation. Lake, Salakhutdinov and Tenenbaum (2015) elaborate on this by stating that humans “can generalize [in other words: learn] successfully from just a single example” where “machine learning algorithms require tens or hundreds of examples to perform with similar accuracy” (p. 1332). In addition to this, humans can apply new knowledge in a meaningful way by using their ideation, imagination, creativity and explanatory capabilities (Brynjolfsson & McAfee, 2014; Lake et al., 2015).

Breaking through the creativity barrier – the future of machine learning?

Can it then be expected that machine learning algorithms are only useful for solving problems that can be well defined in terms of programming rules? Not per se. Recently, a subfield of machine learning called deep learning –referred to as neural networks – gained new attention for its ability to ‘think’ just as human brains. These networks consist of many simple processors which are referred to as the neurons (Schmidhuber, 2015). Similar to the human brain, these neurons constantly make new connections within their network and form “long causal chains of computational stages” (Schmidhuber, 2015, p. 86). Pratt (2015) explains how, unlike traditional machine learning algorithms, neural networks use general learning techniques instead of predetermined rules. In theory, this implies that these neural networks are not limited to their programmed purpose like traditional machine learning algorithms. Until now deep learning approaches are limited to perceptual parts of the brain (i.e. vision, hearing and speech) but Pratt (2015) argues that he believes that neural networks can “replicate the [more] cognitive functions, [as] the architectures of the perceptual and cognitive parts of the brain appear to be anatomically similar” (p. 52). It could be possible that things like creativity or innovation then find their way into the digital domain. Lake et al. (2015), for instance, were already able to let software generate new product concepts by combining existing concepts. However, these techniques are far from being commercially or even operationally ready. And even if they already were, Arntz et al. (2016) and Van den Berge and Ter Weel (2015) do not expect job destruction on a large scale because the utilisation of technology is oftentimes slow, employees adjust to technological changes within their jobs, or switch to new jobs that arise because of technology.

Machine learning and its consequences for jobs – the debate continues

Machine learning applications, as described above, have an exciting future and eventually will support employees or take over tasks from employees. Supporters and opponents of machine learning both seem to agree that machine learning algorithms will influence jobs in some way or another as it will “improve, streamline or remove processes” (Strohmeier & Piazza, 2015; Jones, 2016). There is a fiery debate whether or not machine learning can “replace human judgement or decision” (Frey & Osborne, 2013; Strohmeier & Piazza, 2015; Arntz et al., 2016; Jones, 2016). Opponents of machine learning have argued that concepts like corporate culture, employee passion and dedication, or employee potential and learning agility cannot be captured in a statistical model (Jones, 2016). Supporters of machine learning emphasize how the rise of big data has allowed for the digitalization of “what is traditionally seen as [an] offline activity” such as human sentiment and emotions or interactions and relationships between humans (Strong, 2015, p. 5). Their core assumption here is that almost everything can be measured with data. If this is true, then machine learning applications become even more valid and reliable than they already were which would, theoretically, further decrease the need for HR professionals. However, we already saw that it is highly unlikely that machine learning applications will destroy jobs at a large scale in the near future. The question that arises then is how jobs will look like in the future. Again, there is considerable debate ongoing. Some authors have argued that tasks become increasingly complex while other authors have argued that the remaining tasks are subject to some form of job austerity (Went & Kremer, 2015; Van den Berge & Ter Weel, 2015). So the scientific and professional debate is still ongoing here, more research is, therefore, needed to better understand how technology, like machine learning, will effect jobs.

Barriers for effective HRML

So it is clear that machine learning can have a big impact on employees’ jobs and by extension on HR professionals’ function. Unfortunately, HRML faces more barriers than machine learning application in other business fiels (e.g. finance, marketing). This comes down to the fact that HR data is oftentimes acquired in an obtrusive way by using questionnaires to measure concepts like employee satisfaction, commitment and engagement (three important independent variables used in HR statistical models). The problem here is that this data is measured once or twice a year while machine learning algorithms need tens or even hundreds of examples to accurately make predictions (Lake et al., 2015). Machine learning software needs new data as often as possible in order to continuously improve its advice. Obviously, it is undesirable to have employees fill in various questionnaires every week. Therefore, it is vital for the success of HRML that alternative measurements are found that substitute for traditional measurement instruments. This is what Jones (2016) refers to as 'frictionless' data collection and an example of measuring employee engagement without using surveys can be found in Fuller (2014).

Concluding remarks

In the past thirty years, scientists have studied the HR function and determined what effective HR professionals do, how they add value to the business and what competencies they need in order to do so. As was argued above, this could all change with the entrance of machine learning algorithms in the HR arena. Line and top management but also employees could be empowered to do the HR tasks themselves. With the described machine learning advancements in mind, it is highly interesting to investigate (1) who will be responsible for HR in a machine learning future, (2) what HR professionals do in such a machine learning future, (3) how HR professionals create value in a machine learning future, and (4) what competencies HR professionals need in a machine learning future.

Methodology

The Delphi study

A Delphi study was used to research how machine learning could influence the function of HR professionals. Delphi studies are, among others, a forecasting tool (Linstone & Turoff, 2002; Rowe & Wright, 1999; Landeta, 2006). In consecutive rounds experts identified the possible and probable influence of machine learning on the function of HR professionals. A Delphi study was appropriate since time and cost constraints made frequent group meetings impractical while still activating and accessing collective knowledge, thus thriving the data gathering from respondents' "subjective judgements on a collective basis" (Linstone & Turoff, 2002, p. 4).

Respondents

A diverse group of experts is required to access collective knowledge and to link and build upon that collective knowledge. Therefore, a diverse of respondents were approached to participate in the study. Eventually, 21 experts participated in the study (5 HRM (associate) professors, 2 HRM lecturers, 1 HR director, 3 HR analytics professionals, 4 HR advisors, and 5 HRIT professionals). A balanced mix of 'traditional' and 'data savvy' experts were approached which ensured that the results were not biased because of experts' (lack of) affinity with the subject.

Data collection

The research was cut up into three parts. In the first round of the data collection the experts were asked to answer four broad open questions. Two or three experts from the same university or company were simultaneously interviewed which encouraged experts to actively discuss their answers. The interviews were recorded and transcribed so that codes could be added to the transcribed text. In the second and third round of the data collection the participating experts were asked to rank the outcomes of the interviews on a seven-points Likert-scale. The online survey tool of Google was used to record the survey data.

Additional background information for the experts

Respondents in the sample had a diverse background; a lot of effort was put into providing the experts with clear and easy to understand conceptualization of machine learning and the function of HR professionals. Machine learning was conceptualized as "algorithms that continuously learn from context specific historical data and make future predictions with high accuracy and reliability and can autonomously perform routine and non-routine tasks". The function of HR professionals is explained to the experts by showing the Valverde et al. (2006) definition of the HR function and showing the experts the YouTube movie about what HR professionals do from Monash Business School (2012). In addition, the summaries of four HR machine learning studies were provided to explicitly link machine learning to HR. The interviewer ensured experts' active participation during the introduction questions.

Interview process summary

Before answering the main questions, however, experts were asked to provide an own conceptualization of machine learning and the function of 'the' HR professional. After giving these conceptualizations, the experts were shown the conceptualization of machine learning used in this study, the definition of the function of HR professionals and an introductory movie on HRM. These two introduction questions were not analysed and merely served the purpose of educating the experts on possible new knowledge and to stimulate their elaboration on the main questions. Secondly, the summaries of selected HR machine learning studies were shown to explicitly link machine learning to HR. Thirdly, the experts were asked to indicate on how they think machine learning could change the function of HR professionals. Four broad questions are posed to the experts: (1) 'can you describe how the responsibilities for performing HR tasks will change under the influence of machine learning algorithms?', (2) 'can you describe how the tasks of HR professionals will change under the influence of machine learning algorithms?', (3) 'can you describe the change in how HR professionals add value under the influence of machine learning algorithms?', and (4) 'can you describe how competencies that HR professionals need to add value will change under the influence of machine learning algorithms?' After answering these questions, the interviewer posed follow-up questions to gain more insights into the expert rationale and to possibly question or confirm their answers. Figure 2 shows the interview protocol.

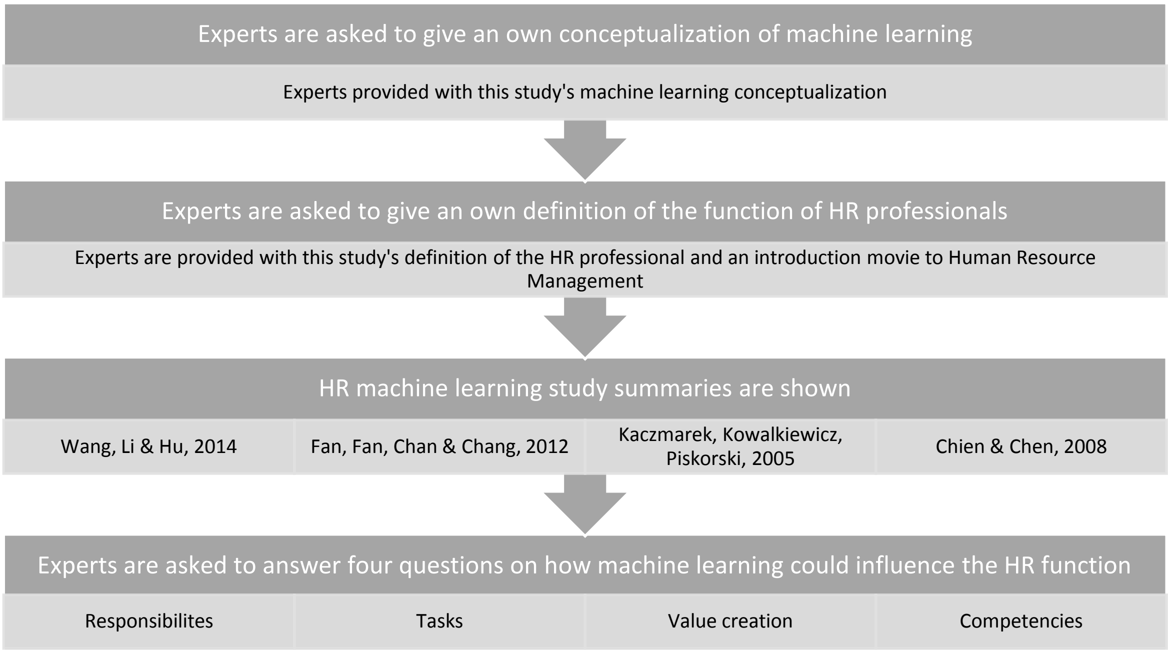

Figure 2 *- Process overview of the round one Delphi survey*

Measurement – round one

First, deductive open coding was used to label the raw data of the four broad questions from round one. The codes used here were similar to the subjects of the four questions (i.e. responsibilities, tasks, value creation, and competencies). Secondly, an inductive approach was used to further label the round one data since no additional a priori knowledge on how machine learning could change the function of HR professionals exists. Third, the raw data was reread and overlapping codes were bundled together ensuring "a valid consolidated list" (Schmidt, 1997, p. 769) for the second round of data collection. The amount of times a statement was mentioned by the experts was counted and translated into a percentage (number of repetitions divided by the maximum possible number of mentions). Eventually the percentages were sorted in a descending direction which showed a first ordering in the experts' answers.

Measurement – round two

The outcomes of the round one interviews were incorporated into a survey. Experts were then asked to rank each of the items on the survey from least probable (1) to most probable (7). A seven-points scale was used since Likert “advises to use as wide a scale as possible” (Allen & Seaman, 2007, p. 64). A major weakness of a Delphi study is the lack of statistical support for its conclusions. Using the non-parametric Kendall’s coefficient of concordance test (W), strengthens the conclusions drawn from ranking-type Delphi studies (Schmidt, 1997). W shows the level of agreement (i.e. correlation) within the groups (Schmidt, 1997) and looks at the sequence of the experts’ rankings. Furthermore, Kendall’s Tau (T) was calculated to compare the level of agreement between the two groups of experts and is determined by looking at the number of concordant and discordant pairs (Schmidt, 1997). Kendall’s W and T was determined for each of the four categories (responsibilities, tasks, value creation and competencies). Thresholds for Kendall’s W were given in Table 1.

Table 1 *- Interpretation of Kendall's coefficient of concordance. Retrieved from Schmidt (1997)*

W	***Interpretation***	***Confidence in ranks***
0.1	Very weak agreement	None
0.3	Weak agreement	Low
0.5	Moderate agreement	Moderate
0.7	Strong agreement	High
0.9	Unusually strong agreement	Very high

Measurement – round three

The survey from the second round of data collection (i.e. the first survey) was also used for the third round of data collection. However, when an expert’s survey one ranking (i.e. second round of data collection) was marked as an outlier, then this expert’s rationale was added to that particular survey 2 statement by checking the transcript and/or audio recordings. This was done since this expert answer had to be considered as ‘right’ instead of as an outlier (Mullen, 2003), this could also initiate a more extensive group thinking process. Furthermore, the expert’s individual ranking from the first survey, all the item means and standard deviations were also included in the round three survey. Adding statistical feedback forces the experts for “more extensive consideration” because they can compare their own ranking with other experts’ ranking and rationale (Landeta, 2006, p. 469). For the third round, the statements from the round two survey were not changed and expert agreement was calculated with Kendall’s W and T.

Results

Interviews

Twenty-one experts were interviewed during ten interviews in order to build up knowledge on how machine learning could change the function of HR professionals. The interviews revolved around four central dimensions (responsibilities, tasks, value creation, and competencies). It was observed that the experts had troubles in discussing these dimensions in isolation. Therefore, the experts' opinions had to be manually recoded to one of the four. Eventually a list with 86 statements divided over the four dimensions was constructed and used as input for the two surveys. Table 2 shows some key concepts that were mentioned most often by the experts in the interviews. Please see Appendix A for the amount of times that an individual statement was mentioned by the experts.

***Table 2** - Amount of times that predictions were mentioned in the interviews*

Dimension	***Predictions***	***#***	***%***
Responsibility	No big changes in the responsibility because the human touch remains important, machine learning only supports HR professionals.	9	43%
	The responsibility for the HR work shifts more and more to machine learning software, however never completely.	7	33%
	HRM becomes even more a shared responsibility, line management fully responsible for operational tasks, HR professionals assist in case of incidents and exceptions.	6	29%
	HR professionals will remain responsible for HR as line management won't use machine learning software themselves because they don't care about it, don't have time for it or are incapable to interpret the outcomes.	5	24%
	An HR-machine learning professional will evaluate and interpret machine learning outcomes and consult and discuss them with line management. There is no 'traditional' HR professional anymore.	4	19%
Tasks	HR professionals act as facilitators for the strategic workforce planning making sure top and line management have the right discussion on the state of the future workforce.	8	38%
	HR professionals will primarily be policy and strategy formulators since machine learning software will give the HR advice.	7	33%

	HR professionals have increasingly more attention for the long-term organizational goals and how HR can contribute to them.	6	29%
	HR professionals are more focused on talent management.	5	24%
	HR professionals coach and guide line management based on HRML data.	5	24%
Value creation	Machine learning facilitates HR professionals to deliver the promise of strategic HR.	9	43%
	Little will change in the way how HR professionals create value, the only difference is that their advice is now supported with data.	8	38%
	The added value of HR professionals in the future lies in facilitating the strategic workforce planning and aligning talent management activities to it.	8	38%
	HR professionals create more value since they are better able to prepare the organization for future workforce challenges and trends.	4	19%
	The added value of HR professionals shifts towards interpreting machine learning outcomes and consulting top and line management about it.	4	19%
Competencies	HR professionals must become more analytical.	8	38%
	HR professionals must be more data and technology minded.	7	33%
	HR professionals must be able to interpret machine learning outcomes in the specific context of an organization.	6	29%
	HR professionals must be more capable of working together interdisciplinary effectively.	5	24%
	HR professionals need to be able to think on a more abstract cognition level.	5	24%

Table 2 shines a first light on how the experts think the function of HR professionals will change because of machine learning. Only the most frequently mentioned statements are shown here, in Appendix A all statements are denoted. Statements that were mentioned only once or twice during the interviews could be perceived as being a less probable future scenario. However, during the surveys these statements could also turn out to be a probable future scenario; this is a big advantage of the Delphi as it emphasizes group learning. Lastly, it must be noted that during the interviews two camps seem to be apparent; experts that were enthusiastic and optimistic about machine learning and experts that were more reserved and pessimistic about the possibilities of machine learning.

Surveys

Sumsion (1998) recommends a response rate of at least 70 percent if the Delphi wants to maintain its rigour. From the twenty-one experts that were interviewed, fifteen took the trouble of filling in both the first and the second survey. This results in a response rate of 71 percent which meets Sumsion's advice. Whether or not the opinions of the two groups of expert (practitioners and academics) should be pooled depends on the within group level of agreement. It appears that the level of agreement deteriorates (Table 3 versus Table 8) when the experts are not appointed to either the practitioner or the academic expert group. This means that it does make sense to indeed treat the two groups of experts as separate groups. Peculiarly, the response stability over two rounds does seem to improve when pooling all expert opinions. This can, likely, be attributed to the fact that individual deviations have a less big effect when using a larger sample size (n = 15 instead of n = 9 and n = 6).

Table 3 *Survey within group response stability for the pooled expert opinions (Kendall's W)*

	Survey 1	Survey 2
Dimension	W	W
Responsibility	0.360	0.309
Tasks	0.360	0.386
Value Creation	0.345	0.345
Competencies	0.411	0.537

Consequently, the results of the first and second survey will be discussed simultaneously for each of the four dimensions where the distinction is made between practitioners and academics. It must be noted that the statements are too long to be presented in a clear manner. Therefore, just as Schmidt (1997), the statements are referred to as numbers. The numbers correspond with the full statements in Appendix A.

Responsibilities

The question posed to the experts here was how they thought that machine learning applications would change who is responsible for carrying out the work of HR professionals in a machine learning future. Statements with a high mean rank are considered to be more probable than those with a lower mean rank. Additionally, the test statistics on the bottom three rows of the table provides information about the level of agreement and the significance of the test statistics. When looking at Kendall's W it is striking to see that there is weak agreement in the practitioner expert group (W = 0.438) and weak agreement in the academic expert group (W = 0.359). Furthermore, the level of agreement deteriorates in the second survey indicating that there is more disagreement within the two expert groups. Additionally, also the level of agreement between the two expert groups is relatively low (T = 0.489) and deteriorates in the second survey (T = 0.358). The low level of agreement can be explained for by investigating the mean scores of the statements. There are quite a few statements with similar or almost similar means, small deviations in second survey lead to relative strong changes in the ordering of most important statements. The academics second survey ranking is not significant; this indicates that there is no real difference in their ordering of probable and not probable future scenarios. This is also an indication that the means of the individual statements show little variation.

Table 4 *- Ranking of statements (responsibility) for survey 1 and 2*

n = 15	Survey 1		Survey 2	
Statements	Mean ranks practitioners	Mean ranks academics	Mean ranks practitioners	Mean ranks academics
1	7.78	7.33	7.72	7.20
2	14.11	13.08	14.06	11.30
3	10.44	9.50	9.28	8.30
4	9.56	13.17	9.50	9.50
5	8.61	9.33	8.56	9.50
6	8.67	5.92	8.44	6.20
7	6.33	8.83	6.33	9.00
8	12.44	12.50	13.17	12.90
9	3.78	5.83	3.28	7.20
10	12.17	8.92	11.83	11.40
11	10.33	6.92	9.83	7.00
12	6.17	6.92	5.83	8.50
13	6.11	7.67	7.00	9.00
14	3.00	2.75	4.22	2.90
15	8.89	8.33	9.50	8.50
16	7.61	9.00	7.44	7.60
Kendall's *W*	W = 0.438	W = 0.359	W = 0.405	W = 0.256
Chi-square	X^2 = 59.085**	X^2 = 32.315*	X^2 = 54.713**	X^2 = 19.185
Kendall's *T*	0.489*		0.358	

*. Correlation is significant at the 0.01 level (two-tailed) | **. Correlation is significant at the 0.001 level (two-tailed)

Both the practitioners and the academics consistently rank statement 1 as one of the least probable scenarios. This means that the experts do not believe that machine learning will only support HR professionals by supporting their decisions with data. What are probable scenarios then according to the experts? Statements that score consistently high for both groups of experts are considered to be an option. Firstly, it is important to point out that the experts believe that operational tasks will no longer be a responsibility for HR professionals (statement

2) as a combination of machine learning, self-service apps and cloud solutions will substitute for them. What cannot be computerized – or not yet – will be the full responsibility of line management, HR professionals can be consulted in case a line manager has incidental errors or exceptions (statement 4). Second, the experts expect that a dashboard will arise that offers insights in all relevant HR data, how that HR data impacts business outcomes and comes up with several suggestions for HR interventions (statement 8). The HR professional discusses with line management what actions to undertake after which line management takes a decision. It is not believed that line management will use such a dashboard without having the possibility of discussing it with an HR professional (statement 15). The experts seem to believe that eventually two fundamental roles in organizations remain; the HR business partner and the HR analytics professional (statement 11). This holds two consequences. First the size of the HR department as a whole decrease (statement 5) and the HR(ML) analytics professional will become increasingly important (statement 10). Although for both groups of experts the referred to statements have the highest mean rankings, the results must still be interpreted with caution because of the low to moderate levels of agreement between the experts.

Tasks

The levels of agreement for the task statements are higher than for the responsibility statements. Kendall's W and T in most cases surpass the thresholds for moderate agreement between the experts. Furthermore, all test statistics have (very) significant corresponding p-values indicating that there is a true difference in the expert ranking. So it is very unlikely that the same ranking would be obtained when ranking all statements randomly. The statements with consistent high mean rankings over two rounds of survey for both groups of experts are considered as the most probable future scenarios.

Table 5 *- Ranking of statements (tasks) for survey 1 and 2*

n = 15	Survey 1		Survey 2	
Statements	Mean ranks practitioners	Mean ranks academics	Mean ranks practitioners	Mean ranks academics
1	9.39	17.83	10.25	9.63
2	13.61	13.92	13.31	9.63
3	16.72	11.42	16.13	10.75
4	20.06	18.58	18.25	17.75
5	10.00	7.58	8.06	7.00
6	12.39	11.17	12.50	11.38
7	18.50	14.58	19.19	15.88
8	20.67	19.00	21.06	18.50
9	5.56	6.75	6.81	5.75

10	14.78	7.17	15.00	5.00
11	15.00	12.92	15.38	11.13
12	15.89	17.17	16.50	15.88
13	16.94	17.00	17.44	17.50
14	12.33	8.67	13.44	12.25
15	6.17	10.83	3.31	8.63
16	7.89	6.50	8.06	7.63
17	16.33	20.25	16.38	22.00
18	8.33	5.83	8.94	6.50
19	20.39	21.75	20.56	22.75
20	15.28	19.75	14.13	18.50
21	12.22	13.58	12.38	14.13
22	8.83	9.25	9.31	12.00
23	17.11	20.08	17.38	23.38
24	21.83	17.08	21.56	18.50
25	8.39	10.58	9.19	13.00
26	13.28	17.08	13.69	18.13
27	20.11	21.67	19.81	24.88
Kendall's *W*	W = 0.379	W = 0.465	W = 0.386	W = 0.555
Chi-square	X^2 = 88.634**	X^2 = 72.596**	X^2 = 80.289**	X^2 = 57.679**
Kendall's *T*	0.532**		0.592**	

**. Correlation is significant at the 0.001 level (two-tailed)

The experts believe that machine learning will allow HR professionals to detect trends in an early stage and discuss with top and line management how to respond to these trends (statement 24). These trends can be various and not per se limited to the workforce, however most of those trends will hold consequences the workforce en thus it must be managed. Therefore, HR professionals will increasingly have attention for the long-term goals of the organization and how HR can contribute to them (statement 8). HR professionals are able to interfere with the long-term direction of the organization because they now have solid data on the impact of HR; consequently, HR professionals will need to enter the organizational political arena and lobby for more attention and investments in HR (statement 13). An important task for HR professionals will be to act as facilitators for the strategic workforce planning. They must make sure that line and top management have the right discussion in order to find out what competencies are needed in the future (given the organization strategy) and how the current workforce relates to this perspective (statement 7). The attention from HR professionals shifts more from being an administrative grey mouse towards a proper business consultant. For instance, the experts foresee more attention for tasks like coaching line management in their day-to-day operations based on HR data (statement 4), deal with resistance to change and to actively shape organizational change (statement 12), take firm stand against too much organizational change (e.g. the yearly 'strategic' reorientation) (statement 19), and have more attention for shaping an appropriate organizational culture (statement 23). These are not tasks that are new to HR professionals, but machine learning can empower HR professionals to effectively perform these tasks. The experts also believe that HR professionals should evaluate the effect of the HR interventions proposed by machine learning (statement 17) – necessary because machine learning still gives predictions based on averages. Finally, the experts do not believe in a complete rationalized organization; HR professionals will still have to take decisions based on gut feeling from time to time (statement 27). Most likely such kind of decisions are appropriate during situations where is referred to in statements 4, 12, 19, and 23.

Value creation

The levels of agreement within the groups (W) is higher for the second survey than for the first survey although the level of agreement is still only weak or nearly moderate. A possible explanation for these relative low levels of agreement are the pro and con machine learning camp that was addressed earlier. However, the rankings are significant indicating that the difference in rankings between the statements is a true difference. Furthermore, the level of agreement between the groups (T) deteriorated from a high level of consensus to a moderate level of consensus. A possible explanation for this decline in agreement are, again, the small differences in statements mean. A small variation in some of the statement means (moving from the first survey towards the second survey) could result in big changes in the level of agreement between the groups. The statements with the consecutive highest mean ranks over the two survey are reported upon as being the most probable future scenarios.

The experts believe that the added value of HR professionals increases since those HR professionals now, because of machine learning, have insights in which HR interventions truly have an impact on the organizational outcomes (statement 21). This added value will increase over time as HR machine learning advice improves over time and thus generates more and more accurate advice (statement 8). However, the experts also argue that it could be possible that the added value of the HR professional him or herself does not increase, but that line and top management only perceive HR professionals as more value adding (statement 18). This could make sense because the HR machine learning advice becomes increasingly accurate over time, however this does not hold consequences for the effectiveness of HR professional him or herself. On the other hand, machine learning will allow HR professionals to act more proactive (statement 3). HR professionals are then able to serve the needs of their customers much better, allowing them to be more effective in managing their teams and the daily operations. The experts finally believe that HR professionals (or HR business partners) add value through the execution of strategy while HRML analytics professionals add value as strategy and policy formulators (statement 4). One expert who's first survey ranking was marked as an outlier commented upon this statement. In essence the expert suggested that the clear distinction between the two roles was too harsh as the two roles will probably need each other. Consequently, the mean ranking of this item is lower in the second survey than in the first survey.

Table 6 *- Ranking of statements (value creation) for survey 1 and 2*

n = 15	Survey 1		Survey 2	
Statements	Mean ranks practitioners	Mean ranks academics	Mean ranks practitioners	Mean ranks academics
1	14.33	11.33	15.11	12.10
2	14.67	13.17	14.61	12.10
3	18.56	15.50	18.72	15.20
4	17.39	14.25	17.22	13.40
5	13.33	15.67	12.56	16.30
6	11.94	10.58	12.11	15.00
7	12.28	13.08	12.83	15.20
8	15.94	16.08	16.11	14.40
9	13.83	13.00	14.72	13.80
10	11.83	13.42	13.11	12.70
11	6.06	11.33	5.94	10.50
12	4.94	5.25	4.94	3.50
13	14.78	11.67	14.78	7.00
14	8.39	9.67	8.44	8.70
15	11.17	9.17	11.61	11.70
16	6.89	6.83	6.28	9.30
17	6.61	8.17	6.22	9.40
18	17.72	17.08	17.00	17.40
19	8.89	12.92	8.11	12.10
20	5.17	8.67	5.06	7.70
21	17.44	16.25	17.56	14.40
22	10.28	11.83	10.28	13.90
23	13.56	11.08	12.67	10.20
Kendall's *W*	W = 0.424	W = 0.297	W = 0.448	W = 0.317
Chi-square	X^2 = 84.012**	X^2 = 39.246*	X^2 = 88.686**	X^2 = 34.869*
Kendall's *T*	0.708**		0.542**	

*. Correlation is significant at the 0.05 level (two-tailed) | **. Correlation is significant at the 0.001 level (two-tailed)

Competencies

The level of agreement within the groups of experts shows a moderate level of agreement after the second survey. The level of agreement within the groups of academics increased from a low level of agreement to a moderate agreement. Despite the separation between the machine learning enthusiast and pessimists this is a fair level of agreement. The level of agreement between the groups of experts (T) increased from 0.579 to 0.704 which is a high level of agreement. So the two groups of experts in the end seem to agree on how the competencies of HR professionals could change in a machine learning future. All test statistics have significant corresponding p-values suggesting that difference in ranks is a true difference.

Table 7 *- Ranking of statements (competencies) for survey 1 and 2*

n = 15	Survey 1		Survey 2	
Statements	Mean ranks practitioners	Mean ranks academics	Mean ranks practitioners	Mean ranks academics
1	13.11	13.00	14.69	15.10
2	14.28	12.75	14.44	16.30
3	13.33	8.83	12.94	14.70
4	17.00	14.33	16.56	16.00
5	14.11	10.08	15.06	13.70
6	5.78	11.50	5.31	11.20
7	9.67	8.50	9.94	9.90
8	3.78	3.17	2.00	2.80
9	14.06	12.75	12.63	12.20
10	14.11	14.17	14.13	13.70
11	6.17	7.00	6.00	7.00
12	10.94	8.33	11.63	6.80
13	7.94	8.08	7.50	5.30
14	11.83	11.67	11.19	8.60
15	7.61	8.50	8.06	7.00
16	8.39	10.92	8.88	7.90
17	4.00	7.42	4.25	6.50
18	7.56	9.17	8.00	7.80
19	6.33	9.83	6.81	7.50
Kendall's *W*	W = 0.534	W = 0.353	W = 0.579	W = 0.574
Chi-square	X^2 = 86.434**	X^2 = 38.081*	X^2 = 83.337**	X^2 = 51.678**
Kendall's *T*	0.579**		0.704**	

*. Correlation is significant at the 0.01 level (two-tailed) | **. Correlation is significant at the 0.001 level (two-tailed)

In a future where machine learning applications enter the HR arena it is suspected that the competencies of HR professionals will change. As mentioned earlier, the experts expect that HR professionals will not have any operational or administrative tasks anymore, it is surprising to see that the experts strongly believe that HR professionals still need high levels of accuracy (statement 8). A possible explanation is that accuracy is a general important characteristic for business professionals; remembering an agreement with a co-worker, attending meetings on time or remembering to send that email to a customer. There seems to be quite some disagreement on the fact whether or not a HR professional must understand databases and know how to link them (statement 6), academics think HR professionals should be able to do this while practitioners don't think so. Academics and practitioner experts do agree on the fact that HR professionals must become more data and technology minded in a machine learning future (statement 2). They need to be able to interpret a machine learning advice in the specific context of an organization (statement 4). In order to do so, HR professionals need to understand basic statistics (statement 5) and must be able to translate this to the context of the organization (i.e. the Ulrich outside-inside approach). This requires from HR professionals that they become more analytical (statement 9) and are able to think on a more abstract level about problems (statement 3) that the organization is facing and that machine learning software could help to solve. Less changes are noticeable for the soft skills of HR professionals. Only organizational sensitivity (statement 14) and working together interdisciplinary (statement 1) make it to the top of the probable scenarios ranking. Lastly, HR professionals must combine all these competencies for maybe the biggest challenge of all: steering the strategy of the organization based on HR data (statement 10). For this HR professionals need to work together with departments, like marketing, finance and IT, they use their organizational sensitivity to navigate through the political arena and they need their analytical mind to think about abstract problems.

Observed response stability

While some authors have opted that a Delphi study should always have three or four rounds of surveys, however, there is not a universal and clear threshold for the desired number of rounds. Linstone and Turoff (2011) argue that the minimal number of rounds "should be bases on when stability in the responses is attained" (p. 1714). Table 8 and 9 shows the progression in the level of agreement within an expert group and between the expert groups. W and T are thus proxies for response stability.

It is clear that the practitioners have seemed to reach a level of response stability on the ranking of the statements (Table 8). Only small deviations are noticeable between survey one and two. Please note that response stability is something different then consensus – expert disagreement can also be a significant outomce (Linstone & Turoff, 2011). The academics, however, have not seemed to reach response stability. A possible explanation for this can be that the sample size for this group of experts is smaller. Smaller sample sizes are more prone to individual deviations than expert groups with larger sample sizes. Because of this, an additional survey would have been desirable. Time constraints, unfortunately, did not allow for an extra round of data gathering.

Table 8 *- Survey within group response stability (Kendall's W)*

Expert Group	Dimension	Survey 1	Survey 2
		W	W
Practitioners n = 9	Responsibility	0.438	0.405
	Tasks	0.379	0.386
	Value Creation	0.424	0.448
	Competencies	0.534	0.579
Academics n = 6	Responsibility	0.359	0.256
	Tasks	0.465	0.555
	Value Creation	0.297	0.317
	Competencies	0.353	0.574

In Table 9 the level of agreement between the two groups of experts is shown. Here it is clear that stability in the responses is not yet obtained. A possible explanation for the variation in T is the small variation of mean scores for statements in each of the four dimensions (despite using the seven-points Likert-scale). Large variations between two groups of experts can arise when individuals in one or both groups change their minds about different statements (e.g. see dimension Value Creation and Competencies) since Kendall's T uses a pairwise comparison. This could very well have happened here since we already saw that the academics did not yet reached response stability. Because of this an extra survey would have been desirable, but again, time constraints did not allow this.

Table 9 *- Survey between group response stability (Kendall's T)*

Dimension	Survey 1	Survey 2
	T	T
Responsibility	0.489	0.358
Tasks	0.532	0.592
Value Creation	0.708	0.542
Competencies	0.579	0.704

Discussion

Limitations

The Delphi uses experts to make predictions about the future. A relevant question then is: "Who is an expert?" While this study investigates how machine learning could change the function of HR professionals, the group of experts did not include any machine learning professionals. Machine learning professionals that were approached to participate in this study did not want to participate since they were too unfamiliar with the function of HR professionals. This limits the trust in the conclusions of this study. However, Pill (1971) suggested that the term expert should be defined in a broad manner as it can refer to anyone who makes a useful contribution. Sackman (1975, as cited in Mullen, 2003) even questions that "responses from experts will be significantly better than those from not-experts who are informed". Therefore, a lot of time was put into informing the respondents of this study through definitions, videos and clear examples.

In this research only the influence of machine learning on the function of HR professionals was investigated. However, in further research it would make sense to not look at machine learning applications in isolation. It is to be expected that the full range of technological possibilities (e.g. the full range of artificial intelligence, self-service apps, cloud solutions, Industry 4.0 et cetera) will have an even bigger impact on the function or HR professionals. This might change the conclusions drawn from this study and might show that more HR tasks could be automated or could be automated to a larger extent. On the other side, a lot of the tasks that now remain for HR professionals require inter-personal contact. Arntz et al. (2016) argue that tasks that require inter-personal contact such as persuading, influencing, negotiating or consulting "remain genuinely human even in the long run" (p. 9).

A key strength of the Delphi is its anonymity. In this study, however, the first round of data collection was not completely anonymous. Interviews were done with two or three experts simultaneously, therefore some of the respondents might know – or might think to know – who provided which statement. This has been a deliberate trade off in order to empower the respondents to elaborate on a topic in which they are informed non-experts. In addition to that, Mullen (2003) argues that only some parts of the Delphi have to be anonymous. It is not particular clear to what part of the Delphi she refers to. An educated guess would be that the surveys have to be anonymous, in this study that is also the case.

Schmidt (1997) points out that ranking type Delphi's often suffer from little distinction in the top of the rankings. This was also observed in this Delphi, this is why minor changes in individual rankings interfere rather strongly with *W* and *T*. Schmidt (1997) argues that it is therefore wise to let the experts choose ten statements, from all the statements, that they find most important. However, as Schmidt (1997) continues, this would also impose the threat that important issues are not taken into account in consecutive rounds of the Delphi. Because this is a highly explorative study this would have been undesirable. Another reason not to ask the experts to make such a top ten is because of time constraints. These time constraints were also the reason that no third survey was sent out to the experts despite that the response stability suggests that a third survey would be desirable.

Conclusion

Various papers have, in the past couple of years, discussed the susceptibility of jobs to computerization and the outcomes are diverse and oftentimes conflicting. This paper addresses that same question but adopts a micro perspective and focusses exclusively on the function of HR professionals. The most important finding of this research is that machine learning does not seem to form an existential threat for HR professionals. Line and top management will still feel the need to closely work together and discuss workforce related challenges and opportunities wit HR professionals. This holds true even when a machine learning system empowers line and top management to come to the same conclusion without the interference of an HR professional.

Machine learning can facilitate HR professionals in creating value for organizations in three ways:

- Machine learning, as an integrated part of various HRM technologies, has the potential to take over the administrative and repetitive tasks of HR professionals. This leaves HR professionals with more time to create value for the organization.
- Machine learning can make sure that HRM is taken seriously in organizations. HR decisions are backed up with data and the added value of HR cannot be denied by other departments or professionals.
- HRML will give better advice than humans alone can give, therefore it is more clear what HR interventions truly have an impact on business outcomes. The importance of working with reliable and valid advice cannot be underestimated. HR professionals benefit from this when they focus their attention on tasks like strategic HR management, organization development, strategic workforce planning or talent management. Already important tasks for HR professionals, even without HRML, but those tasks will get a revamp as they become more important.

In the theory there is not only debate whether or not machine learning can destroy jobs, but also if jobs become less or more complicated. This research shows that the jobs that remain in HR will be more complicated than before; HR professionals seem to have, because of HRML, no excuse anymore to not add value to organizations. What does this mean for HR professionals? In the end two roles within HR will be the most dominant ones: the HR business partner and the HRML professional. The two must work in close harmony as they both are necessary to successfully implement and operate HRML within companies. Competencies of the HR professionals of the future include skills like: 1) analytical capabilities, 2) knowledge of statistics, 3) interpreting machine learning advice in the organization context, 4) a high abstract thinking level, 5) organizational sensitivity, and 6) working together interdisciplinary. It is likely that not everyone in HR can live up to these expectations. But to quote Dave Ulrich: “It’s an exciting time to be in HR”.

Practical recommendations

For organizations who seek to get started with HRML a few things are important to realize. First, a well-known phrase is: “garbage in is garbage out”. Organizations must get their (HRM) data straight, this is a vital precondition for HRML. Even the best coded algorithm cannot perform wonders on a broken data warehouse. Organizations oftentimes, form my own experience, overestimate the quality and accessibility of their data. Second, it is very hard to implement something as radical as HRML when the organizations – or the HR department – is not ready for it. Therefore, it would make sense to start of modest and first experiment with HR analytics (HRA). HRA can pave the way for HRML in organizations as it, oftentimes, delivers even better advice than HRA. Thirdly, it makes sense for organizations to invest in HR professionals that already have knowledge of statistics and possess an analytical thinking style since it seems a matter of time before HRA and HRML are not seen as ‘nice to have’ but ‘need to have’. Lastly, it was argued that organizations should first start off with HRA instead of HRML. Another reason to start of with HRA is because HRML is not yet ready for a large scale business implementation. Organizations who are acquainted with HRA will benefit heavily when HRML systems are available.

Recommendations for further research

One of the biggest problems regarding HRML is the frequency with which new HRM data is available. In the theoretical framework it was already mentioned that constructs like engagement, satisfaction and commitment are only measured once or twice a year. Not enough for an algorithm to continuously improve its advice. HR data on employee performance ratings suffers from the same low ‘refresh rate’. Or what about employee career wishes or the potential of an employee to develop a certain competency? It would not be a surprise if these employee characteristics are completely unknown for organizations. To make HRML work it is necessary to find alternative measurements or proxies for those ‘obtrusive-once-a-year-survey measurements’. One could think of the case study that Fuller (2014) did on an alternative engagement measurement. Or what about developing a mini game that employees can play on the intranet of an organization that determines the extent to which an employee has the potential to develop a specific competency.

Another important line of research to pursue is the replication of this study in different contexts. Do similar groups of experts come to the same conclusions as the experts in this study? Furthermore, it is also interesting to validate this study by doing a follow-up study that uses a different group of experts, for instance machine learning professionals. Such a follow-up study would, however, require a different methodology. In this study a lot of tasks that HR professionals will and will no longer perform were identified, in a follow-up study machine learning professionals could be asked to what extent these tasks can or cannot be automated.

Lastly, an interesting and highly relevant line of research would be to not look at machine learning applications in isolation. In the theoretic framework the concept of Artificial Intelligence (AI) was briefly touched upon. The full-range of AI, and not just machine learning, could have a more radical influence on the function of HR professionals. HR professionals have surplus over machine learning because line and top management prefer to talk and discuss about the implication of an advice rather than blindly following an advice that a machine learning system shows them on a computer screen. But what if an AI system could substitute for that discussion between the HR professionals and line and top management, much like Apple’s Siri or Microsoft’s Cortana or Google’s Now?

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Appendix A – List of statements from the interviews

Responsibilities

1. I expect that, under the influence of machine learning, the responsibility for HRM will not change since the human touch remains important. Machine learning only supports HR professionals to better execute their role because their decisions are supported with data.
    - Mentioned 9 times

2. I expect that, under the influence of machine learning, simple and operational tasks are no longer a responsibility for HR professionals. The responsibility for those operational tasks will be taken over by a combination of different technological advancements like machine learning, self-service apps and cloud solutions.
    - Mentioned 2 times

3. I expect that, under the influence of machine learning, the responsibilities for HRM in smaller organizations change less than in bigger organizations because small organizations do not possess enough data to do machine learning.
    - Mentioned 4 times

4. I expect that, under the influence of machine learning, HRM becomes even more a shared responsibility of line management and HR professionals. Line management will be responsible for the operational work whilst HR professionals are the business partner that can be consulted in case of incidents and exceptions.
    - Mentioned 6 times

5. I expect that, under the influence of machine learning, the size of the entire HR department will decrease considerably, the remaining HR professionals will advise much more teams and departments than they do now.
    - Mentioned 3 times

6. I expect that, under the influence of machine learning, the responsibilities of the HR professional will shift more and more towards software like machine learning, however never completely.
    - Mentioned 7 times

7. I expect that, under the influence of machine learning, a dashboard will arise that offers insights in all relevant HR data. Notifications will provide suggestions to line management what actions to undertake. Line management then makes the decision based on their understanding of the context, there is no role for the HR professional here.
    - Mentioned 2 times

8. I expect that, under the influence of machine learning, a dashboard will arise that offers insights in all relevant HR data. Notifications will provide suggestions to HR professionals what actions to undertake. The HR professional and line management mutually discuss these suggestions; it is up to line management to take a decision.
    - Mentioned 4 times

9. I expect that, under the influence of machine learning, the responsibility for HRM will shift towards big consultancy firms (data consultants). These external consultants use data from different organizations for making their analysis. The external consultants then support line management with the implementation of their advice.
    - Mentioned 1 time

10. I expect that, under the influence of machine learning, there will be a special function that is solely working on evaluating and interpreting machine learning outcomes. This professional is in direct contact with line management to elaborate on the consequences of the machine learning advice. There is no ‘traditional’ HR professional anymore.
    - Mentioned 4 times

11. I expect that, under the influence of machine learning, eventually two fundamental HR roles in organizations remain. The HR business partner and the HR analytics professional.
    - Mentioned 4 times

12. I expect that, under the influence of machine learning, HR professionals will become functionally but not hierarchically responsible for HR decisions.
    - Mentioned 2 times

13. I expect that, under the influence of machine learning, the responsibilities for HRM do not change much because line management will not use the machine learning software themselves as they don't care about it, don't have time for it or are incapable to interpret the outcomes.
    - Mentioned 5 times

14. I expect that, under the influence of machine learning, the responsibilities for HRM do not change much because in order to collect all data we violate employees' privacy. Machine learning is then not or only partly possible.
    - Mentioned 4 times

15. I expect that, under the influence of machine learning, the responsibilities for HRM do not change much because line managers still feel the need of discussing their workforce and business problems with an HR professional.
    - Mentioned 1 time

16. I expect that, under the influence of machine learning, a digital marketplace (e.g. like Uber) will arise that will allow the organization to form project teams of self-employed professionals based on the specific competency desires of any given project. After the project has finished, the project team will dissolve. Project managers are responsible for operational HR tasks.
    - Mentioned 1 time

Tasks

1. I expect that, under the influence of machine learning, HR professionals have more monitoring tasks to check if line management implements and executes the machine learning advice properly.
    - Mentioned 2 times

2. I expect that, under the influence of machine learning, HR professionals will have a decisive vote on HRM policies and investments.
    - Mentioned 1 time

3. I expect that, under the influence of machine learning, HR professionals will be more policy and strategy formulators since most of the HR advice will be given by machine learning software.
    - Mentioned 7 times

4. I expect that, under the influence of machine learning, HR professionals will be more empowered to coach line management based on HR data.
    - Mentioned 5 times

5. I expect that, under the influence of machine learning, HR professionals will still be responsible for harder operational tasks as line management often times is unwilling or unable to perform those tasks.
    - Mentioned 4 times

6. I expect that, under the influence of machine learning, HR professionals will be more focussed on talent management.
    - Mentioned 5 times

7. I expect that, under the influence of machine learning, HR professionals will be process facilitators for the strategic workforce planning. They make sure that top and line management have the right discussion in order to find out how the workforce will look like in the future and what competencies the company will need.
    - Mentioned 8 times

8. I expect that, under the influence of machine learning, HR professionals will increasingly have attention for the long-term goals of the organization and how HR can contribute to them.
    - Mentioned 6 times

9. I expect that, under the influence of machine learning, HR professionals will not have any recruitment tasks anymore.
    - Mentioned 3 times

10. I expect that, under the influence of machine learning, HR professionals become responsible for making sure that the used data is reliable.
    - Mentioned 1 time

11. I expect that, under the influence of machine learning, HR professionals will not have administrative and repetitive tasks anymore.
    - Mentioned 7 times

12. I expect that, under the influence of machine learning, a considerable part of an HR professional's task is to deal with resistance to change and to actively shape organizational change.
    - Mentioned 6 times

13. I expect that, under the influence of machine learning, HR professionals will be much more involved in the organizational political arena. HR professionals now have solid data to actively lobby for more attention and investments in HR.
    - Mentioned 1 time

14. I expect that, under the influence of machine learning, HR professionals will set norms for the machine learning software. 'What is an acceptable absenteeism rate?' or 'when is an employee considered successful?' are examples of such norms.
    - Mentioned 1 time

15. I expect that, under the influence of machine learning, HR professionals will have more attention for the wellbeing of employees in the organization.
    - Mentioned 3 times

16. I expect that, under the influence of machine learning, the tasks of HR professionals will not change that much.
    - Mentioned 1 time

17. I expect that, under the influence of machine learning, HR professionals will evaluate the effect of the by the machine learning proposed HR interventions.
    - Mentioned 1 time

18. I expect that, under the influence of machine learning, HR professionals will not have to evaluate the effect of HR interventions because the machine learning software will do this for them.
    - Mentioned 1 time

19. I expect that, under the influence of machine learning, HR professionals must take a firm stand to prevent that the organization changes its policies and strategies too much.
    - Mentioned 2 times

20. I expect that, under the influence of machine learning, HR professionals do not have to look for errors in organizational processes anymore because machine learning applications can do this for them.
    - Mentioned 1 time

21. I expect that, under the influence machine learning, HR professionals are still necessary to interpret the results of machine learning software. Not everything can be captured in a statistical model.
    - Mentioned 5 times

22. I expect that, under the influence of machine learning, HR professionals will have to select the right data that will be entered into the machine learning software.
    - Mentioned 3 times

23. I expect that, under the influence of machine learning, HR professionals will continuously shape and build the organizational culture.
    - Mentioned 3 times

24. I expect that, under the influence of machine learning, HR professionals will be empowered to detect trends in an early stage and collaborate with top and line management to figure out how to respond to these trends.
    - Mentioned 2 times

25. I expect that, under the influence of machine learning, HR professionals will have less contact with employees.
    - Mentioned 2 times

26. I expect that, under the influence of machine learning, there will be a stronger differentiation between HR professionals. Lower educated employees perform the administrative tasks and higher educated employees perform the strategic tasks.
    - Mentioned 1 time

27. I expect that, under the influence of machine learning, HR professionals from time to time still have to take decisions based on gut feeling.
    - Mentioned 3 times

Value creation

1. I expect that, under the influence of machine learning, HR professionals will have more time to add value to the organization.
    - Mentioned 4 times

2. I expect that, under the influence of machine learning, HR professionals will have more attention for the needs of their customers.
    - Mentioned 2 times

3. I expect that, under the influence of machine learning, HR professionals will act more proactive based on their data.
    - Mentioned 3 times

4. I expect that, under the influence of machine learning, HR professionals will add value through the execution of the strategy while HR analytics professionals add value as strategy and policy formulators.
    - Mentioned 1 time

5. I expect that, under the influence of machine learning, HR professionals will have a more signalling task in noticing unusual deviations in employee behaviour.
    - Mentioned 2 times

6. I expect that, under the influence of machine learning, the added value of HR as a whole increases since less time is being spend on all HR activities.
    - Mentioned 2 times

7. I expect that, under the influence of machine learning, the added value of HR professionals lies in facilitating the strategic workforce planning and aligning talent management activities to it.
    - Mentioned 8 times

8. I expect that, under the influence of machine learning, the added value of HR professionals will increase because HR advice will become more and more accurate.
    - Mentioned 1 time

9. I expect that, under the influence of machine learning, the added value of HR professionals will increase because HR professionals can now understand and respond to problems much better.
    - Mentioned 1 time

10. I expect that, under the influence of machine learning, HR professionals will be able to deliver the promise of strategic HR.
    - Mentioned 9 times

11. I expect that, under the influence of machine learning, little will change in the way how HR professionals add value, the only difference is that their advice is now supported with data.
    - Mentioned 8 times

12. I expect that, under the influence of machine learning, the added value of HR professionals is diminished because line management will be empowered to do HR without HR professionals.
    - Mentioned 4 times

13. I expect that, under the influence of machine learning, the added value of HR professionals will increase because they are better able to prepare the organization to future workforce challenges and trends.
    - Mentioned 4 times

14. I expect that, under the influence of machine learning, the added value of HR professionals shifts towards only interpreting machine learning advice and consult top and line management about it.
    - Mentioned 4 times

15. I expect that, under the influence of machine learning, HR professionals are empowered to seize a spot at the boardroom table.
    - Mentioned 1 time

16. I expect that, under the influence of machine learning, the added value of HR professionals will not change too much because I don't believe that machine learning will improve the power base of HR professionals in organizations.
    - Mentioned 1 time

17. I expect that, under the influence of machine learning, the added value of HR professionals will not change much because HR professionals are not capable of acting as a strategic partner to line and top management.
    - Mentioned 1 time

18. I expect that, under the influence of machine learning, the added value of HR professionals will be perceived as higher since HR actions are now backed up with data.
    - Mentioned 1 time

19. I expect that, under the influence of machine learning, the added value of HR professionals does not change much since a considerable part of the function is to cope with irrationality, emotions and political games in order to find support for HR interventions.
    - Mentioned 4 times

20. I expect that, under the influence of machine learning, the added value of HR professionals decrease since line management might feel if HR spies upon them and tries to interfere with how they manage their teams.
    - Mentioned 1 time

21. I expect that, under the influence of machine learning, the added value of HR professionals will increase as machine learning will provide insights in which HR interventions truly have an impact on organizational outcomes.
    - Mentioned 1 time

22. I expect that, under the influence of machine learning, the added value of HR professionals will increase as machine learning allows HR professionals to talk in the same jargon (e.g. business outcomes) as line and top management.
    - Mentioned 1 time

23. I expect that, under the influence of machine learning, the added value of HR professionals will increase because HR professionals now objectively know what keeps their line managers up at night. Therefore, they can better support line management, this deepens the relationship between HR professionals and line management.
    - Mentioned 1 time

Competencies

1. I expect that, under the influence of machine learning, HR professionals must be more capable to work together interdisciplinary.
    - Mentioned 5 times

2. I expect that, under the influence of machine learning, HR professionals must be more data and technology minded.
    - Mentioned 7 times

3. I expect that, under the influence of machine learning, HR professionals will need to think on a more abstract level about problems.
    - Mentioned 5 times

4. I expect that, under the influence of machine learning, HR professionals must be able to interpret machine learning advice in the specific context of an organization.
    - Mentioned 6 times

5. I expect that, under the influence of machine learning, HR professionals must understand the basics of statistics in order to interpret machine learning outcomes.
    - Mentioned 2 times

6. I expect that, under the influence of machine learning, HR professionals must understand databases and know how to link them.
    - Mentioned 1 time

7. I expect that, under the influence of machine learning, HR professionals must become more persuasive.
    - Mentioned 1 time

8. I expect that, under the influence of machine learning, HR professionals do not need high levels of accuracy anymore.
    - Mentioned 1 time

9. I expect that, under the influence of machine learning, HR professionals must be more analytical.
    - Mentioned 8 times

10. I expect that, under the influence of machine learning, HR professionals need to be able to steer the strategy of the organization based on the HR data.
    - Mentioned 2 times

11. I expect that, under the influence of machine learning, HR professionals must become more empathic.
    - Mentioned 3 times

12. I expect that, under the influence of machine learning, good communication skills for HR professionals become more important.
    - Mentioned 1 time

13. I expect that, under the influence of machine learning, being able to cope with resistance becomes more important for HR professionals.
    - Mentioned 2 times

14. I expect that, under the influence of machine learning, organizational sensitivity becomes more important for HR professionals.
    - Mentioned 2 times

15. I expect that, under the influence of machine learning, HR professionals need to be abler to enthuse the organization for HRM.
    - Mentioned 1 time

16. I expect that, under the influence of machine learning, HR professionals must act more as business leaders who inspire.
    - Mentioned 1 time

17. I expect that, under the influence of machine learning, the competencies of the HR professional as strategic partner don't change much.
    - Mentioned 2 times

18. I expect that, under the influence of machine learning, soft skills in general become more important for HR professionals.
    - Mentioned 5 times

19. I expect that, under the influence of machine learning, HR professionals must have a stronger personality in order to be effective in board rooms.
    - Mentioned 2 times