Quarterly Newsletter

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INTELLIGENCE · DATA · ANALYSIS · STRATEGY

3Q23

The use of Artificial Intelligence for human resources management

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Introduction

Artificial Intelligence (AI) is a pivotal and crucial technological advancement in the 21st century. It has the capacity to transform various domains, altering fundamental approaches and challenging conventional frameworks. One such domain, where AI's impact is especially significant, is Human Resources (HR). HR was traditionally regarded as a field that depended on human competencies, such as communication, empathy, and judgment. However, HR is experiencing a radical transformation, indicating a departure from its customary image. Currently, HR is at the threshold of a new era, characterized by data-driven decisions, predictive analytics, nuanced employee experiences, and advanced automation.

This transformation is not only manifested in the practices and processes of HR, but also in the adoption and investment of AI solutions by HR practitioners. According to Anderson et al. 2022 [1], the adoption of AI in HR has increased considerably in recent years, particularly in areas such as diversity and inclusion, talent acquisition and development, and employee engagement and retention. However, there are challenges and risks of employing AI solutions in HR, such as potential biases, ethical dilemmas, and privacy concerns. Therefore, HR leaders should adopt a rigorous and responsible approach to implementing AI solutions in their organizations, so that they are aligned with their strategic objectives and values.

One example of the adoption of IA in the field of HR can be found in the multinational company Unilever. Operating in 190 countries and having processed approximately 1.8 million job applications in its 20FY, Unilever has turned to AI to enhance its recruitment efficiency. Through collaborations with some AI recruitment specialists, Unilever has integrated AI-driven tools into its hiring procedures. According to [2], utilizing platforms such as LinkedIn and game-based evaluations, the company has achieved a time saving of 25%, equivalent to 50,000 hours, and reduced costs by £1 million. Moreover, the incorporation of AI has played a significant role in advancing the firm's diversity goals, leading to the recruitment of its most diverse cohort in terms of ethnicity and gender.

Until recently, the use of data analytics and AI for the domain of HR has been limited since there has been particular challenges due to the nature of the available information (both structured and unstructured). However, with the advent and deployment of innovative solutions (for example, systems designed to capture the employee's voice), there are new possibilities of obtaining a comprehensive 360-degree view of the employees, thus knowing them more deeply and accurately. Despite these advances, there's a critical element to consider: the General Data Protection Regulation (GDPR). This regulation mandates the legitimization of an AI system's use case before its development, and sets limits on the location and duration data can be stored, among other stipulations. These requirements, designed to protect customers and service users within the European Union, can restrict the implementation of certain analyses and AI services by companies.

This newsletter aims to provide an in-depth exploration into the use of AI within HR. In the subsequent Technical Review section, some underlying technologies that enable AI are described, shedding light on the innovations driving its current and future direction. Transitioning from the technical to the practical, the Practical Applications section unpacks the diverse benefits AI introduces to HR ranging from the improvements in productivity – facilitated by AI's ability to process vast amounts of data with unparalleled efficiency – to the complex task of matching candidates to open positions – a problem where AI pursues to efficiently match job roles and candidates.

Technical review

In HR Analytics, advanced statistical techniques are commonly used to extract valuable insights from large volumes of data related to employees and workforce management. These techniques enable organizations to make data-driven decisions and optimize various HR processes. In what follows some of the common machine learning techniques used in HR Analytics are reviewed:

Regression analysis

It is used to understand the relationship between dependent and independent variables, allowing HR professionals to make data-driven decisions related to workforce management. For example, HR may use regression analysis to examine how performance ratings (dependent variable) are influenced by factors such as years of experience, training hours, or job satisfaction (independent variables). By conducting regression analysis, HR can identify which factors have a significant impact on performance and use this information to design targeted performance improvement plans, allocate resources more effectively, and optimize talent management strategies.

Classification analysis

These analyses are used to categorize employees into different groups based on specific characteristics or outcomes. One of the primary applications of classification analysis in HR is predicting employee attrition [3]. HR departments can use classification algorithms, such as, decision tree, random forest, or k-nearest neighbours (k-NN) to analyse historical data, such as employee tenure, job satisfaction, performance ratings, and engagement scores, to categorize employees into high fight risk and low fight risk [4]. This proactive approach enables HR to implement targeted retention strategies, such as targeted career development plans or addressing potential concerns raised by employee feedback.

Clustering

This is a technique to describe data and to find general patterns when available data are not labelled (unsupervised learning). Clustering is utilized to categorize employees into groups based on their similarities in characteristics, behaviours, or performance, thereby creating distinct segments of employees with shared attributes. HR departments can apply these algorithms to categorize employees into distinct groups based on attributes such as age, tenure, job role, performance metrics, and engagement scores. As an example, in Kakulapati et al. 2020 [5], clustering techniques based on the performance metrics similarity were used to analyse employee performance. By identifying different segments within the workforce, such as high-performers, mid-career professionals, or employees with specialized skills, HR can tailor talent management strategies, learning programs, and engagement initiatives to meet the specific needs of each group.

Anomaly detection

Anomaly detection involves identifying unusual or atypical patterns or behaviours within employee data. It is valuable for detecting outliers that deviate significantly from the norm, helping HR professionals address potential issues proactively. By analysing employee clock-in/out data, the system can flag unusual patterns, such as consistently late arrivals or early departures, which may indicate attendance policy violations or potential productivity concerns. Another example is the use of LSTM Autoencoder for the identification of anomalous behaviour in access control systems [6]. Unusual access patterns to sensitive information or facilities could indicate security breaches or insider threats, prompting timely investigation and mitigation.

More particularly in the field of deep learning, recent advancement have allowed this technology to play a crucial role in data science, and people analytics is no exception. The following are some of the deep learning techniques used in human resources analytics:

Sentiment Analysis

Sentiment analysis models in HR Analytics are used to automatically assess and understand the sentiment or emotional tone of employee feedback, survey responses, performance reviews, and other text data. These models help HR professionals gauge employee sentiments, satisfaction, engagement levels, and burnout. One use case of sentiment analysis in HR Analytics is analysing employee engagement survey responses [7]. By applying sentiment analysis to survey comments, organizations can quickly identify positive and negative sentiments expressed by employees towards several aspects of the workplace, such as leadership, work-life balance, or career development. HR can then prioritize areas for improvement, address concerns, and implement targeted initiatives to enhance employee satisfaction and retention.

Recommendation systems

These methods are used to suggest personalized learning paths, development opportunities, and career plans for employees based on their skills, interests, and career aspirations. These systems help HR departments provide targeted training and growth paths, enhancing employee engagement and performance. A common use example of these technics is in learning and development. By analysing employees' past training history, skills, and job roles, recommendation systems can suggest relevant courses or training programs that align with their career goals and help them acquire new skills. This not only empowers employees to take ownership of their professional development but also enables HR to optimize training investments and bridge skill gaps strategically. Recommendation systems in HR Analytics improve employee satisfaction and foster a culture of continuous learning, which contributes to organizational success and talent retention. In recent years, there has been a growing interest in organizing workshops [8] focused on recommendation models for recruitment processes, with a particular emphasis on addressing ethical issues related to their implementation [9].

Large Language Models (LLM)

Large Language Models [10] have revolutionized HR Analytics with their natural language understanding capabilities and the ability to generate human-like text responses, opening exciting possibilities for various HR applications. These models can assist in automating various HR tasks, improving communication with employees, and providing personalized support.

LLM can assist in talent acquisition by screening and ranking resumes. They can analyse job requirements and match them with candidates' skills and experiences, helping HR professionals identify the best-fit candidates more efficiently.

Apart from automating HR tasks and improving communication, chatbots powered by LLM play a crucial role in providing real-time employee support [11] [12]. Employees can interact with chatbots to inquire about HR policies, benefits, leave requests, and even seek career advice, offering a seamless and personalized HR experience.

However, the growing application of LLM and other advanced methods in HR Analytics also raises important ethical considerations, particularly regarding data privacy and potential biases [13]. To ensure responsible usage, HR departments must prioritize data protection, ensuring that sensitive employee information is handled securely and compliant with data regulations.

Use cases

People Analytics is a key application of data science in the field of Human Resources. As mentioned in the previous section, various data-driven techniques and methodologies can be applied to extract valuable insights from HR-related processes, facilitating informed decision-making. Examples of use cases include:

- Predictive Analytics: This technique involves using historical HR data to make predictions about future HR trends, such as employee turnover, performance, or recruitment needs. By employing algorithms, HR professionals can anticipate potential challenges and take proactive measures to address them.

- Employee Sentiment Analysis: Sentiment analysis utilizes natural language processing (NLP) to analyse employee feedback, surveys, and social media posts to gauge the overall sentiment of the workforce. This technique helps organizations understand employee satisfaction, identify areas of improvement, and create a positive work environment.

- Attrition Analysis: Attrition refers to the rate at which employees leave the organization. By applying data science techniques like decision trees, logistic regression, or survival analysis, HR analysts can identify factors contributing to attrition, enabling them to design better retention strategies.

- Improvement productivity: Through data analysis, HR professionals identify key factors affecting productivity, including training, workload, work environment, and team dynamics. Predictive models aid in resource planning, while targeted interventions, such as training and process optimizations, streamline operations. Continuous monitoring ensures ongoing improvements and optimized workforce performance, ultimately leading to increased business success.

- Recruitment Analytics: Data-driven recruitment techniques involve optimizing job descriptions, analysing candidate profiles, and predicting the best sources for talent acquisition. Machine learning algorithms can help HR teams find the right candidates more efficiently.

- Skills Gap Analysis: This technique assesses the disparity between the skills possessed by the current workforce and the skills required for future business objectives. Data science methods help in identifying skill gaps, facilitating targeted training and development initiatives.

Use case 1: Improvement of productivity

In the dynamic landscape of businesses, productivity plays a pivotal role in driving success and growth. Productivity is a critical factor that directly influences a company´s overall performance and prosperity. It refers to the efficiency and effectiveness with which employees utilize their time, skills, and resources to accomplish tasks and contribute to the organization's objectives. Understanding the significance of productivity from an employee's standpoint is crucial, as it nurtures a thriving and motivated workforce while maximizing employee productivity, which, in turn, is essential for enhancing operational efficiency, reducing costs, and cultivating a good working atmosphere.

For employees, productivity serves as a catalyst for career growth, recognition, and personal satisfaction. By consistently delivering high-quality work in an efficient manner, individuals enhance their chances of career advancement, access to greater responsibilities, and potential salary increases. Moreover, increased productivity often translates to a better work-life balance, reducing stress and enhancing overall well-being.

From an organizational perspective, productivity directly impacts profitability, customer satisfaction, and competitiveness. Efficient utilization of resources leads to cost savings, enabling companies to invest in innovation and expansion. A highly productive workforce fosters a positive work culture, improving employee retention and morale, while also enabling companies to adapt quickly to market demands.

To enhance productivity effectively, businesses must maintain records and take proactive measures. Records, such as individual and team performance metrics, allow companies to identify top performers and address any underperforming areas. These records also serve as the foundation for developing targeted action plans that focus on employee development, skill enhancement, and addressing productivity bottlenecks.

Measuring productivity is essential for businesses seeking to optimize their operations and achieve their strategic objectives. Effective measurement mechanisms allow organizations to gain valuable insights into their performance, identify areas for improvement, and foment a culture of continuous enhancement. However, when it comes to certain employees, particularly those in higher managerial positions, assessing productivity can be more challenging. Nevertheless, in large corporations, for the 90% of the workforce, this problem has been effectively resolved through powerful tools for measuring productivity, such as Key Performance Indicators (KPIs) or feedback mechanisms.

KPIs serve as powerful tools for measuring productivity in various aspects of a business. These metrics may include sales targets, customer satisfaction scores, project completion rates, employee performance, efficiency ratios and more. By aligning KPIs with strategic goals, companies can quantitatively assess productivity levels, identify areas of improvement, and track progress over time. In addition to KPIs, feedback mechanisms play a critical role in understanding employee experiences and challenges. Regular performance evaluations, one-on-one feedback sessions, and anonymous surveys provide valuable insights into employee satisfaction, engagement, and potential areas for improvement.

A more innovative approach is to understand why certain employees are more productive than others and explore the possibility of replicating that high level of productivity. By delving into the factors that contribute to their exceptional performance, organizations can identify best practices and strategies that can be adopted by other team members to enhance overall productivity.

For this purpose, data analytics and artificial intelligence play a significant role in identifying patterns and correlations between various factors and productivity levels. Leveraging these technologies can provide a deeper understanding of what drives productivity and help tailor individualized approaches for different employees based on their unique strengths and challenges.

Using regression ML models, it is possible to infer employee productivity based on variables such as work mode, years of experience, number of workers in each team, amount of overtime, salary, number of unfinished items, etc. as well as variables related to the employee's manager, team, and organization. The focus is on understanding why one employee is more productive than another. Hence, interpretable models such as decision trees or linear regressions may be utilized for this purpose. However, an alternative approach would involve using non-interpretable models and applying explainability techniques such as LIME (Local Interpretable Model-agnostic Explanations) [14] or SHAP (SHapley Additive exPlanations) [15]. LIME generates local explanations for individual predictions, simplifying complex models with interpretable surrogate models. On the other hand, SHAP allocates feature importance values, enabling organizations to understand each variable's contribution to employee productivity predictions.

Following, a simplified applied example involving a decision tree is examined. Consider a simple dataset where productivity is dependent on three variables: age, years of experience, and remote work status, a binary indicator (1 for telecommuting, 0 for non-telecommuting). The target variable is productivity, representing the level of output or performance for each employee. Upon training a decision tree with this dataset, the most significant predictors of productivity can be ascertained.

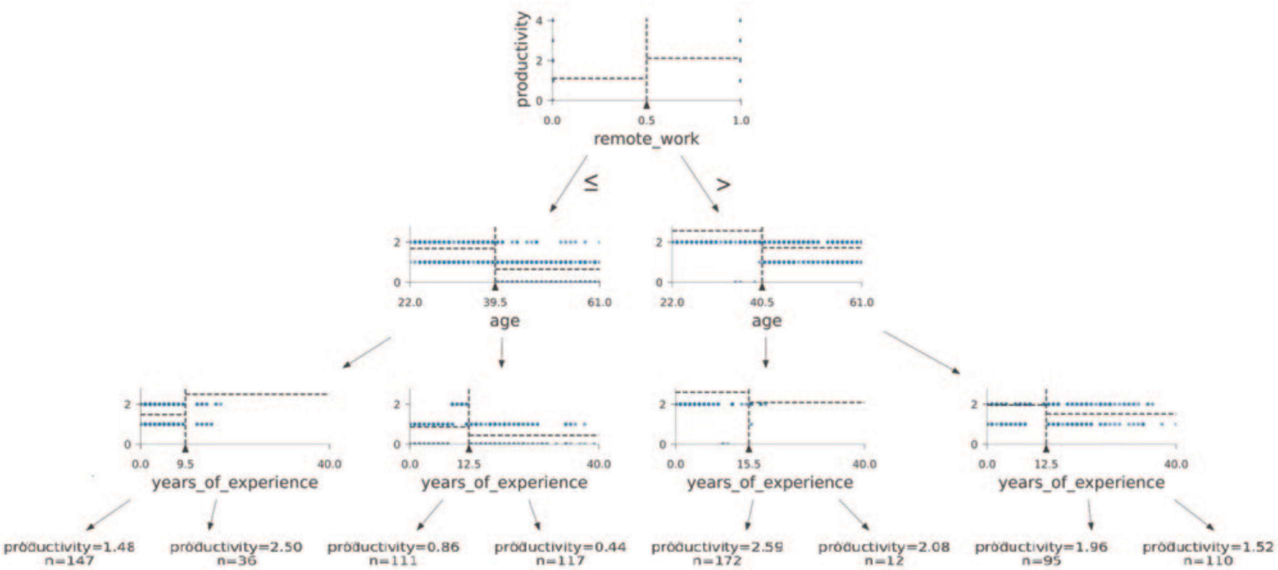
The decision tree algorithm learns from the dataset and identifies patterns and relationships between the predictors (age, years of experience, and telecommuting) and productivity levels. Each node within the decision tree represents a decision point based on the predictors, and the branches denote the potential outcomes.

After training the model, its structure can be thoroughly examined to discern the most crucial predictors that effectively split the data, enabling accurate productivity predictions. In that case, the decision tree reveals that age, years of experience, and telecommuting are pivotal predictors of productivity. The implication is that older employees who do not engage in remote work tend to exhibit significantly lower productivity compared to other groups of employees (see figure 1).

However, it is essential to note that while age and years of experience may emerge as strong predictors of productivity, they may not necessarily be the direct causes of low productivity in certain cases. For example, some employees with higher age and experience may exhibit lower productivity levels due to factors such as lack of motivation, burnout, etc., which the decision tree alone might not capture. Note that the variables mentioned in the previous sentence are difficult to capture and may not always be available for model development. For that reason, they were not included initially.

By thoroughly interpreting the decision tree and considering additional contextual factors, organizations can obtain actionable insights into the specific attributes influencing employee productivity. This valuable knowledge can guide strategic decisions related to workforce planning, skill development, and work arrangements, ultimately fostering a

Figure 1: a simplified decision tree model applied to the analysis of productivity (source: own elaboration)



more productive workforce. By identifying underlying causes of variations in productivity, organizations can implement targeted interventions to address potential issues and enhance overall employee performance.

In the example under examination, the data indicates that lower productivity levels are observed among older employees who do not engage in telecommuting. Interestingly, it has been observed that within this age group, those who do participate in telecommuting exhibit higher productivity ratios. Consequently, this insight offers a potential strategic decision to be considered.

One possible strategic decision could involve enabling telecommuting options for the group of older employees with lower productivity. By allowing them to work remotely, the organization may tap into the productivity benefits associated with telecommuting, which have been evident among their peers within the same age bracket.

Another possible action could be implementing reskilling programs. Adjusting job roles for these older employees may prove to be a valuable strategy. Targeted training equips them with needed competencies, while aligning responsibilities with strengths boosts job satisfaction and performance.

More measures that could be taken could be elevating productivity in other sectors where performance is relatively low, such as the domain of young and inexperienced individuals who do not engage in remote work. Like the case of older employees, the introduction of telecommuting options is linked to heightened productivity, suggesting the application of analogous strategies.

However, in a real-world scenario, it is crucial to consider the risk-benefit balance when making significant decisions. The complexities involved in this decision-making process can be illustrated with the following non-exhaustive examples:

- Return on Investment (ROI) analysis: When contemplating the decision to enable telecommuting for older employees with lower productivity, a thorough ROI analysis is essential. The organization needs to evaluate how an increase in productivity will impact the overall return. Assessing the potential financial gains resulting from improved productivity and comparing them to the costs associated with implementing telecommuting arrangements will provide valuable insights.

- Cost-benefit analysis for job role modifications: Modifying job roles and responsibilities for the targeted group of older employees requires careful consideration. It is essential to perform a comprehensive cost-benefit analysis to understand the financial implications. This analysis will help determine if the potential gains in productivity outweigh the expenses incurred in the reskilling process.

- Analysing potential risks: Every strategic decision comes with inherent risks, and this one is no exception. The organization must carefully assess the potential risks associated. Possible risks could include decreased team cohesion, potential communication challenges, or difficulties in monitoring remote employees. Understanding these risks and developing mitigation strategies will be crucial for a successful implementation.

- Long-term impact assessment: Considering the long-term impact of the decision is vital. It involves analysing how productivity changes over time and assessing whether the measures taken continue to yield positive outcomes in the future.

In conclusion, productivity is a major factor influencing overall performance, employee satisfaction and organisational competitiveness. Data science techniques, utilizing metrics like key performance indicators and feedback mechanisms, yield insights into productivity drivers and enable the design of customized strategies for employee enhancement. Business decisions necessitate comprehensive analyses that consider risks, benefits, and potential returns. Prioritizing informed decisions through effective predictive modelling is crucial for cultivating a more productive and motivated workforce.

Use case 2: Matching between candidates and open positions

Recruiting the right talent is one of the most important and challenging tasks for any organization. The traditional recruitment process can be time-consuming, costly, and prone to human errors and biases. However, since online recruitment begun, many HR-related tasks are increasingly becoming automated, such as screening resumes, scheduling interviews, and assessing candidates [16].

It has to be noted that using algorithms for recruiting, which relies on external data, is different from using them to manage own employees. Companies can create detailed and secure databases when it comes to employee management. These databases ensure data protection and confidentiality. Employees may be open to sharing their data with the company for their career growth, as long as the company commits to using the data responsibly. A company that prioritizes and safeguards its employees' data can better handle career development, work-life balance challenges, and employee motivation. However, this is not necessarily the case for candidates from outside the company, which can lead to difficulties in the application of algorithms.

AI can offer several benefits for HR professionals, such as improving efficiency, reducing costs, enhancing candidate experience, and finding the best fit for each role. This section explores how AI can be used to optimize the initial screening of CVs, which is often the most tedious and labor-intensive part of the recruitment process.

One way to optimize the initial screening of CVs is to use AI tools that can extract relevant information from a CV and store it in a tabular form, creating a candidate database. This can be done by using natural language processing (NLP) techniques, such as named entity recognition, keyword extraction, and sentiment analysis, to identify and categorize the information in each CV, like name, contact details, education, work experience, skills, achievements, and personality traits of the candidate [17].

A practical way to automate this process is as follows. First, an online portal can be set up on the corporate website, where candidates can upload their CV along with their job application. Next, the online portal would automatically send the CV to a cloud based LLM service to extract the relevant data and parse it into a tabular form. For example, Azure OpenAI offers the State-Of-The-Art GPT4 [18]. It is also worth mentioning that a similar process could be applied with CVs of employees in rotation, to further reduce HR overhead.

Of course, privacy issues must be considered. For example, in the European Union, any online application portal, cloud-based LLM service and candidate database must be in strict compliance with the General Data Protection Regulation (GDPR). This is not only just a legal mandate but is also crucial for maintaining trust with users and candidates. This translates into requirements such as establishing time limits to keep the received sensitive information and ensuring that the data is securely stored, using state-of-the-art encryption methods and best practices to prevent unauthorized access or breaches.

Once the candidate data is extracted in a structured form, AI techniques can be used to match the candidates with open positions. Here, two options are explored: defining a score for the match of a candidate's qualifications and those of an open position and using historical data to predict the productivity of each candidate for each position.

Defining a score for a given candidate and an open position

This approach involves calculating a numerical value that represents the degree of fit between a candidate's profile and a job's requirements. The score can be based on numerous factors, such as education level, work experience, skills, achievements, and personality traits. Each factor can be assigned a different weight depending on its importance for the role.

Suppose a company is hiring for a software engineer position that requires a bachelor's degree in computer science, at least 3 years of experience in Java programming, and strong problem-solving skills. Without using an AI solution , the company assigns the following weights to these factors: 40% for education level, 30% for work experience, and 30% for problem-solving skills. If the candidate has a master's degree in computer science, 2 years of experience in Java programming, and strong problem-solving skills. To calculate the score for the open position, a value of 1.0 for their education level can be assigned (since they have a master's degree), 0.0 for their work experience (since they do not have the required 3 years of experience), and 1.0 for their problem-solving skills (since they have strong skills). Multiplying these values by their respective weights and summing them up gives us a score of 0.4 * 1.0 + 0.3 * 0.66 + 0.3 * 1.0 = 0.9 for the candidate. A threshold may be established to select CVs with a higher score. It is also possible to filter CVs based on minimum scores on certain qualifications.

One example of an application which uses a score-based approach is Talent Matching Hub [19], which aggregates the individual matches for all requested skills and activities presented in the position against the candidates' work history. It also considers the recency and duration of skills used in professional experience when calculating the match score. In this case, as it is a service meant to be directly used by HR professionals, the application already does the CV data extraction as a part of the service using NLP.

Using a supervised model to predict the performance of a candidate based on CV data

This approach requires historical data on previous employees who occupied the same or similar roles in the company. The model can then learn from their CVs at the time they were hired and their performance outcomes (such as productivity, retention, satisfaction, etc.) to identify patterns and features that are associated with success or failure. The model can then use these features to predict how likely a new candidate is to perform well or poorly in the role.

Depending on the predicted outcome, a regression or classification model would be used. By way of illustration, if the goal were to select candidates with a higher productivity for an open position, a decision tree model could be fitted with data from previous employees for that position or other similar ones, similarly to the previously mentioned example for improvement of productivity. One example of an AI tool that uses a predictive approach is Harver [20], which uses machine learning to help recruiters predict quality of hire based on pre-employment assessment data. In this case, the tool can also provide an estimate of the ROI of hiring a professional. Another similar tool is Beamery [21], that uses candidate skills and potential of the candidate to evaluate the match, but also places more focus than Harver on the explainability of the models. Both tools include automatic data extraction from provided CVs as well, hinting that this has become a basic requirement for most HR recruiting tools.

The supervised model approach does, however, introduce some issues. The first one is the need of data to fit the models, which depending on the used model may be very large. Finding enough data of similar profiles to the expected one of the candidates is a challenging and expensive task. Additionally, while the empirical approach of unsupervised models may seem less biased than the score-based approaches, as they often require a manual specification of the weights, the data used by the supervised models can have biases, which are learnt in the fitting process. Concerns about bias should be addressed using appropriate data treatment and/or by ensuring sufficient data is used to build the model.

If the data is not representative of the target population or contains historical or societal biases (such as gender, race, age, etc.), then the models may inherit or amplify these biases and produce unfair or discriminatory outcomes. For instance, Amazon's AI recruiting tool, which scored candidates between up to five stars, had to scrap it after detecting a consistent discrimination against female candidates, regardless of the actual necessary qualifications for the position, due to most of the employees being men in the past [22].

Another issue is the design or implementation of the AI models. If the models are not transparent or explainable enough, then it may be difficult to understand how they make decisions or what factors they consider. This may lead to mistrust or confusion among HR professionals or candidates. Human interpretation or use of AI models is relevant as well. If the HR professionals or candidates do not have enough knowledge or awareness of how AI works or what its limitations are, then they may rely too much or too little on its outputs or recommendations. This may lead to overconfidence or skepticism about the AI models [23].

To address these risks and ensure the responsible use of AI in recruitment, some best practices include:

- Conducting regular audits and evaluations of the AI models to check their accuracy, validity, reliability, fairness, and ethics.
- Providing clear and comprehensive documentation and communication about the AI models' purpose, scope, methods, assumptions, limitations, and outcomes.
- Seeking feedback and input from various stakeholders (such as HR professionals, candidates, employees, managers) on how they perceive and experience the AI models.
- Providing training and education for HR professionals and candidates on how to use and interpret the AI models effectively and appropriately.

Conclusions

In today's rapidly evolving technological landscape, the fusion of Artificial Intelligence (AI) with the domain of Human Resources (HR) represents more than just a simple merging of technology and talent management. This intersection hints at a transformation in the traditional paradigms that guide how organizations, regardless of size, perceive, oversee, and engage with their most invaluable assets – the workforce. As explored in this newsletter, the integration of AI into HR is not limited to streamlining operations. Instead, it heralds a transformative phase in talent acquisition and management, promising both notable improvements in productivity and a more sophisticated, data-informed strategy for employee engagement and retention.

However, like all significant technological shifts, the integration of AI into HR processes comes with inherent challenges. Ethical concerns, pressing privacy issues, and potential biases embedded within AI algorithms necessitate continuous scrutiny, thorough assessment, and adaptability. The goal remains to achieve a delicate equilibrium: harnessing the capabilities of modern technology while ensuring that the foundational values integral to Human Resources remain undisturbed and intact.

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