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Department of Social and Organizational Psychology

**Artificial Intelligence in Human Resource Management: Exploring endorsement through normative dimensions**

Maria do Carmo Pinto Leite Pereira Coutinho

Master in Social and Organizational Psychology

Advisor:
Doutor, Nelson Campos Ramalho, Associate Prof., ISCTE Instituto Universitário de Lisboa

September, 2023

CIÊNCIAS SOCIAIS
E HUMANAS

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# Resumo

A Inteligência Artificial (IA) ganhou centralidade na sociedade e nas organizações, com um potencial inigualável de mudança nos ambientes de trabalho e na forma como os trabalhadores se relacionam com os empregadores. A Gestão de Recursos Humanos (GRH) não é exceção, pois existem muitas propostas e implementações de aplicações baseadas em IA que substituem ou auxiliam os processos de GRH. Ainda assim, a mudança não acontece sem dúvidas e, sem aceitação a mudança está condenada ao fracasso ou, no mínimo, a uma eficácia subóptima.

Este estudo foi concebido para testar em que medida os indivíduos aceitam a GRH automatizada com base em dimensões normativas, nomeadamente ao nível da responsabilização, da justiça, da legitimidade, da explicabilidade e da reversibilidade. Com base numa amostra de 253 trabalhadores, os resultados obtidos através de modelos PLS-SEM revelaram que a legitimidade é a variável-chave que explica a aceitação da IA nos domínios funcionais da GRH, os quais contribuem globalmente para a aceitação geral da automatização da GRH. Os resultados são discutidos à luz da teoria e são retiradas conclusões para o seu futuro, embora os resultados globais sugiram que os construtos ainda não são suficientemente claros para permitir inferências feitas em bases sólidas.

***Palavras-chave:*** Inteligência Artificial; Gestão de Recursos Humanos; Aceitação; Dimensões normativas

***Códigos de classificação da APA*:** 3600 Psicologia Organizacional e Recursos Humanos

# Abstract

Artificial Intelligence (AI) gained centrality in society and organizations, with an ongoing unparalleled potential for change in work settings and in how workers relate to employers. Human Resource Management (HRM) is not an exception as there are many proposals, and implementations, of AI-based apps that replace or aid HRM processes. Still, change does not come without doubts and without general endorsement, change is doomed to failure or at the minimum, to suboptimal effectiveness.

This thesis is designed to test to which extent individuals endorse automated Human Resource Management (a-HRM) based on normative dimensions, namely accountability, fairness, legitimacy, explainability, and reversibility. Based on a sample of 253 employees, findings using PLS-SEM models showed that legitimacy is the key variable explaining HRM functional domains AI endorsement, which overall are contributive to general a-HRM endorsement. Findings are discussed in light of theory and of the conclusions inferred towards its future albeit overall findings suggest constructs are not yet clear enough to allow for inferences made on solid ground.



***Keywords:*** Artificial Intelligence; Human Resource Management; Endorsement; Normative dimensions

***APA classification codes***: 3600 Organizational Psychology and Human Resources

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# Introduction

In the last few years, the exponential technological advancement in the field of Artificial Intelligence (AI) in conjunction with the permanent search for productivity, efficiency, and cost saving, opened the doors to the creation of AI tools that started being used at various levels of the organizations (Enholm et al., 2022). This includes AI being used at the level of production, data analysis, data collection and processing (Venkatesh, 2022), due diligence, smart contracts drafting, among others (Kauffman & Soares, 2020). AI experts sustain that ultimately, each and every task with a repetitive nature or guided by data analysis patterns can be carried out by AI. It is thus unsurprising to witness advanced AI-based algorithms gaining ground in Human Resource Analytics (HRA) as a critical source of information to optimize decision making. This field is also known as "People Analytics" and "Workforce Analytics" (Tursunbayeva et al., 2018).

In a recent systematic review of HRA field focused on extant knowledge and future challenges, Margherita (2022) explored venues for research within three lines: enablers, applications, and added value of HRA. Among these, the organizational enablers (e.g. Analytic skills of HR professionals, Performance pay policy, Analytics function centralization, Academic and practitioner integration, Data governance and ethics) are more strongly within the reach of decision makers, and among these organizational factors, some (e.g. Employees' perceived accuracy and fairness, ethics issues in HR data analysis and use, degree of individual adoption, awareness of challenges and criticisms) are fundamentally psychological in nature. This means that such psychological factors are not so much dependent on structure or structural changes that can be made by managers because they entail a behavioral complexity that requires extra attention.

This is especially true for algorithm-based HR Analytics because it opens venues for autonomous decision-making (Wiblen & Marler, 2021) that not only concerns issues that might be taken lightly (e.g., identifying and sending a greeting card for an employee's birthday, (Nawaz et al., 2019) but also to issues that are absolutely critical for employees (e.g. dismissing an employee based on an algorithm output, Maasland & Weißmüller, 2022).

It is our view that among organizational enablers identified by Margherita (2022) those of a psychological nature are the most difficult to manage and that their influence on the HRA actual application and added value is critical because there is zero effectiveness in designing, implementing and investing in HRA enabling technology, or organizational structures or processes if workers (or any other key stakeholders) reject the use of algorithm-based HRA. This concern motivates this research.

This study is designed to offer insights about where employees draw the line between what is acceptable and what is unacceptable in using AI-based Human Resource Management (HRM). Namely, how they conceive the specific AI applications in HRM taking into consideration Strohmeier's (2022) normative dimensions: accountability (who should be responsible in case of a wrongdoing?), legitimacy (what is and isn't legitimate use of AI in HRM), explainability (to which extent can the organization explain the reasons that sustain a given decision?), and fairness (to which extent can the organization guarantee that the decisions are fair?) together with a fifth concerning that is reversibility (to which extent can one be compensated or the situation reinstated in case of wrong decisions) not only to guarantee built-in decision making procedural fairness (Starke et al., 2022) but also accounting for the (im)possibility to fully compensate or revert the effects of a given decision.

Firstly, the ensuing thesis will review literature pertaining to the evolution of Strategic HRM and HRA. It will then define HRA, its process and how it is managed. Subsequently, we will introduce AI and its applications in HRM and HRA, namely the application of AI in the functional domains of HRM: AI-based recruitment and selection, onboarding, performance appraisal, compensation, training and development and career management, employee engagement, employee exiting decisions and strategic HRM. The ensuing section will list the main advantages and disadvantages of AI-based HRM. After that, we will focus on the endorsement of AI-based HRM through the lens of the main acceptance theories, as we consider acceptance to be a condition precedent for endorsement. Furthermore, we will analyze the contribution of Psychology to explain the main acceptance theories, specifically the acceptance of technologies. We will highlight trust as a general critical attitude towards AI and the literature review will conclude with the introduction of five normative dimensions (accountability, fairness, explainability, legitimacy and reversibility) that are identified in the literature as socially constructed normative dimensions that may be instrumental to explain what is and is not acceptable in AI-based decision-making processes, especially when final responses are wrong and raise sensitive ethical questions. This will combine into a conceptual model that integrates all the hypotheses under scrutiny.

Secondly, we will describe the methods adopted within an empirical study focused on subjective appraisal of AI applications in several HR practices and their endorsement, characterizing the procedure, sample, measures, and data analysis strategy. Once the method is depicted, we will show the findings both pertaining to descriptive, bivariate statistics and hypotheses testing. These findings will be then discussed in light of theory and will draw our conclusions by reference to the guiding question and will signal the respective implications.

# 1. Literature Review

## 1.1. The rise of Strategic HRM and the role of HR Analytics

In the late 1990s, the interest for researching Human Resources (HR) as a strategic business partner and the link between HR practices and business outcomes grew strongly (Kaufman, 2015). This interest established itself as a line of research and application known as Strategic Human Resource Management (SHRM) (Kim et al., 2022). It is thus logical to accept that HRA is a *sine qua non* condition to uphold SHRM. Although today this is a well-established view on HRM, it has not always been like that and the fact is, how HRM is approached will condition the role of HRA.

The HR function itself has existed for as long as there has been employers and employees, but it was not until the 19$^{th}$ century that it was formally recognized. In the 19$^{th}$ century, the so-called "welfare secretaries" emerged, whose role was to ensure and control the welfare of employees (Cohen, 2015). Economic growth and industrial transformation prompted the creation of HR as a department within corporations. When HR first emerged, its goal was to handle organizational difficulties and generate value by managing and streamlining the employee relationship in an efficient manner (Ulrich & Dulebohn, 2015).

The Industrial Revolution and the era of "scientific management" marked the evolution of the Human Resources domain. Employers needed to manage and direct their employees, while ensuring their well-being, whilst companies grew, and the agrarian economy gave way to industry. It was necessary to respond to the challenges faced by organizations, namely, to minimize turnover and increase the workforce productivity (Cohen, 2015). Professional engineers became the main designers of production processes by the end of the 19th century. The pioneer was Frederick W. Taylor, who is considered the founder of Scientific Management (SM). Taylor's study was based on several axes that contributed to increase the efficiency of work performance. According to the author, a task should be divided into its component parts, the best workers should be selected for each task, workers should be trained and given the necessary motivation before performing the task, and work performance should be scientifically planned (Taylor, 2004). Scientific Management created and introduced work analysis into the management practice. This had an impact on HR, more than that, it brought a new perspective for management practice (Birnbaum & Somers, 2022). HRA at this stage was restructured to the use of some descriptive indicators but we are not aware of any report about its use for decision making in a systematic manner.

During World War I, companies began to experience labor shortage. To alleviate this problem, departments were created to ensure effective personnel management. However, in the post-war economic boom the HR function came to be regarded as purely administrative, i.e., it was necessary, but it was believed to bring no value (Ulrich & Dulebohn, 2015).

Several academic and business institutions criticized the traditional personnel management function and approach, arguing that in face of the profound changes in the nature of the workforce, not only in relation to people but also in relation to environmental aspects, this function fell short of addressing these uncertainties. As a response, HRM emerged as a necessity to overcome these challenges both at an operational and strategic level (Armstrong & Taylor, 2020). HRM also replaced the human relations management method, developed by Elton Mayo (1933) which was based on the results of the project known as the Hawthorne investigations (Armstrong & Taylor, 2020). These investigations were concerned with understanding how workers' performance can be affected by working conditions. The researchers concluded that physical factors played a minimal role as productivity and job satisfaction are strongly correlated, and that people would work harder if someone they respected showed interest for them (Belias et al., 2019). HRA can here be depicted as gaining momentum by establishing the first explanatory equations with indicators that come closer to the psychosocial nature of work.

A shift in the focus occurred when in Europe the concept of HRM itself was questioned and accused of reducing the human being to a "resource" only. A resource per se may neglect the true human nature of work relations, as well as fostering an idea that people are a liability instead of an asset. In the USA, this problem was quickly solved by acknowledging the value of people with the emergence of SHRM by Fombrun et al. (1984) HRM matching model. According to this model, the HR systems and organizational structure should be in line with organizational strategy (Bondarouk & Brewster, 2016). The model proposed by Beer et al. (1984), known as "Harvard framework", was widely adopted outside of the United States because it was more comprehensive and arguably featured a less neo-liberal and more holistic perspective of the subject. However, the Harvard Model of HRM is often ignored in the literature. Still, Bondarouk and Brewster (2016) argue that this model assumes, to this day, the ability to portray the HRM landscape in organizations. Beer et al. (1984) started from the concept that any management decision or action that has an impact on the type of relationship that exists between workers (human resources) and the organization should be part of HRM. The model is also governed by the idea that one should take a broader and more strategic view of HR. In addition, all individuals inside an organization should be seen as a potential asset, rather than a variable cost. These authors were the first to state that the domain of HRM is the responsibility of line managers and they should ensure the orientation of HR policies and competitive strategy (Armstrong & Taylor, 2020). At present date and at this stage, HRA reflects this variety of variables and issues and HRM now looks for predictors of business outcomes with a focus on strategic alignment.

The naming of the HR function has informative value to understand how HRA evolved. Ulrich and Dulebohn (2015) proposal of a four-wave development are instrumental to understand this (Figure 1.1).

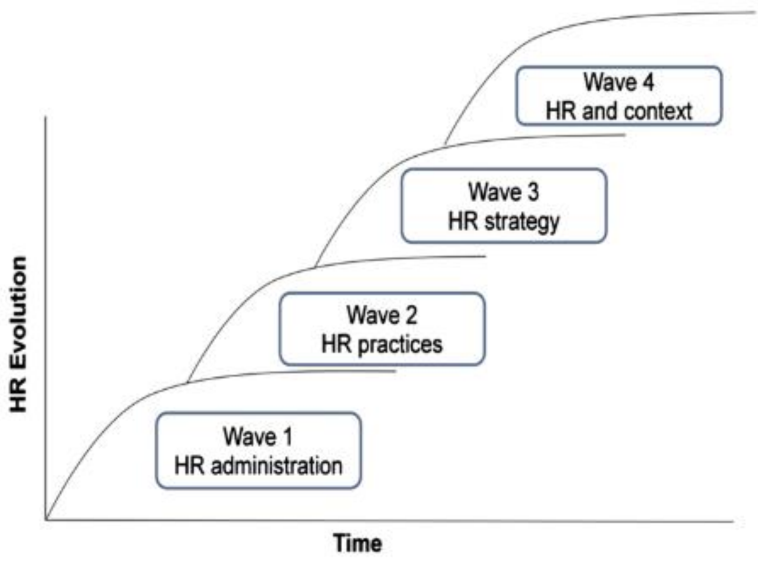


Figure 1.1 - HR's transformation waves (Ulrich & Dulebohn, 2015, p. 190)

According to these authors, the replacement of the term Personnel Management (PM) by HRM, departed from the first wave – where the administrative view of HR prevailed. In the first wave, Personnel was merely seen as a cost and the fundamental principles deriving from such a perspective were that comparative advantage was obtained by decreasing costs and increasing efficiency (Lemmergaard, 2009). The second wave, known as HR practices, is characterized by the development of new HR practices in the areas of people. For example, for different positions, it may be necessary to use a different approach in recruiting. It was found with this wave that HR personnel with specific skills, such as the ability to customize HR practices, were needed (Ulrich & Dulebohn, 2015). The third wave emerged with the positioning of HR as a strategic business partner for organizations. The idea has been developed that HR systems should be the focus, rather than individual practices, as these may be dependent on other practices in the system (Boon et al., 2019). Thus, HRA evolved from non-relevance into critical relevance by offering the means to not only monitor HRM efficiency but mostly because it established the analytical basis to enable SHRM. In this evolving process, the fourth wave witnessed an HRM move from an internal focus (i.e. a focus on internal indicators such as absenteeism, accidents, productivity) towards external focus connecting HRM to the broader business context in which the company operates. The assumption is that HRM becomes even more valuable if its practices, which serve the organization's internal goals, are aligned with expectations outside the organization. Taking the example of a company that wants to achieve the title of "top employer", HRM must ensure that the internal services it provides are in line with external expectations. In this way, HRM assumes a position of full partnership, as it not only has the role of reacting to the strategy, but also has the duty to fully help developing it (Ulrich & Dulebohn, 2015). HRA is then gaining complexity, by incorporating a variety of indicators that may not operate as simple predictors but rather perform the role of mediators and moderators in complex systems (Hamilton & Sodeman, 2020).

Nowadays, the evolution continues by tackling the challenges and opportunities that are having an impact, positive or negative, on the field of HRM. Namely the economic, sociodemographic, and technological changes have been notorious (Santana & Cobo, 2020). Harney and Collings (2021) state there is an urgent need to reassess the context of HRM. The authors argue that even before the transformations caused by the Covid-19 pandemic, the main observations about the changing nature of work were widespread.

The shift from a manufacturing-based economy to a service-based economy requires organizations to change their HR practices. It is quite evident that the old HR processes, designed in the industrial era and focused on creating restricted jobs where short-term results were paramount, no longer make sense. Nowadays, there is a need to attract competent workers with the necessary knowledge to ensure the success of companies and, most importantly, there is a concern with talent retention (Stone & Deadrick, 2015).

The rise of globalization has had an impact on the HR processes of companies operating on a global or international scale. Large companies operating in different countries, with different cultures and languages, have been confronted with new needs and questions regarding the influence HR practices can have in different geographies, how to develop a cohesive organizational culture, and how to train employees to operate in a diverse cultural environment (Jackson et al., 2014).

Alongside with the diversity management, other dimensions emerged from the globalization of HRM, namely within the context of international uncertainty and crisis (Ererdi et al., 2022). In these circumstances not only HRA becomes more complex as it requires faster and more precise data collection, data processing and knowledge production for decision makers. Technology is then a natural emerging factor (Santana & Cobo, 2020).

The pervasive nature of technology in HRM has various expressions. Nowadays, internet is becoming currently used to advertise a job vacancy, to send and receive job applications (Pillai & & Sivathanu, 2020). Technology has also allowed organizations to use the internet, intranet systems, videoconferencing, among others, to train employees (Vrontis et al., 2022). Moreover, thanks to technological advances, organizations have the possibility to offer new ways of working, such as telework and virtual teams, which brings more flexibility to employees and contribute to a greater diversity of organizations (Garro-Abarca et al., 2021).

On the one hand, technology has contributed to a significant reduction in the administrative burden of HR, which increases productivity and makes it possible for this area to strengthen its strategic focus (Rodgers et al., 2023) but on the other hand, technology does not come without risk and challenges. There is an ongoing debate concerning the use of information technology to produce analytics in HRM, how data is collected, stored, used to produce indicators, causal nexus, and decisions.

## 1.2. HRA comes to age

### *1.2.1. Defining HRA*

It is within these challenges that HRA gained criticality in effectively linking HR practices with business outcomes and organizational performance (Larsson & Edwards, 2022). To understand this status today, one needs to capture the distinct views about it.

Over the past 10 years, the focus of research on HRA has been placed upon its definition. As in so many other fields, HRA is found to mean different things to different authors (Falletta & Combs, 2021). HRA has been defined only from a descriptive HR perspective, e.g. by Van den Heuvel and Bondarouk (2017, p.160) "the systematic identification and quantification of the people-drivers of business outcomes, with the purpose of making better decisions" but HRA has also been defined as a complex set of predictive modelling techniques, e.g. by Bassi (2011, p.16) “HR analytics is an evidence-based approach for making better decisions on the people side of the business; it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modelling". Recently, authors have adopted a more procedural perspective, in which HRA is seen as a systematic approach (Wirges & Neyer, 2022). In general terms, HRA is broadly defined as an approach that uses data analytics to manage people and make more objective and rational decisions in organizations (Margherita, 2020). More specifically, it can be defined as a “HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making” (Marler & Boudreau (2017, p.15). Falletta and Combs (2021, p.53) define it as “a proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives”.

Although there are several definitions, all share the idea that it is an approach that seeks to benefit organizations through HR decisions with a stronger analytical basis that consequently leads to smarter actions (Cayrat & Boxall, 2022) and they all refer to the nature of the activity (data analysis), its object (data related to HR domains crossed with organizational performance) and its purpose (to feed decision making based on data, Gal et al., 2017). However, we would like to stress Falletta and Combs (2021) choice for using the word “ethically”, meaning that HRA entails important ethical issues and, when including it in its definition, we are making explicit a very important dimension of its use.

### *1.2.2. The process of HRA*

Apart from definitional issues, HRA is currently consensually linked to business strategy (Petrovic et al., 2018) and this is an underlying motive for its exponential emergence in organizations. Three main factors that influence its growth are: data quality, analytical skills, and the strategic ability to act. It thus becomes evident that there is a relation between HRA and HRM, as HRA can assume a strategic capability to improve organizational decision-making (Minbaeva, 2018). Its process has been receiving attention from researchers and it is important to grasp its nature (Wirges & Neyer, 2022).

The first phase concerns in viewing HRA as a possible approach to solving a particular problem inside the organization. The second phase consists of the identification by the HRA analysts of the data needed to determine and solve the issue. Subsequently, there is an analytical third phase of interpretation and identification of significant data. The fourth phase (action) converts the typical analysis of the research articles into knowledge that motivates management action. Finally, the outcome of HRA projects is evaluated (Edwards et al., 2022). Another proposal identified three stages (Cayrat & Boxall, 2022): descriptive, predictive, and prescriptive. In the descriptive stage, data is processed so as to identify objects, their past and present relations. The leading questions are: "What has happened?", and "What is happening?" (Margherita, 2020). Basic statistical procedures are used to portray trends and normalized reporting of HR data such as employee turnover levels (Cayrat and Boxall, 2022). In the predictive stage, data is processed so to infer on current relationships between objects and extrapolate to the future. The leading question is "What will happen?" (Margherita, 2020). At this stage, descriptive analysis can give rise to qualitative and/or quantitative studies of data understanding. For this it is necessary to know the "Why it has or is happening?" (as an intermediary step between the descriptive and predictive stages) (Cayrat & Boxall, 2022). Statistical modelling and forecasting are key components of predictive analytics to predict potential future outcomes (Sivarajah et al., 2017). Lastly, once such predictive models are found, data can be used to anticipate courses of action and their outcomes. By knowing in advance what consequences will most likely derive from each option, the decision maker can answer the leading question of "What should be done?" (to maximize goal fulfilment) (Pape, 2016).

### *1.2.3. Managing the HRA process*

Because not all data is equally suitable for a high-quality decision, HRA must provide information that is objective, measurable, and whenever possible, quantitative (Gal et al., 2017). To achieve this, HRA conforms to four requisites according to Margherita (2020): it is based on evidence (not opinion), it applies systematic methods and data analysis techniques (not ad hoc), it is eclectic in the sense of using whatever tools or approaches that may serve its purpose (not disciplinary bounded) and finally, it does serve the purpose of providing top decision makers with actionable knowledge (not just generating information for general purposes). In the HRA process it is important to acknowledge that its use and effectiveness not only depends on technology capabilities but also (if not mostly) on psychosocial dynamics linked to its adoption.

Socio-technical system theory argues that for the successful implementation of a new system, it is necessary to consider both social and technical systems at an equal level (Cherns, 1976). In light of this theory, Wirges and Neyer (2022) identified four key areas for the successful implementation of HRA in companies. Two areas related to the technological system – data and technology, and two areas related to the social system – HR business partner and intra-organizational context. Data takes a central position in the HRA function and can be of various types, such as traditional HR data (e.g., absence monitoring), business data (e.g., development management and performance) (Tursunbayeva, 2019), or even data that is obtained through personal instruments (e.g., health and location of employees) (Peeters et al., 2020).

The quality of HRA data helps making the HRM metrics more credible. Decisions made by HRM are often based on subjective sources of information, such as performance appraisals or feedback, and therefore data presentation must be reliable (Shet et al., 2021).

Data must be accessible to HRM because a significant amount of work is required in order to control input and output values in various processes and because employee data is quite diverse. Since not all HRM operations are technologically controlled, significant work is required to collect and manage the data obtained through these processes. In addition, there is sensitive information and even information that does not pertain to the HR department, which can make it difficult for HR professionals to access it (Marler & Boudreau, 2017).

Technology itself is crucial in ensuring the acceptance and use of HRA in organizations. While there has been an increase in the supply of tools that enable new data analytics functionality, for predictive and prescriptive HR analytics the existing tools have not been developed for HR business partners, as they are too complex and these professionals do not yet possess the necessary analytical skills (Fernandez & Gallardo-Gallardo, 2021).

This requirement highlights the linkage between the technological and social system. It is noted that HR business partners tend to not yet have the necessary analytical thinking and skills to handle HR data (Álvarez-Gutiérrez et al., 2022).

Rasmussen and Ulrich (2015) found that most HR professionals are not attracted to the possibility of working with data analytics and statistical methods. However, the authors state that when these individuals have contact with analytics and realize how this can assist them in their jobs, some of them show interest in acquiring analytical skills and these are the ones that organizations need to train.

Finally, it is also important to consider the intra-organizational context as an explanatory factor for the realization of HRA (Falletta & Combs, 2021). In this sense, it becomes necessary to identify the stakeholders that are involved in the HRA process. Peeters et al. (2020) identified those stakeholders by allocating them in functional groups: HR professionals, top and line management, all employees in general and other analytical teams.

In addition, some organizations outsource to analytics specialists, while others try to stimulate the analytical skills of their in-house HR professionals who are in charge of the analytics area (Wirges & Neyer, 2022).

To provide for the best, timely, executive decision making, HRA must be able to concomitantly deal with high volumes of data, process the data with complex data analysis techniques, while simultaneously being able to report it in a comprehensive but simple and easily understandable format without losing informational value (Margherita, 2020). This information adds value to any top decision maker in identifying people-related risks, and all the important HR functions such as recruitment & selection (Cheng & Hacket, 2021), training and development (Maity, 2019), career management, and other complementary responsibilities such as employee engagement or culture (Poquet & Laat, 2021).

As stated, in managing the HRA process, data collection and data analysis reliability are paramount alongside its timely deployment to which advanced IT are critical, among which the use of Artificial Intelligence algorithms (Meijerink et al., 2021).

## 1.3. AI and its applications in HRM and HRA

AI is one of the most important fields of computer science that can be applied in various fields, such as HR, as it is proposed to bring several advantages (Kaushal et al., 2023). As part of the AI exponential increase amongst organizations, AI has been increasingly used for HRM, at various levels. Several AI tools have and are constantly being designed and improved to increase efficiency and effectiveness within HRM covering functions such as workforce planning, training, recruitment and also for measuring and optimizing the performance of the workforce (Giermindl et al., 2022).

AI designates a set of theories and techniques that are used to create machines capable of correctly interpreting cognitive and human capabilities. These theories and techniques encompass "natural language processing, machine learning, intelligent agents and rational decision-making" (Tredinnick, 2017, p.37). Mikalef and Gupta (2021, p.3) define it as “the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals”.

To bridge the mathematical nature of AI with the human communication, natural language processing (NLP) has emerged as one of the AI strands that serves as a mediator for AI-based chatbots and digital assistants to receive inputs and provide outputs to users, through some form of conversational user interface (Maedche et al., 2019). The Big Four IT companies that have driven this transformation in the interaction of humans with the digital world by creating their own digital assistants are known to all: Apple (Siri), Amazon (Alexa), Google (Assistant) and Microsoft (Cortana). NLP has been increasingly used in HRM as it allows to automate various services and functions by extracting information from text documents. Chatbots and conversational agents have also been used and appear to bring advantages by automating communication with candidates, employees, and managers (Laumer & Morana, 2022).

Machine learning consists of a central method of AI that allows the development of practical software for various applications such as robot control, computer vision, natural language processing (Janiesch et al., 2021). Several experts and creators of AI systems agree that machine learning makes the work easier, because it is no longer necessary to manually program a system, but it is trained to know how to respond in the desired way to any type of input received (Jordan & Mitchell, 2015). Machine learning has driven quite visible changes in the HR field allowing HRM tasks to supported or even replaced by machines (Garg et al., 2022).

According to Strohmeier (2022) the application of the Gartner Hype Cycle Model to the use of AI in HR can be grouped into a life-cycle model of digital technologies. As in any Gartner Hype Cycle model applied to specific types of technology, the shape of the curve for new technologies can be explained by considering expectations of the technology's value (y-axis) relative to time (x-axis). Linden and Fenn (2003) explain that at an initial phase an advance in technology gives rise to the respective technology (trigger phase), then there is an excessive increase in expectations regarding the technology (peak phase) which is followed by a disappointment phase since expectations cannot be fully met. Finally, there are two phases of recovery as there is a continuous elaboration of the technology allowing for a more considered assessment and consequently, an improvement in the application of the technology.

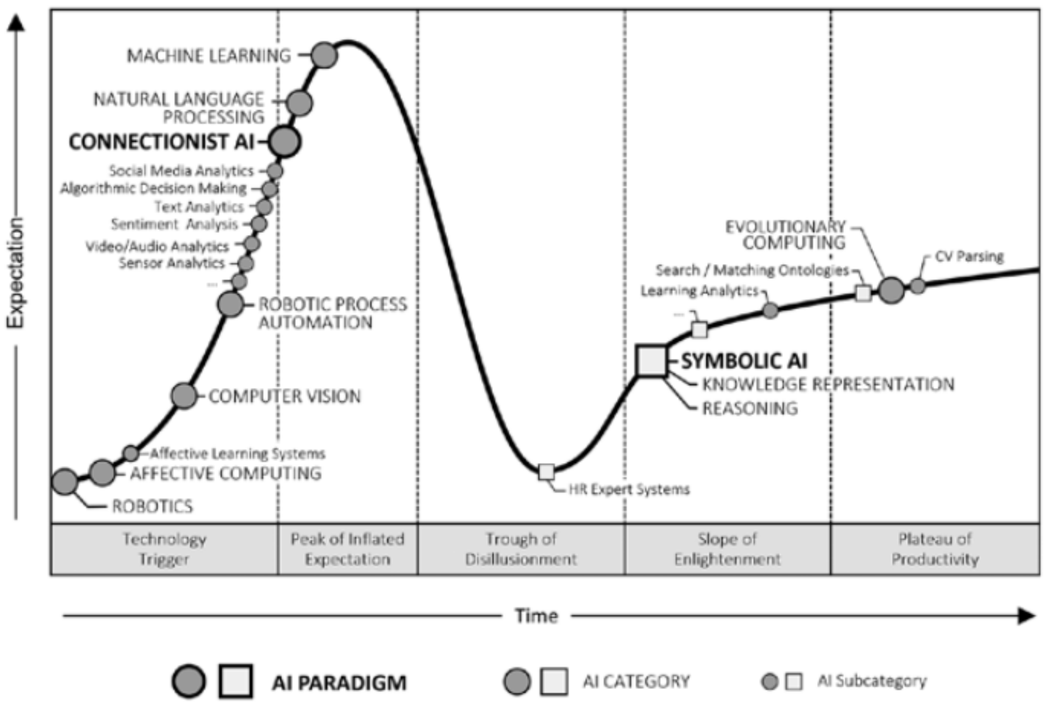


Figure 1.2 - Hype model of AI in HRM (Strohmeier, 2022, p. 10)

This model is important to gain awareness about current applications of AI in HRM. Namely: 1) There are different categories and subcategories of AI in HRM contributing to heterogeneity of AI in HR; 2) There are "ups and downs" of AI application, i.e., the phases of positive and negative expectations; 3) The robustness of AI tools has enabled today conversational chatbots which fall closer to symbolic AI than ever before; 4) High expectations concerning AI refer essentially to three categories of connectionist AI: machine learning, natural language processing, and robotic process automation; 5) There is currently a phase of positive expectations of connectionist AI, but the model predicts that this will be followed by a phase of disillusionment.

Irrespectively of the phase where organizations stand as regards the use of AI for HRM purposes, AI is acknowledged as being capable of rationally processing unlimited data at an extremely fast speed, which appears to bring advantages to managers in the decision-making tasks and processes of organizations (Leyer & Schneider, 2021).

Quite naturally, AI is often studied in parallel with concepts such as HRA (Qamar & Samad, 2022) and Algorithmic HRM. The latter is defined as "the use of software algorithms that operate on the basis of digital data to augment HR-related decisions and/or to automate HRM activities" (Meijerink et al., 2021, p.2547).

Augmentation means that technology supports human decision makers in performing a particular task and/or decision-making (Johnson et al., 2022a). Machines collaborate with humans by providing information, with the human being the final decision maker and can intervene and provide data during the process (Burton et al., 2020). As an example, Genie AI is a company that has developed a tool that can assist lawyers in writing contracts, through software algorithms that makes an exhaustive analysis of contracts written in the past and suggests the clauses that are best suited for each case. Thus, this tool supports lawyers, but does not decide for them. The final decision to accept or reject the tool's suggestions always lies with the human being (lawyer) (Leyer & Schneider, 2021). On the other hand, automation may also result in the total replacement of workers in the process, in such manner that the final decision maker is a non-human agent (Johnson et al., 2022a). In such cases, tasks are handed over in their entirety to algorithms without any human intervention (Raisch & Krakowski, 2021). To give an example again related to lawyers, LawGeex is a startup that provides an AI-based tool capable of automating contract reviews. The only human intervention occurs when the tool identifies a problem (Leyer & Schneider, 2021).

It is thus unsurprising that in the field of algorithmic HRM, an increasing shift of responsibility in decision-making processes from humans to machines is being witnessed. AI-based algorithms are gradually replacing the human being, who has little or no intervention in certain HRM tasks (Meijerink & Bondarouk, 2023).

The progressive automatization of HRM is enabled by AI advanced cognitive capabilities such as reasoning and learning and problem-solving (Brynjolfsson & Mitchell, 2017). Thus, organizations are adopting AI for several HRM functions.

### *1.3.1. AI-based Recruitment & Selection*

The first HRM function where AI is being increasingly used concerns recruitment and selection. Organizations are adopting AI in their recruitment processes by changing application and candidate selection practices (Köchling et al., 2022). Indeed, organizations consider that digital recruitment should be a strategic priority in view of the crucial role that human capital has assumed in the evolution of value creation for companies (Oncioiu et al., 2022). This need also arises from the simple fact that job candidates increasingly occupy their time in the digital world, namely on social media (Van Esch & Black, 2019). These days, there are already more than four billion people using social media (Montag & Elhai, 2023). Digitalization has made the process of passing information between companies and candidates faster and less expensive, which has contributed to a substantial increase in the number of candidates per vacancy (Yam & Skorburg, 2021).

Regarding the process of job applications, whether done directly or indirectly, websites are able to use AI not only to do filtering, but to identify among all, which candidate makes the best fit with the open position (Saling & Do, 2020).

The application of AI tools in recruitment boosts competition for the search for the best talent, as it allows organizations to access, through LinkedIn, Facebook, and other networks, millions of passive candidates (i.e., without much reason to look for new vacancies). Incidentally, machine learning makes it possible for AI tools to be able to learn what characteristics (e.g., color and font size) an email or banner should have to attract specific candidates (Black & van Esch, 2021). AI can measure physiological characteristics, such as the recognition of facial features and expressions, and behavior, such as voice patterns and variations (Van Esch et al., 2019).

### *1.3.2. AI-Based onboarding*

Onboarding a new hire is one of the most resource intensive HRM tasks (Chandar et al., 2017) and therefore the desire to automate onboarding has been fruitful. Machine learning has been studied to provide assistance in the onboarding phase of employees through AI-supported chatbots (Fernández-Martinez & Fernández, 2022). In a study of 344 recent hires, the authors used a chat agent – Chip – to facilitate employee onboarding. This system that the authors created was available to everyone through an immediate messaging service. With this study, it was concluded that “Chip” has the ability to compete with current information channels (such as the professionals responsible for integrating new hires) (Chandar et al., 2017).

Virtual assistants can also help new hires become aware of their job responsibilities. In addition, they can assist them in completing their mandatory trainings, they can collect references about the employee's skills, and they can also, based on other employees in similar positions, recommend relevant content and skills related to the tasks of the new position (Chowdhury et al., 2023).

### *1.3.3. AI-Based performance appraisal*

AI can also be used in the field of performance appraisal. Virtual assistants can distinguish "good" or "bad" performance patterns and automatically classify an agent's interactions with a customer and thus determine the skills and knowledge that can be worked on (Smith, 2019). Chatbots can also compare the performance achieved by an employee against the goals set by the employee and based on the results, it can recommend to the manager skills that should be improved, performance awards and promotions and to the employee himself also make recommendations (Chowdhury et al., 2023).

Some closely related activities concern performance monitoring, but these entail many ethical concerns such as those mentioned by Ravid et al. (2020) such as internet usage monitoring, wrist microchip implants or heat sensors placed at the desk to detect presence of the workers.

### *1.3.4. AI-Based compensation*

The application of AI in the domain of compensation has been ignored and there is still little research on this topic (Malik et al., 2022). Despite this, Johnson et al. (2022b) state that AI tools make it possible to process huge volumes of data on employee salaries and benefits to calculate market-based pay rates for particular skills or abilities. Professionals can use these analytics for more thorough data processing and present more up-to-date and accurate salary benchmarks.

AI could thus be used to ensure fair practices with regards to pay and benefits. Organizations can compare employees in similar positions and understand whether they are receiving identical salaries if they are working the same hours, without considering variables such as gender, age, or race (Votto et al., 2021). Also, Robert et al. (2020) refers to exceptional situations where algorithms may fail as regards distributive fairness and provide an example where a maternity leave could harm the fairness of a pay raise decision if no policy concerning counting work time is reflected on the algorithm.

As compensation inequity has been known to leverage employee voluntary turnover (Colquitt & Zipay, 2015), Cheng and Hackett (2021) report that Google implemented a predictive algorithm that adjusts compensation packages so to mitigate attrition, which is an example on how AI can be implemented to improve the strategic value of compensation and benefits policies and practices.

### *1.3.5. AI-Based training and development and career management*

Training based on AI tools empowers organizations to fulfil the training needs of each employee (Maity, 2019). AI technologies can thus be used to: i) create a collective knowledge base; ii) analyze the current skills and job requirements of each individual and based on that draw up specific training plans for each one; iii) provide trainers, respond to concrete training requirements, monitor learning progress, use chatbots to answer questions in immediate; iv) offer feedback based on employees' performance in trainings (Chen, 2022).

In companies, there are unstructured documents that concern CVs and employee evaluation forms that give managers the information about the skills and experience level of their employees. Bafna et al. (2019) proposed a Task Recommendation System that automatically groups the information that exists in the unstructured documents. Thus, data is extracted from the two types of documents (CVs and documents that present the required competencies) and based on that the System groups the extracted features into “synset groups”. In this way, it is possible to map the set of competencies that have been extracted and gauge that against the set of required competencies. Based on this, the system can identify which employees need extra training and furthermore, it can improve the productivity of organizations by assigning tasks to the right employees according to their skills.

On the one hand, supervisors gain an insight into the points for improvement and thus determine the necessary training and also gain insight into the positive points of the agents. On the other hand, employees are given the opportunity for training and can subsequently be recognized and rewarded if they show improvement and acquire new skills (Smith, 2019).

Lee and Ahn (2020) implemented AI-based software with the goal of matching employees' careers according to the skills elected by organizations and the candidates' own skill preferences. In addition, the authors also rely on the Myers-Briggs Type Indicator (MBTI) that represents the personality traits and characteristics of candidates and key employees of organizations. The results show that this method is advantageous for career management in that it contributes more quality than conventional methods.

### *1.3.6. AI-Based employee engagement*

Employee engagement is a crucial factor for organizations (Braganza et al., 2021) and according to Dutta et al. (2022) AI applications in HRM can foster employee engagement in three ways: more awareness of employee’s current engagement, better trust climate, and better personalized employee experience.

Data analytics and digital technology can be used to understand and report on employees' connection and engagement with organizations. For example, the network awareness tool uses data on employees' interactions on organizational social networks to insight and make an analysis of employee engagement. Especially when employees have a problem or need help, this AI-based tool contributes to an increased awareness for value creation in work practices by joining professional networks and/or communities to which individuals can turn for help (Poquet & Laat, 2021).

Dutta et al. (2022) report that chatbots contribute to increasing the level of engagement by promoting the development of a climate of trust in companies. The chatbot positive effect occurs because employee engagement can be produced by support from supervisors and direct voice (Holland et al., 2017).

The implementation of AI in the domain of the employee engagement function can also provide employees with a personalized experience in line with their role in the organization, their needs, commitments, goals, and schedules (Chowdhury et al., 2023).

### *1.3.7. AI-Based employee exiting decisions*

Data mining algorithms allow organizations to build reliable methods of predicting employee attrition. Through this method it becomes possible to hypothesize which employees are most likely to leave the organization (Zhao et al., 2018). This AI technique also allows for the construction of retention techniques by assigning a rating to each employee (Shankar et al., 2018).

Guerranti and Dimitri (2022) used AI and machine learning methods to study the probability of an employee leaving the company and the reasons for doing so. The authors sustain that among the methods used, Random Forests (RF) and Logistic Regression (LR) are the most effective and were able to demonstrate the variables that HRM should consider predicting employee attrition. These include home-work distance, very low pay, little involvement at work. These findings suggest that organizations by being aware of the variables that contribute to the likelihood of an employee deciding to leave the company, can create new measures and reduce turnover.

### *1.3.8. AI-Based Strategic HRM*

SHRM covers all functions mentioned above but, in this case, it is used to name transversal managerial functions related e.g., with budgeting, resource allocation and the overall design of decision making.

Advanced analytics through AI applications has contributed to HRM discovering rich and practical information and predictions about HRM (Margherita, 2021). Exemplifying, AI-based algorithmic monitoring makes it possible for strategically relevant numerous information about employees to be recorded autonomously and in real time, such as, emotions, movements, and health status, browsing history, employee calendar and employee engagement with organizations (Parent-Rocheleau & Parker, 2022).

AI enables HRM to redefine the way in which it manages its workforce (Giermindl et al., 2022). According to Trunk et al. (2020) organizations can leverage the potential and strength of AI-based systems to make decisions with more significant strategic value. Workforce analytics has different levels of maturity: operational reporting, advanced reporting, strategic analytics, and predictive analytics (Chornous & Gura, 2020).

In addition to this, Tambe et al. (2019) state that the adoption of AI in HRM brings long-term advantages and can contribute to an improvement in the efficiency of the functions carried out by HRM. It is important that HR managers go about measuring the effects of AI so that their decision-making on resource allocation is prevented as well as that the use of AI is strategically advantageous.

One of the important functions in HRM (as in any management domain) is the resource allocation, also under the budgeting function, which can be streamlined with AI support (Chowdhury et al., 2023). An optimal resource allocation is a required condition to attain maximum organizational performance, and therefore, deciding on staffing services with the right number and right profile of employees, and providing the exact resources needed to attain objectives can be enhanced by AI algorithms (Rosenblat & Stark, 2016).

## 1.4. The advantages and disadvantages in AI-based HRA

### *1.4.1. Advantages*

The use of technology in HR is not new, however, HRA has enabled a shift from purely descriptive and administrative analyses on historical employee data, to predictive analyses capable of transforming this same data into information and results that can be used in future-oriented decision-making processes (Wirges & Neyer, 2022). Moreover, the scope, accuracy, and effectiveness of the cognitive activities that AI is able to perform, distinguish it as innovative and distinct from the other technologies that were already used for HRM (Charlwood & Guenole, 2022). It is thus unsurprising to witness many supporters of HRA claiming that this new field is giving a push to HRM to assume a stronger strategic role, capable of increasing the performance of organizations and highlighting the role of HR (Wirges & Neyer, 2022).

This advocacy has been gaining momentum and organizations are increasingly considering it as a key tool for human capital analysis (Greasley & Thomas, 2020). HRA is taken as adding value to organizations by supporting operational and strategic decision-making processes based on data (Ellmer & Reichel, 2021).

These advantages stem from the functional applications reviewed as employees and companies can benefit from HRA in a variety of ways (Chatterjee et al., 2022).

As reviewed, HRA offers useful insights into employee performance, workforce trends, and HR procedures through the use of data and sophisticated analytical methodologies. These insights can lead to improvements in HR decision-making, business results, and overall organizational performance (McCartney & Fu, 2022). Digitalized processes can also make organizations gain more knowledge on job candidates and their former employees (Marler & Boudreau, 2017), as it can work efficiency (Gross, 2022), especially in a time we are witnessing a significant increase in the amount of data (Cheng & Hacket, 2021). AI has thus enabled large volumes of data to be processed automatically (Johnson et al., 2022a). AI-enabled software surpasses standard software algorithms, as unlike these AI has the ability to learn large volumes of disparate data at different time intervals and can still make decisions based on this data (Leyer & Schneider, 2021).

Big Tech, such as Google and Microsoft, currently have platforms and software capable of analyzing HRM processes and effects, such as hiring, compensation and employee turnover (Cheng & Hacket, 2021). Indeed, HRA can produce actionable information for all phases of the employee lifecycle, from workforce planning, through onboarding and development, to employee retention (Giermindl et al., 2022). Additional advantageous features provided by HRA include automated hiring, retention, and firing processes (Behl et al., 2022). Another way HRA helps organizations is by assisting managers in making decisions regarding to training, scheduling, and allocation of resources (Rosenblat & Stark, 2016). Lastly, uncovering hidden talent in organizations is within the reach of algorithmic decision making (Köchling & Wehner, 2020). Overall, heightened performance in several HR functions due to AI use is generally reported in literature (Singh et al., 2020).

Access to AI has become increasingly easier in terms of technological cost, data access, distribution of computing skills and knowledge, which leads to the uptake of organizations. Predictions indicate that AI will affect virtually every job function (Johnson et al., 2022a). Van den Heuvel and Bondarouk (2017), forecasted that by 2025, HRA will be a well-defined field with proven effects on organizational outcomes and a major role in strategic decision-making processes.

### *1.4.2. Disadvantages*

Organizations are aware of the benefits that can be created by HRA and AI, but this seems to remain only "in words". In practice, before embedding HRM into their operations, organizations need to consider how analytics should be used to collect, organize, and maximize HR data to create significant strategic value (Shet et al., 2021). Moreover, there is no doubt that research on HRA is still at an early stage and there are few critical or empirical studies on this domain that would allow us to clearly judge the full range of effects of HRA on HRM (Greasley & Thomas, 2020).

In a lively manner Levenson and Fink (2017, p. 147) stated that "HR analytics is a bit of a wild, wild, west, with too few consistent frameworks to drive powerful action and improvement for organizations". Albeit almost 6 years have elapsed from this critique, more recently, Meijerink et al. (2021) reinforce it by calling attention to the of different concepts in this field to refer to the same thing, which demonstrates the confusion that exists on this topic and the reason why we do not yet have a consistent literature on HRA.

Several articles and research available on this topic focus essentially on the question and challenge of defining HRA. Contrary to this, it is curious that practitioners are increasingly publishing articles and projects in which data science and statistical methods are applied that lead people to think that HRA is already well understood by practitioners and is already in a consolidated state (Edwards et al., 2022). Worse than that, the danger lies in the fact that organizations are increasingly using data and analytics for HRM decision-making processes without having sufficient analytical expertise to do so (Harney & Collings, 2021).

It is therefore logical that non-acceptance of HRA stems also from the lack of analytical skills by HR professionals (Cayrat & Boxall, 2022). Another cause can originate from the peripheral positioning of HR in organizational hierarchies (Angrave et al., 2016). All of these can hinder the mobilization of support and the application of analysis results, however for SHRM, it is critical that there is support from top manager (Hamilton & Sodeman, 2020).

Data access is a significant barrier for HR as a lot of work is required to track input and output values in various processes and because employee data is quite diverse (Andersen, 2017). Since not all HR operations are technologically controlled, significant work is required to collect and manage the data obtained through these processes. In addition, there is sensitive information and even information that does not pertain to the HR department, which makes it difficult for HR professionals to access it. Clarifying the ownership of data, which can be controversial, is crucial to help organizations make data more accessible to HR (Shet et al., 2021).

In addition to this, the quality and composition of the data that is used for algorithmic decision-making may bring challenges at the level of ethics. The issue of discrimination will not disappear as a risk, for example in recruitment and selection, because AI has the power to reinforce this bias by embedding it in technology (Kelan, 2023). If algorithms are trained with biased data, the probability of them producing or replicating biased decisions is high. In an extreme case, it may be the case that the historical data used to build algorithms is composed of historical biases that cause the algorithm to produce biased results (Köchling & Wehner, 2020).

According to Lee (2018, p.12), algorithms "lack human intuition, only measure quantifiable metrics, and cannot evaluate social interaction or handle exceptions". For this reason, another major current concern is the over-reliance on technology. While it has the ability to make processes simpler, it does not have the capacity to measure non-quantifiable aspects, so it is important to have a coherent and correct delegation between humans and computers (Bankins, 2021).

Another major concern is privacy threatened by the intrusive use of analytics. There are companies, such as Walmart and Microsoft, that use tracking systems to collect data about their employees throughout the workday. For example, geolocation, audio and accelerometer data (Hamilton & Sodeman, 2020). Additionally, privacy in the workplace is also a risk that arises in connection with the use of technology in organizations (Vrontis et al., 2022).

## 1.5. Endorsement of AI-based HRM

It is not enough to dispose of an AI tool to make it effective. It is mostly important that individuals take a positive approach to it and are willing to use it. Therefore, in AI and in any technological change, acceptance is an antechamber of its endorsement and use.

In explaining AI applications, many theoretical lenses have been proposed. In marketing only, Mariani et al. (2022) identified over 400 different approaches which they have clustered in eight groups: acceptance models, game theory, theory of mind, theory of planned behavior (TPB), computational theories, behavioral reasoning theory, decision theories, and evolutionary theories.

Among the most popular models, the UTAUT (Unified Theory of Acceptance and Use of Technology, Venkatesh, 2003) later revised by Dwivedi et al. (2019) has a long history of integrating psychological theory ever since the pioneer Technology Acceptance Model (Davis, 1989) was published.

UTAUT originated when Venkatesh et al. (2003) found that the presence of computer and information technologies in organizations has expanded dramatically, so that research in the field of Information System has gained a focus on the study of users' acceptance of new technologies. Venkatesh et al. (2003) conducted a review of the user acceptance literature and a comparative analysis of extant theories and models. Among these models the authors gave special attention to three: Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), and Technology Acceptance Model (TAM). TRA originated from social psychology (Fishbein & Ajzen, 1975) and is a forerunner to many models and a widely applied explanation of human behavior to explain technological adoption (Venkatesh et al. 2003). According to TRA, each person's behavior is determined by their own behavioral intention, which is in turn influenced by their attitude towards that behavior and their perceptions of social standards (Fishbein & Ajzen, 1975). Based on this theory two proposals emerged: TPB (Ajzen, 1991) and a more efficient and widely used TAM (Davis 1989; Davis et al. 1989).

TPB introduces a new variable to TRA, perceived behavioral control, i.e., people's perception of the ease or difficulty of carrying out a desired activity. Thus, this variable changes according to situations and different ways to perform actions. The author considers that perceived behavioral control and behavioral intention can predict the performance of behavior (Ajzen, 1991).

TAM argues that an individual's intention to engage in each technology directly influences that individual's actual behaviors, which results in his or her attitudes towards the technology (Davis, 1989). Furthermore, an individual's general attitude towards the use (or not) of Information Systems & Technology, is the result of two fundamental beliefs: i) perceived usefulness (PU), which is outcome-oriented (e.g., effects of using the new technology) and ii) perceived ease of use (EoU), which is more process-oriented (e.g., the effort it takes to adopt a new technology) (Park et al., 2021a).

By integrating these theories Venkatesh et al. (2003) formulated UTAUT that differs from its precursors by presenting four moderators that increase the predictive power of the model (gender, age, experience, and voluntariness). The model outperformed all others on intention to use, accounting for 70% of the adjusted R2. This model has been criticized and recently revised by Dwivedi et al. (2019) to exclude the four moderators (because they believe that these are not applicable in all contexts) and putting back attitude as a mediating variable. They called this the UTAUT2 model.

Moriuchi (2021) conducted a UTAUT based study to understand the perceptions of users regarding the acceptance and use of the Voice Assistants to conclude that there is a need for the Voice Assistants to be more human as this has implications for users' expectation of what it can do. Another study found that librarians' intention to adopt and implement AI is strongly influenced by the performance expectancy of AI tools and the effort expectancy while social factors, such as social influence and peer pressure, also played a significant role (Andrews et al., 2021). More recently, a study on intention to adopt robo-advisors in fintech industry found that individual attitudes and subjective norms are important predictors (Roh et al., 2023) which is in line with Parvez et al. (2022) findings that perceived usefulness and ease of use have a positive impact on accepting robots as co-workers. The adoption of HRA technologies clearly fall within this line of research. Shet et al., (2021) stress that its acceptance depends on employees’ perception on its importance and effectiveness (performance expectancy).

Thus, Psychology and Social Psychology greatly contributed to support these studies and UTAUT models incorporate many of the components of such acceptance process. In a study on intrinsic motivation for innovative behaviors, based on the influence of exposure to the capabilities of online ideation platforms, it was proven, through the Expectancy Theory, that these platforms increase motivation and enhance the willingness of employees to adopt innovative behaviors (Kruft & Kock, 2021). The Expectancy Theory presented by Vroom (1964) argues that employees show higher levels of motivation to perform a given task, i) when they think they can perform it effectively, ii) when they trust that the successful completion of this task is essential to the achievement of an outcome and iii) when they believe that this outcome brings them satisfaction (Fairbank et al., 2003). Hence, in the context of this study, employees' intention to approve general HRM depends on whether employees believe that i) automated HRM functions are effective and contribute to better job performance, ii) they are instrumental in achieving expected results and iii) the results bring job satisfaction.

In a study on AI acceptance by workers (Choi, 2021) identified factors capable of increasing workers' willingness to accept the adoption of AI-based technology. Firstly, the roles of the user and the AI itself should be clearly defined for higher levels of approval. Furthermore, the user's motivation and capabilities contribute to AI acceptance. Privacy concerns have been shown to be a factor with a negative impact on AI approval.

So, overall, psychological theory highlights the importance of the general attitude towards implementing AI in HRM especially because the recency of the topic, the uncertainties it entails (which can be considered as a threat), and the lack of objective knowledge about its functioning can trigger negative emotions that lead to its rejection as well as possible unrealistic positive expectations that foster an acritical acceptance. The problem with these extremes is that the first has a possible opportunity costs while the second leads to frustration and plausible disappointment with the consequences of AI adoption.

Overall, we hypothesize that:

*H1: Functional a-HRM domains endorsement is positively associated to General a-HRM endorsement*

More specifically,

*H1a: Endorsement of AI in Recruitment & Selection is positively associated to the General a-HRM endorsement*

*H1b: Endorsement of AI in Employee Orientation & Development is positively associated to the General a-HRM endorsement*

*H1c: Endorsement of AI in Performance Management is positively associated to the General a-HRM endorsement*

*H1d: Endorsement of AI in SHRM is positively associated to the General a-HRM endorsement*

Among critical general attitudes towards AI, literature has highlighted trust. Mayer et al. (1995) defined trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712). Trust consists of an uncertain interpersonal relationship established between a trustor and a trustee. However, the trustor is always subject to the danger that the trustee will not deliver the expected results (Park et al., 2021b). This refers to interpersonal trust but there are other types of trust in psychological literature, namely: i) general trust, as a personality trait that tells how trustworthy a person is in general; ii) social trust, which measures how trustworthy a person is towards other individuals and institutions, is built on interpersonal relationships and shared values (Verberne et al., 2012). In addition to all this, the literature presents another type of trust: technological trust that is established between human-machine (Schmidt et al., 2020). Several studies have shown the importance of understanding this type of trust to explain different domains of behavior, such as interaction in work teams (McKnight et al., 2011).

Because trust entails three components (competence, integrity, benevolence, Mayer et al., 1995) we think AI-based HRM endorsement must be explained by three principles: 1) that the algorithm is effective in achieving its purposes, 2) that the algorithm does what it is said to do, and 3) that the algorithm is designed with a do-no-harm principle.

Vance et al. (2008) studied to what extent the attributes of trust in people (competence, integrity, and benevolence) can be used to study trust in websites. Based on TRA, the researchers have shown that a trustor's beliefs towards a trustee lead to the intention to trust the trustee which in turn leads to trusting behavior wherein, in an uncertain scenario, the trustor is exposed to the trustee. Therefore, trust beliefs regarding IT artefacts are key to predict whether individuals were determined to rely, or not, on the IT artefact. This trust in the IT artefact depends on attributes that are distinct from those associated with trust in individuals, namely it depends on the quality features of the system (e.g., navigation structure). Among other results, the authors found that culture impacts the level of people's trust in the IT artefact.

In the field of automation, trust is defined as an attitude, in that in a situation of uncertainty, an individual will achieve his or her goals with the assistance of an agent (Park et al., 2021a). Moreover, in situations where an algorithm shows an unfeasible solution and where trust is placed in another person rather than in an automated system or technology, an individual's trust in automation can be explained (Chiou & Lee, 2023). This technology-based trust comprehends three fundamental elements: I) performance, is the capacity of automation to accomplish operator goals; ii) the term "reliable" refers to the accuracy and dependability of the processes and algorithms guiding the behavior of the automation, and iii) purpose or helpfulness as the degree to which automation is used in accordance with the designer's intention. These similarities do not preclude fundamental differences compared to trust between humans (Park et al., 2021b). However, the literature points to a certain aversion towards AI and individuals tend to trust algorithms less compared to trusting humans (Dietvorst et al., 2014). Interestingly, when given the possibility to change some part of the AI predictions, the likelihood of people trusting algorithms doubles (Schmidt et al., 2020).

## 1.6. Normative dimensions and AI-HRM endorsement

HRA is not immune to the ethical challenges that its deployment in organizations may raise. Although data-driven organizational decisions occur in virtually all areas of an organization (Wirges & Neyer, 2022), in the field of HRM, data used to make decisions regarding the human resources of the organization i.e. data are used to decide about people (Ellmer & Reichel, 2021) have inescapable consequences on people's lives (Ferrario et al., 2020). The literature shows that algorithms have the ability to silently structure our lives, for example, they can determine whether an employee should be promoted, or a candidate should be hired (Martin, 2019a). As HRA projects become more sophisticated and rely on more employee data, ethical concerns will grow (Edwards et al. 2022).

This is a legitimate concern because, contrary to popular belief, AI-based decision making is not purely rational (Leyer & Schneider, 2021). These authors sustain that algorithms can fully replace individuals, but they need to be trained by programmers who, being human beings, are not able to escape their biases when building the algorithm and cannot fully avoid that the data they use to train the algorithm is unbiased. As such, all algorithmic decisions are, like any other decision, susceptible to errors and biases (Martin, 2019b).

It is thus not surprising that the advances in AI technology are matched by a growing interest on AI-ethics as practitioners are beginning to doubt and show concern at the level of control humans have over AI systems (Rodgers et al., 2023). In HRM alone, workers are divided and confused about the level of trust they can place in AI-based HRM (Burton et al., 2020).

In large part this concern is related to professionals' lack of understanding of this issue. HR professionals do not yet have the necessary analytical skills to perform functions in the HRA domain (Cayrat & Boxall, 2022). The lack of knowledge and skills of professionals, coupled with the increasing loss of human control in decisions made by algorithms (Leyer & Schneider, 2021) may lead to professionals not trusting algorithms to make such important decisions (Burton et al., 2020). Conversely, the opposite situation may entail hazards. Caution is needed as overconfidence in decisions made by machines (termed automation bias) leads to disregarding problems and errors of commission and omission (Zweig & Raudonat, 2022).

So, AI intrinsically raises ethical issues and decisions concerning AI implementation, such as HRA, must seeks to understand which values are used to guide behavior in organizations (Edwards et al., 2022) thus giving business ethics a central position in management decision making (Tóth et al., 2022).

Especially when it turns out that a decision-making process has triggered a wrong final response, ethically sensitive questions can find answers in socially-constructed normative dimensions (subjective norms) that establish what is or not acceptable. Among these dimensions, literature on AI (e.g. Strohmeier, 2022) has highlighted accountability (Zweig & Raudonat, 2022), legitimacy (von Lewinski & Fritz, 2022), explainability (Langer & König, 2022), and fairness (Fisher & Howardson, 2022) to which reversibility of effects (Shneiderman, 2020) may also add value.

We thus hypothesize that:

*H2: Normative dimensions are positively associated to the Functional a-HRM domains endorsement*

### *1.6.1. Accountability*

The concept of accountability can take on different facets. However, it refers to the way of finding out who is responsible for a certain decision, intended or not, made through an AI system (Zweig & Raudonat, 2022).

It is known that algorithmic decisions are often critical and can be biased. The question then becomes, who should be responsible when a wrong decision is made based on AI systems (Martin, 2019b)?

Some divergence persists in the literature on this topic. Some authors claim that we are seeing a shift of decision-making responsibility from individuals to machines (e.g. Meijerink & Bondarouk, 2023). However, there is one capability that technology does not yet have which is to recognize and take responsibility for the decisions that are made by it (Leyer & Schneider, 2021). This leads us to wonder about who is actually the person or institution that should be held responsible for such a decision when something does not go as expected (Rodgers et al., 2023).

Thus, since it is not possible to assign responsibility to the software with AI, when there is a biased result that originates errors, the designer who created the tool will likely be responsible for the decision made (Martin, 2019b). It turns out that sometimes even designers cannot understand how the software arrived at a certain result (Leyer & Schneider, 2021).

In addition to this, one cannot ignore the fact that managers are responsible for the correct application of the tool used to make decisions. Managers have the autonomy to decide at which point and in what way the AI-based tool should be used. However, managers can also become the agents responsible for the decisions made by the machines and therefore must have the necessary skills to correctly assume the role of responsible decision maker (Burton et al., 2020).

The study by Tóth et al. (2022) provides a framework that explains accountability in AI robot-based decision making. The framework presents four clusters, each corresponding to a group of accountability essential for the application of AI in organizations. The clusters were created taking into account two axes that concern the focus of morality and moral intensity. As higher levels of moral intensity and AI agency occur, the nature of accountability will disperse. Thus, in a situation where there is low moral intensity and no AI agency, when a worker makes an unethical decision, it is not difficult to understand who should be held accountable because there is not much dispersion. However, in situations where AI robots are used, where there is high moral intensity and little human action, many more accountability groups are attracted. In these situations, when there is an unethical issue, for example caused by a mistake, the complexity of assigning responsibility is much greater: should it be the AI robot, the programmer, the company that implemented it, or the manager that supervises it? Eventually the law maker than enabled wrongful uses?

As regards accountability in AI based HRA, there are few studies (Loscher & Bader, 2023). These authors conceptualized three forms of accountability that are included in HRM as a result of HRA implementation. "Exposure accountability" highlights how the HRA shapes employees' and managers' perceptions as well as their behavior. As an example, when employees find through the HRA that the organization is placing greater importance on understanding turnover intentions, they modify their behavior to demonstrate they have low turnover intentions and thus can advance their careers (Bader & Kaiser, 2019). "Accountability through design" lies in claiming an organizational problem as an HR analytical problem. HRM by taking responsibility for the problem, commits to come up with solutions and makes its activities transparent, as well as demonstrating its strategic value (Losher & Bader, 2023). Finally, "connectivity accountability" refers to the rise of the HR profession as other professions in organizations come to depend on its input (e.g., data scientists).

Thus, as an expression of hypothesis 2 applied to this domain we hypothesize that:

*H2a: Accountability is positively associated to the AI-Recruitment & Selection endorsement (H2a1), the Employee Orientation & Development (H2a2), the Performance Management (H2a3), and the SHRM (H2a4)*

### *1.6.2. Fairness*

In a very simple way, fairness implies following established social norms and treating others as we would like to be treated. Algorithmic fairness is also a key issue in AI (Teodorescu et al., 2021). This concept can be understood from an epistemological perspective, as we are interested in understanding how we can know what it means for something to be fair or unfair (Fisher & Howardson, 2022). There is no agreed definition of fairness among humans, just as there is no global definition of fairness in computer science (Teodorescu et al., 2021).

Individuals believe that a decision-making process is fair when i) it is consistent, ii) it is based on accurate information and iii) it is not influenced by decision-maker biases (Newman et al., 2020). These three criteria comprise the notion of organizational justice which ensures that there is fairness in organizations (Van den Broek et al., 2019). However, the literature points to a discrepancy that exists between what AI promises and what it actually delivers in HRM (Tambe et al., 2019). Consequently, workers exhibit lower levels of job satisfaction and lower confidence when they perceive HRM decisions to be unfair (Fisher & Howardson, 2022).

Van den Broek et al. (2019) conducted a study in a multinational company where an AI application was implemented for hiring employees and concluded that fairness gains centrality in AI-based decision making. The authors found that it is only when stakeholder groups started using AI that they start to question themselves and it causes conflicts among employees who perceive the scope of equity in recruitment differently. Literature shows that an unfair HR decision in hiring, or promotion caused by a human error is more acceptable than unfair decisions caused by errors of an algorithm (Fisher & Howardson, 2022). Moreover, individuals affected by HR algorithm-based decisions consider the results to be reductionist, as they argue that algorithms only decide based on quantitative aspects and do not include qualitative ones. This could be a valid reason why people consider AI decisions to be less fair (Newman et al., 2020).

One of the barriers that hampers the sense of fairness in machine learning models concerns dealing with subgroups (such as race, religion, age, nationality). Diversity within these variables attached to patterns observable in societal domain, makes it more difficult it is to guarantee the fairness of the decision. Through a specific data analysis technique, ROC curves (Gonçalves et al., 2014), an equitable decision can be attained by the intersection of the curves. However, with the existence of several groups, the requirements of each group may not be satisfied when trying to reach a solution that is equitable for all (Teodorescu et al., 2021).

Fairness in AI based management can be unachievable if one conceives management overpowering control as intrinsically unfair, and AI can paradoxically offer the best data for fair decision making but simultaneously it can empower management to levels never witnessed before. HR professionals perform an important role here if they decide to engage and acquire the necessary skills to understand AI systems and thus ensure that fairness will always be a central factor in AI-based HRM (Charlwood & Guenole, 2021).

Thus, as an expression of hypothesis 2 applied to this domain we hypothesize that:

*H2b: Fairness is positively associated to the AI-Recruitment & Selection endorsement (H2b1), the Employee Orientation & Development (H2b2), the Performance Management (H2b3), and the SHRM (H2b4).*

### *1.6.3. Explainability*

The explainability of AI in HRM consists of understanding AI algorithms and systems and the decisions based on these systems, especially in more sensitive and ethically risky situations (Langer & König, 2022). This notion relates to employees' understanding of the criteria on which analytical decisions are based (Tambe et al., 2019).

The term eXplainable Artificial Intelligence (XAI) was introduced to promote clarification of the internal processes that AI algorithms use to make decisions (Minh et al., 2022). However, what we find is that AI systems are often titled a "black box" because there is no transparency and practitioners have problems interpreting and exposing how AI-based decisions are made (Köchling & Wehner, 2020).

Thus, when talking about XAI it is crucial to consider three key components: transparency, interpretability, and explainability (Roscher et al., 2020). Practitioners have called for more transparency when developing and implementing AI systems in organizations (Meijerink et al., 2021). The degree of transparency of AI differs according to the analysis task, the attributes and the parameters that are defined (Roscher et al., 2020). Interpretability consists of the process of mapping an abstract concept into domains that are understandable and interpreted by humans, for example, an image (which is formed by several pixels) (Montavon et al., 2018). Finally, explainability is an essential component in HRM, in that information about the human context and HRM expertise are needed to be able to formulate an explanation about the different interpretations and arrive at answers about how algorithms work and the reasons they use to make the conclusions they present (Köchling & Wehner, 2020).

AI systems opacity can be attributed to the existence of different subsystems designed to perform different tasks which brings complexity and blurs how decision is produced and how information is moved between subsystems (Rodgers et al., 2023). Furthermore, the systems can analyze a huge amount of data, words, pixels, which generates complexity in the input data and makes the human understanding of these processes even more difficult (Langer & König, 2022). The opaque nature of algorithms and their complexity make them unpredictable and enigmatic, which in turn makes it even more difficult to assign responsibility (Martin, 2019a). Programmers themselves may find it difficult to explain how the algorithms they have developed work (Leyer & Schneider, 2021). It becomes clear that with no one able to explain the logic that AI systems follow to make decisions, the likelihood that HR managers will accept and believe that AI-based decision making adds value to HRM and organizations is low (Chowdhury et al., 2022).

Thus, as an expression of hypothesis 2 applied to this domain we hypothesize that:

*H2c: Explainability is positively associated to the AI-Recruitment & Selection endorsement (H2c1), the Employee Orientation & Development (H2c2), the Performance Management (H2c3), and the SHRM (H2c4)*

### *1.6.4. Legitimacy*

Legitimacy of the HRA is crucial for its implementation (Wirges & Neyer, 2022). In an ecosystemic context, such as an organization, in which individuals interact with each other and with the external environment, it is a challenge to obtain legitimacy (Thomas & Ritala, 2022).

According to Sowerno et al. (2019) legitimacy is understood as a condition in which a company's values are found to conform to the broader set of societal values. Legitimacy can be understood in different ways, as the values of a given organization must be adapted to the values and beliefs of the society where the organization is (del-Castillo-Feito et al., 2022). Therefore, legitimacy can be taken as expressing the perceived value fit between organizations and their environment, i.e. between organizations and their stakeholders.

From another perspective, legitimacy can be ascribed due to a shared perception of usefulness. In HRA, the success of HR teams depends on their performance and ability to promote mutual aid with everyone from managers, other analytical teams, HR business partners, employees (Cayratt & Boxall, 2022). This will lead management to support HRA which is crucial in ensuring legitimacy. Legitimacy can here be conceived as expressing a collective sense of usefulness. Still, as Wirges and Neyer (2022) highlight, often HRM analytics results are passed on to other areas, specific departments, or management, without the results being effectively evaluated, i.e., in raw. The legitimacy of the use of analytics in HRM is thus threatened and in such situations HR professionals fail to demonstrate the benefits of its use.

Legitimacy can also be approached from a legal perspective. AI is impacting the world of work in the same way that 200 years ago the emergence of steam engines changed the entire organizational dynamics. This global-level impact of AI on organizations brings challenges for legal practitioners.

Currently, there still is very few legislation governing the use of AI but it is worth noting initiatives led by private organizations and aggregating a variety of different entities in order to address this matter, such as the Dubber et al. (2020). Likewise, the European Parliament issued in June 2023 a negotiation position based on the AI act (Madiega, 2021).

Although laws on AI as a technology are yet incipient, when talking about the legitimacy of AI in HRM from a legal standpoint, it is important to consider essentially three areas of law: data protection law, labor law, and anti-discrimination law (von Lewinski & Fritz, 2022).

Organizations need to collect and have at their disposal information concerning their employees, such as, their ability, motivation, integrity. In addition, they should ensure that employees have ethical and legal behaviors at work and, for example, do not take too many breaks in working hours or even ensuring that employees do not steal from customers or the organization itself (Bhave et al., 2020). It turns out that this information collection carries legal issues and there is a certain tension between the requirements that organizations demand and the rights of individual employees and the privacy of their data (Rodgers et al., 2023). In fact, privacy concerns brought by AI use in organizations weaken the relationship between role transparency and employee acceptance of AI (Choi, 2021).

Additionally, algorithm-based decision making runs the risk of being unfair and discriminative (Lindebaum et al., 2019). If algorithms are trained with biased input data they are susceptible to generating or even reproducing biased decisions (Köchling & Wehner, 2020). Indeed, there are reports about large companies, such as Amazon and Apple, that have misused AI, resulting in discrimination (Enholm et al., 2022). In the case of Amazon, hiring algorithms discriminated against women by creating a huge disadvantage compared to men, eventually leading the company to cease algorithmic hiring decisions (Robert et al., 2020).

Therefore, discrimination that results from algorithmic decision-making (even if well-intentioned) can happen because in the decision-making process the algorithm reproduces patterns of discrimination that already existed, it can receive the prejudices of the former decision-makers or it can even mirror the prejudices of society (Lepri et al., 2018).

Regarding human intervention, several jurisdictions still do not allow algorithms to be the final decision-makers and it should be humans who certify and prove automated decisions (von Lewinski & Fritz, 2022).

Thus, as an expression of hypothesis 2 applied to this domain we hypothesize that:

*H2d: Legitimacy is positively associated to the AI-Recruitment & Selection endorsement (H2d1), the Employee Orientation & Development (H2d2), the Performance Management (H2d3), and the SHRM (H2d4)*

### 1.6.5. *Reversibility*

A given AI decision may entail negative effects (intrinsic to the fallible nature of decision algorithms) that may not be entirely anticipated. If, however, such effects could be reversed by putting back the previous status, compensate victims of the decision so to reinstate their rights or resources, the risks may not be taken as seriously as if there was no way to reverse the negative effects. This dimension should be considered when discussing the risks of AI in HRM decisions and has been greatly overlooked.

This dimension is critical as visible in environmental studies. For example, irreversibility of effects is one of the key issues in arguing against climate hazardous decisions because, once created, ecological systemic failure cannot be turned back (Lenton et al., 2019). Likewise, in clinical domain, the irreversibility of negative decisions pertaining to medical acts (Pugh, 2019) make them particularly critical such as decision whether to unplug a machine-assisted patient in keeping the vital functions, or to proceed to an invasive surgery in a risky location of a tumor (Covvey et al., 2019), or simply the controversial decision of euthanasia (Schuurmans et al., 2019). Also, in Law and ethics studies, the irreversibility argument is one of the key issues in rejecting the death penalty as any wrongful deliberation (due to judgment error, flawed evidence, or institutional flaws in the justice system) cannot be corrected (Efrat & Richemond-Barak, 2023).

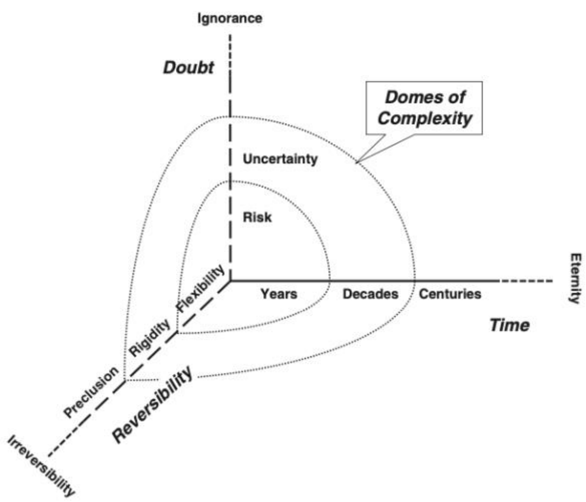


Figure 1.3 - Decision context (Verbruggen, 2013, p. 23)

The context of a decision can be defined by i) future time, ii) doubt and iii) reversibility. Time, because decisions always carry consequences for the future (although humans tend to decide with the short term in mind, because they prefer more immediate gains). Doubt implies three levels: risk, uncertainty, and ignorance, and is especially important when there is no certainty about the long-term future. Reversibility is commonly understood as the ability to undergo change, including the ability to " turn back" to a previous condition. This ability ranges from flexibility to absolute irreversibility (Verbruggen, 2013). This scholar advocates that there are domes of complexity where reversibility of effects is one of the key dimensions. The more irreversible the effects, the higher the complexity.

Irreversible change implies lasting results that are virtually impossible to undo, even if there is the motivation, will, resources, and even knowledge to do so. In the domain of technology, AI capabilities if used more broadly can permanently alter crucial fields in limited but significant ways (Gruetzemacher & Whittlestone, 2022). It is in these scenarios, where decisions based on AI systems impact people's lives, that ethical concerns arise (Borenstein & Howard, 2021).

Indeed, Shneiderman (2020) claims that when the opposite is true, that is, when AI-based systems make mistakes that are possible to rectify, they can gain human trust, as well as it is easier to assign responsibility and ensure ethical standards. AI technologies that involve reversible decision-making are more likely to become more reliable and secure.

The irreversible negative effects of AI-based decision-making are the result of serious ethical problems. For instance, having private data disclosed or biased decisions made, may not be reversible. Such is the case of AI algorithms threatening the privacy of employee data (Varma et al., 2023) and replication of human biases and discrimination (Walkowiak, 2023). For example, hiring algorithms can be used to screen CVs, and if they are biased, they can exclude candidates just because the data is reflecting biases, affecting people's career paths unfairly (Yam & Skorburg, 2021).

Thus, as an expression of hypothesis 2 applied to this domain we hypothesize that:

> *H2e: Reversibility is positively associated to the AI-Recruitment & Selection endorsement (H2e1), the Employee Orientation & Development (H2e2), the Performance Management (H2e3), and the SHRM (H2e4)*

Because of the first hypothesis, a logical inference on the mediating role of functional HRM domains is made as follows:

> *H3: Normative dimensions are positively associated to the General a-HRM endorsement via functional a-HRM domains endorsement*

In detail:

> *H3a: There is a positive indirect effect of Accountability on General a-HRM endorsement via the AI-Recruitment & Selection endorsement (H3a1), Employee Orientation & Development (H3a2), Performance Management (H3a3), and SHRM (H3a4)*

*H3b: There is a positive indirect effect of Fairness on General a-HRM endorsement via the AI-Recruitment & Selection endorsement (H3b1), Employee Orientation & Development (H3b2), Performance Management (H3b3), and SHRM (H3b4)*

*H3c: There is a positive indirect effect of Explainability on General a-HRM endorsement via AI-Recruitment & Selection endorsement (H3c1), Employee Orientation & Development (H3c2), Performance Management (H3c3), and SHRM (H3c4)*

*H3d: There is a positive indirect effect of Legitimacy on General a-HRM endorsement via AI-Recruitment & Selection endorsement (H3d1), Employee Orientation & Development (H3d2), Performance Management (H3d3), and SHRM (H3d4)*

*H3e: There is a positive indirect effect of Reversibility on General a-HRM endorsement via AI-Recruitment & Selection endorsement (H3e1), Employee Orientation & Development (H3e2), Performance Management (H3e3), and SHRM (H3e4)*

The integration of all the hypotheses is depicted in Figure 1.4 below.

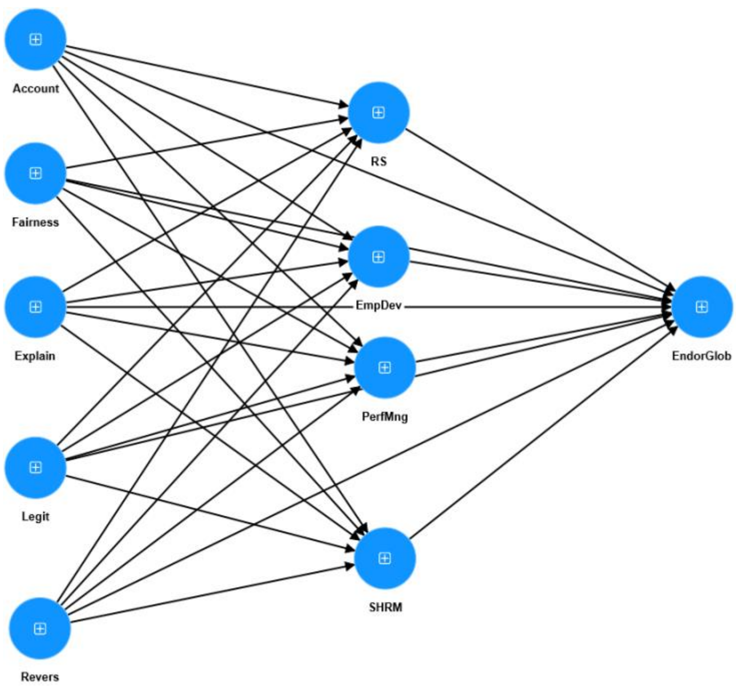


Figure 1.4 - Conceptual Model

# 2. Method

## 2.1. Procedure

A questionnaire comprehending the scales that measure constructs depicted in the conceptual model as well as control variables was designed in Qualtrics software. This questionnaire comprehended a Portuguese version as well as an English version, with the Portuguese version resulting from Brislin (1970) translation-backtranslation procedure. Qualtrics produces a link to anonymously access and answer online the questionnaire while blocking repeated participations from the same internet provider address. The questionnaire was preceded by a presentation text with informed consent request stating the context of the request, the voluntary and anonymous nature of the participation with possibility to quit at any time, the estimated length of the questionnaire and an email was made available should the participant had any doubt or wanted to validate the invitation.

Individuals with at least 18 years-old were eligible for participation and the sampling procedure is non-random with the link and invitations been sent via social networks (LinkedIn, Facebook, Instagram, WhatsApp) with request to snowball, together with invitations sent to professional contacts directly. Because the topic concerns HRM and IT we endeavored to contact a diverse array of individuals in these domains but also many other that are stakeholders of decisions pertaining to autonomous HRM.

## 2.2. Data analysis strategy

Data was firstly curated for missing values and drop out cases that rendered the entries useless. Afterwards, we tested the psychometric quality of the measures, namely its validity and reliability. To test construct validity, we applied confirmatory factor analysis (with AMOS 28 software) which is a data analysis technique that can gauge how much a given theoretical structure that proposes the latent constructs is verified in the empirical data. The suitability of the factor structure is judged with fit indices according to the following: Normed Chi-square should be non-significant and falling below 3; Confirmatory Fit Index (CFI) and Tucker-Lewis Index (TLI) should achieve .95. Additionally, a commonly reported index is the Root Mean Squared Residual of Approximation (RMSEA) that should not exceed 0.08 with the respective confidence intervals (90%) achieving a non-significant PClose statistic ($p$>.01). Alongside, a suitable construct should also show convergent validity which we measured with Fornell and Larcker (1981) Average Variance Extracted (AVE) which should reach 0.500. Additionally, a measure must have discriminant validity, whenever more than a single latent construct is depicted in the model, which is expressed with HTMT (Henseler et al., 2015) with the threshold of .85. In addition, measures are required to be reliable, i.e. that they are consistently measuring the same construct, which we tested with Cronbach's alpha (at least .70).

Due to the many estimates the multiple interactions previewed in the model entail, we opted to run a robust structural equation model (SEM) that is based on a Partial Least Squared algorithm (PLS). It is less biased by a relative low ratio of observed cases to estimates and has been gaining ground in the last couple of decades as a trustable alternative to covariance-based SEM (Hair et al., 2019). PLS-SEM has validity indices (SRMR below .08 and NFI over .90) and gives estimates of the effects (f2) and explained variance. It also provides bootstrapped valued for direct and indirect effects. The confidence interval defined for these tests was set at 95%.

## 2.3. Sample

A total of 253 individuals participated in the study with the majority (63.5%) being female, with ages ranging from 18 to 71 years-old, averaging 33.4 (SD=12.9). The sample is highly educated (92.7% has at least an undergraduate degree) with most individuals (47.2%) working in large organizations (over 250 employees).

## 2.4. Measures

HRM AI applications were measured with Chowdhury et al. (2023) HR functional dimensions, which we used to design 11 descriptions focused on automation applications in HRM. We purposely left any reference to augmentation out because we reason that augmentation does not raise as many issues pertaining to accountability, legitimacy, explainability, fairness or reversibility because the ultimate decision maker is human. Conversely, automation as any autonomous decision, will open doors to all sort of doubts as regards these dimensions since the decision originates from a non-sentient agent. The applications and respective descriptions are depicted in Table 2.1.

Five measures were developed to comprehend the normative dimensions judgment as regards each of the 11 HRM AI applications. For each application participants were expected to state how much they agree (7-point Likert scale: 1=Strongly disagree; 7=Strongly agree) that each application would not allow for the expression of the normative dimension.

A-HRM AI Accountability was measured with one item per HRM application: “In case something goes wrong it is very difficult to verify responsibilities” totaling 11 expressions which have good reliability (Cronbach alpha=.916). After some covariances added to error terms due to Lagrange indicators, the model has good fit indices (CMIN/DF=1.628, p<.01; CFI=.972; TLI=.961; RMSEA=.066 90% CI [.034; .095] PClose=.179). The measure has also good convergent validity (AVE=.541).

Table 2.1 – HR functional dimensions descriptions

| Functional domain | Description |
|---|---|
| Job Applications | Chatbots that enhance the candidates' experience by answering their questions quickly, showing candidates how the organization works, what their role will be, who they will work with. This algorithm-based software can identify high quality candidates and provide feedback to all candidates. |
| Candidate Recruitment | Virtual Assistant that autonomously pre-screens high quality candidates and estimates the probability of a candidate accepting a job offer by scanning the CV and other information, and also predicts the candidate's future performance and the probability of the candidate leaving the organization after "x" years. |
| Onboarding | Virtual Assistant that helps new employees becoming aware of their role and tasks, helping them complete their mandatory training and recommending work-related skills and learning content, based on employees performing similar functions. |
| Employee Engagement | Virtual Assistant that provides a personalized experience to employees based on their needs and daily tasks, schedules, appointments, to facilitate decision making, engagement and collaboration within a team. |
| Career Development | Virtual Assistant that identifies for each employee their career ambitions and identifies opportunities, skills, and appropriate training to maximize their potential and increase motivation. |
| Employee Performance Appraisal | Virtual Assistant that calculates a performance score for each employee and informs both employee and manager while predicting and comparing performance against objectives. |
| Compensation Packages | Virtual Assistant that makes smart salary compensation based on employee data, such as current and past performance, competitiveness, among others. |
| Employee Skills Development | Virtual Assistant that maps employees' skills to identify training needs and content, taking into account their contributions, job title, learning history, business team and manager. |
| Employee Attrition Detection | Virtual Assistant that predicts the probability of an employee leaving the organization through data on their profile, activities and evaluations by other employees and through historical data on other employees who have left or continue to work in the organization. |
| Workforce Management Analysis | Virtual Assistant that collects information on employee behavior, team functioning, to measure wellbeing, presenteeism and increase motivation and team engagement. |
| Human Resources budget and Resource Allocation | Virtual Assistant that processes information from available sources to automatically provide efficient budget allocation for better management track spending to decide on cost optimization. |

A-HRM AI Fairness was measured with one item per HRM application: “The decisions are not considering any sense of justice” totaling 11 expressions which have good reliability (Cronbach alpha=.895). After some covariances added to error terms due to Lagrange indicators, the model has good fit indices (CMIN/DF=1.633, *p*<.01; CFI=.962; TLI=.946; RMSEA=.066 90% CI [.034; .095] PClose=.175). The measure has also below optimal but still relevant convergent validity (AVE=.489).

A-HRM AI Explainability was measured with one item per HRM application: “It is very difficult to explain the decisions made by the algorithm” totaling 11 expressions which have good reliability (Cronbach alpha=.921). After some covariances added to error terms due to Lagrange indicators, the model has good fit indices (CMIN/DF=1.924, *p*<.001; CFI=.959; TLI=.944; RMSEA=.080 90% CI [.053; .107] PClose=.037). The measure has also good convergent validity (AVE=.558).

A-HRM AI Legitimacy was measured with one item per HRM application: “It is not legitimate to trust an algorithm to make such important decisions” totaling 11 expressions which have good reliability (Cronbach alpha=.888). After some covariances added to error terms due to Lagrange indicators, the model has good fit indices (CMIN/DF=1.770, *p*<.01; CFI=.964; TLI=.943; RMSEA=.073 90% CI [.042; .102] PClose=.102). The measure has also below optimal but still relevant convergent validity (AVE=.487).

A-HRM AI Reversibility was measured with one item per HRM application: “Any error involving such a decision would have serious and irreversible consequences” totaling 11 expressions which have good reliability (Cronbach alpha=.900). After some covariances added to error terms due to Lagrange indicators, the model has good fit indices (CMIN/DF=1.687, p<.01; CFI=.960; TLI=.948; RMSEA=.069 90% CI [.040; .096] PClose=.129). The measure has also below optimal but still relevant convergent validity (AVE=.470).

A-HRM AI applications endorsement was measured based on 11 HRM AI applications focused on Chowdhury et al. (2023) HR functional dimensions. For each HRM functional dimension we have asked participants to state how strongly they would recommend the adoption of this technology in their own organization. Four formative constructs have been built based on functional proximity, namely: Recruitment & Selection (2 items: “To administratively manage job applications”, “To do CV analysis, analyze recruitment interviews and predict future candidate performance”); Employee Orientation and Development (3 items: “To guide newly arrived employees to familiarize themselves with the organization and the work”, “To organize employees' schedules and tasks”, “To identify career opportunities for employees and advise on necessary training and promotions”). Performance Management (2 items: “To evaluate employee performance”, “To set compensation and decide on bonuses”), and Strategic HRM (4 items: “To measure HR key performance indicators”, “To identify employees' skills and training needs”, “To profile employees in order to anticipate the likelihood of their leaving voluntarily”, “To allocate the HR budget”).

Global a-HRM endorsement was measured with a single item “At a global level, considering all the functions of Human Resources Management...” which the respondents were asked to complete by choosing the option that made more sense to them: 1) “I am totally against the use of autonomous AI”, 2) “I am against the use of autonomous AI”, 3) “I am slightly against the use of autonomous AI”, 4) “I am neutral”, 5) ““I am slightly in favor of the use of autonomous AI”, 6) “I am in favor of the use of autonomous AI or 7) “I am all for the use of autonomous AI”.

Sociodemographic variables were measured both for descriptive and control purposes: Gender (1=“Masculine”, 2=“Feminine”, 3=“Non-binary / third gender”, 4=”Prefer not to say”), Age (the exact age in years), Education (1=“Below 9th grade”, 2=“9th grade or equivalent”, 3=“12th grade or equivalent”, 4=“Bachelor's degree”, 5=“Graduate school degree: Master's or Doctorate degree”), HR/non-HR (0=“non-HR”, 1=“HR”), IT (0=“non-IT”, 1=“IT”), organizational size (1= “Up to 10 people”, 2= “10-49 people”, 3= “50-249 people”, 4= “250 people or more”, 5= “I am currently not working”).

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# 3. Results

Results will start by showing descriptive and bivariate statistics followed by the hypotheses testing findings. For ease of interpretation, we reversed the scale for normative dimensions so that higher values express higher acknowledged normative association for each HRM application.

## 3.1. Descriptive and bivariate statistics

As shown in Table 3.1, the means for the normative dimensions used to judge a-HRM AI suggest individuals take a moderate stance towards it or, at the very minimum, individuals believe such normative dimensions hardly apply. Reminding that a 7 position in the scale indicates the respondent think it totally has ability to abide by that normative dimension, the normative dimensions that fall below the scale's midpoint (4) indicate individuals believe they hardly apply to a-HRM. These are legitimacy (Mean=3.75, SD=1.07, t(252)=-3.254, $p$<.01), accountability (Mean=3.84, SD=1.28, t(252)=-1.969, $p$<=.05), and reversibility (Mean=3.85, SD=1.13, t(252)=-2.140, $p$<.05). Conversely, explainability falls above the midpoint (Mean=4.77, SD=1.07, t(252)=2.276, $p$<.05) thus suggesting individuals believe a-HRM algorithms are more explainable than non-explainable, while fairness can be seen as a neutral aspect of algorithms (or that individuals, overall, are undecisive). The lowest mean is observed for legitimacy suggesting individuals find it harder to legitimately use the a-HRM AI applications.

The only endorsed application for a-HRM AI that is not placed above the scale's midpoint concerns Performance Management (Mean=3.81, t(173)=-.1508, p=.133). The highest endorsed application concerns Employee Orientation & Development (Mean=5.01, SD=1.11, t(197)=12.922, $p$<.001), followed by SHRM (Mean=4.54, SD=1.15, t(185)=6.400, $p$<.001), and Recruitment & Selection (Mean=4.34, SD=1.49, t(196)=3.207, $p$<.01). The general a-HRM endorsement falls above the scale midpoint also (Mean=4.45, SD=1.38, t(217)=4.757, $p$<.001).

As regards bivariate statistics, there are some associations between sociodemographic variables and those in the conceptual model. Namely, in relation with the normative dimensions, females tend to report lower perceived means as compared to males as regards accountability, fairness and explainability dimensions. Likewise, older participants tend also to report lower means for all the normative dimensions to the exception of reversibility. However, the magnitude of the correlations found are quite modest. All the remaining sociodemographic variables have no association with any of the conceptual model variables to the exception of a modest one found for working in IT and legitimacy (r=.146, p<.05).

The associations between general endorsement of a-HRM and the functional domains of a-HRM encourage part of the conceptual model as all of them are statistically significant for p<.01 and have strong correlation coefficient magnitudes (ranging from .571 to .730). Likewise, the associations found between normative dimensions and all of the functional a-HRM domains as well as with the general a-HRM endorsement are all positive and also encourage the conceptual model.

Table 3.1 – Descriptive and bivariate statistics

| | Min-Max | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Gender | 1-2 | - | - | 1 | | | | | | | | | | | | | | |
| 2. Age | 18-71 | 33.27 | 12.85 | .076 | 1 | | | | | | | | | | | | | |
| 3. Educ | 3-5 | 4.36 | .61 | -.054 | .012 | 1 | | | | | | | | | | | | |
| 4. OrgSize | 1-5 | 3.57 | 1.25 | .099 | -.160* | -.123 | 1 | | | | | | | | | | | |
| 5. IT | 0-1 | .07 | .26 | -.161* | -.037 | .053 | -.045 | 1 | | | | | | | | | | |
| 6. HRM | 0-1 | .19 | .39 | .139* | -.096 | .104 | -.087 | -.140* | 1 | | | | | | | | | |
| 7. Account | 1.27-7 | 3.84 | 1.28 | -.151* | -.192** | -.038 | .024 | .029 | .013 | 1 | | | | | | | | |
| 8. Fairness | 1-7 | 4.09 | 1.17 | -.147* | -.141* | .023 | .012 | .090 | .024 | .642** | 1 | | | | | | | |
| 9. Explain | 1-7 | 4.77 | 1.07 | -.164* | -.148* | .061 | -.038 | .083 | .039 | .637** | .829** | 1 | | | | | | |
| 10. Legit | 1-7 | 3.75 | 1.23 | -.123 | -.138* | .033 | .052 | .146* | .006 | .612** | .827** | .765** | 1 | | | | | |
| 11. Revers | 1-7 | 3.85 | 1.13 | -.055 | -.040 | .104 | -.005 | .036 | .077 | .605** | .654** | .678** | .721** | 1 | | | | |
| 12. R&S | 1-7 | 4.34 | 1.49 | -.094 | -.046 | .159* | .082 | .129 | .038 | .213** | .424** | .403** | .489** | .300** | 1 | | | |
| 13. EmpDev | 1-7 | 5.01 | 1.11 | -.087 | -.061 | .060 | .053 | .156* | -.086 | .215** | .378** | .355** | .380** | .184** | .465** | 1 | | |
| 14. PerfMng | 1-7 | 3.81 | 1.63 | .019 | -.025 | .032 | .048 | .053 | -.053 | .279** | .393** | .395** | .439** | .294** | .520** | .470** | 1 | |
| 15. SHRM | 1-7 | 4.54 | 1.15 | -.048 | -.016 | .090 | -.046 | .098 | .083 | .303** | .515** | .464** | .536** | .414** | .659** | .583** | .672** | 1 |
| 16. Gen aHRM | 1-7 | 4.45 | 1.38 | -.083 | -.026 | .044 | -.021 | .077 | -.009 | .360** | .505** | .469** | .553** | .459** | .586** | .571** | .629** | .730** |

*$p<.05$, **$p<.01$

## 3.2. Hypotheses testing

The model has slightly below than ideal fit for SRMR=0.087 albeit still within acceptance range (Kline et al., 2023 set <.10 as the upper acceptance threshold) and NFI is also slightly below the threshold (0.897) but still too close to the threshold (0.900) to be discarded. To the exception of Employee Orientation and Development, the model has acceptable predictive power on all the endogenous variables as indicated by Stone-Geisser's $Q^2$ and $R^2$ (Table 3.2) and there is no indication of multicollinearity (highest VIF = 1.801).

Table 3.2 – Model's predictive power

| | $Q^2$ predict | PLS-SEM _RMSE | PLS-SEM _MAE | LM _RMSE | LM _MAE | $_{Adj}R^2$ | VIF (predic. Global a-HRM) |
|---|---|---|---|---|---|---|---|
| R&Selection | 0.177 | 1.194 | 0.914 | 1.197 | 0.916 | 19.7% | 1.477 |
| EoD | -0.006* | 0.982* | 0.706* | 0.932* | 0.652* | 13.5% | 1.322 |
| Perf. Mng. | 0.110 | 1.279 | 0.95 | 1.286 | 0.957 | 13.7% | 1.525 |
| SHRM | 0.214 | 0.878 | 0.652 | 0.881 | 0.658 | 23.3% | 1.801 |
| Global a-HRM | 0.223 | 1.133 | 0.898 | 1.138 | 0.898 | 48.9% | - |

*Indicators suggest poor predictive power

The direct effects found are shown in Table 3.3 and graphically depicted in Figure 3.1.

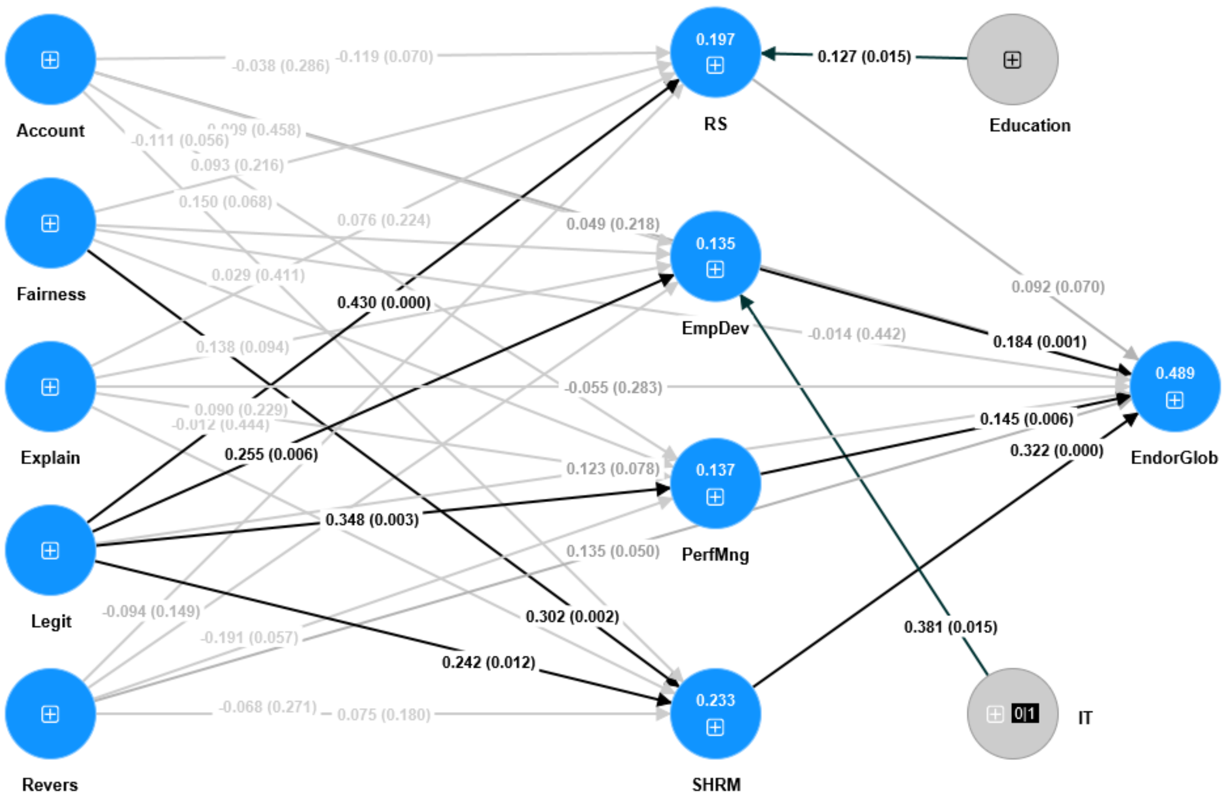


Figure 3.1 – Conceptual model coefficients

Table 3.3 – Direct effects

| | Original sample (O) | Sample mean (M) | Bias | CI95% LB | CI95% UB | $f^2$ | HH | Test |
|---|---|---|---|---|---|---|---|---|
| **Direct effects** | | | | | | | | |
| R&S -> Gen_a-HRM endors. | -0.092 | -0.094 | 0.002 | -0.014 | 0.192 | | H1a | Not sup. |
| EO&D -> Gen_a-HRM | -0.184 | -0.184 | 0.000 | 0.089 | 0.275 | **.050** | H1b | Supported |
| PerfMng -> Gen_a-HRM | -0.145 | -0.146 | 0.001 | 0.051 | 0.237 | **.027** | H1c | Supported |
| SHRM -> Gen_a-HRM | -0.322 | -0.318 | -0.004 | 0.220 | 0.438 | **.107** | H1d | Supported |
| Accountability -> R&S | -0.119 | -0.121 | 0.001 | -0.250 | 0.019 | | H2a1 | Not sup. |
| Accountability -> EO&D | -0.038 | -0.044 | 0.005 | -0.147 | 0..074 | | H2a2 | Not sup. |
| Accountability -> PerfMng | -0.009 | -0.008 | -0.001 | -0.148 | 0.138 | | H2a3 | Not sup. |
| Accountability -> SHRM | -0.111 | -0.114 | 0.003 | -0.226 | 0.002 | | H2a4 | Not sup. |
| Fairness -> R&S | 0.093 | 0.094 | -0.001 | -0.106 | 0.283 | | H2b1 | Not sup. |
| Fairness -> EO&D | 0.150 | 0.158 | -0.008 | -0.018 | 0.307 | | H2b2 | Not sup. |
| Fairness -> PerfMng | 0.029 | 0.027 | 0.001 | -0.178 | 0.239 | | H2b3 | Not sup. |
| Fairness -> SHRM | 0.302 | 0.301 | 0.001 | 0.143 | 0.479 | **.026** | H2b4 | Supported |
| Explainability -> R&S | 0.076 | 0.078 | -0.001 | -0.088 | 0.241 | | H2c1 | Not sup. |
| Explainability -> EO&D | 0.138 | 0.130 | 0.008 | -0.039 | 0.297 | | H2c2 | Not sup. |
| Explainability -> PerfMng | 0.090 | 0.083 | 0.006 | -0.098 | 0.295 | | H2c3 | Not sup. |
| Explainability -> SHRM | -0.012 | -0.012 | -0.001 | -0.163 | 0.123 | | H2c4 | Not sup. |
| Legitimacy -> R&S | 0.430 | 0.431 | -0.001 | 0.257 | 0.599 | **.060** | H2d1 | Supported |
| Legitimacy -> EO&D | 0.255 | 0.252 | 0.003 | 0.084 | 0.416 | **.019** | H2d2 | Supported |
| Legitimacy -> PerfMng | 0.348 | 0.354 | -0.006 | 0.139 | 0.559 | **.036** | H2d3 | Supported |
| Legitimacy -> SHRM | 0.242 | 0.241 | 0.001 | 0.069 | 0.421 | **.020** | H2d4 | Supported |
| Reversibility -> R&S | -0.094 | -0.100 | 0.005 | -0.240 | 0.059 | | H2e1 | Not sup. |
| Reversibility -> EO&D | -0.191 | -0.186 | -0.005 | -0.396 | 0.002 | | H2e2 | Not sup. |
| Reversibility -> PerfMng | -0.068 | -0.070 | 0.002 | -0.247 | 0.117 | | H2e3 | Not sup. |
| Reversibility -> SHRM | 0.075 | 0.074 | 0.001 | -0.062 | 0.208 | | H2e4 | Not sup. |

R&S: AI-based Recruitment & Selection; EO&D: AI-based Employee Orientation & development; PerfMng: AI-based Performance Management; SHRM: AI-based Strategic HRM; Gen_a-HRM: General AI-based HRM.

Overall, findings show the general a-HRM endorsement is predicted by three out of the four functional a-HRM domains, namely the application of AI for Employee Orientation & Development (M=0.184, 95%CI [.089; .275], f2=0.05), for Performance Management (M=0.145, 95%CI [.051; .237], f2=0.027) and for SHRM (M=0.322, 95%CI [.220; .438], f2=0.107) predict general a-HRM endorsement although Recruitment & Selection failed to do so (M=0.092, 95%CI [-.014; .192]). This supports H1b, H1c, and H1d but rejects H1a.

Table 3.4 – Indirect effects

| Indirect effects | Original sample (O) | Sample mean (M) | Bias | CI95% LB | CI95% UB | HH | Test |
|---|---|---|---|---|---|---|---|
| Accountability -> R&S-> G_a-HRM | -0.011 | -0.011 | 0.000 | -0.039 | 0.001 | H3a1 | Not sup. |
| Accountability -> EO&D-> G_a-HRM | -0.007 | -0.009 | -0.002 | -0.033 | 0.011 | H3a2 | Not sup. |
| Accountability -> PerfMng -> G_a-HRM | -0.001 | -0.001 | 0.001 | -0.023 | 0.022 | H3a3 | Not sup. |
| **Accountability -> SHRM-> G_a-HRM** | **-0.036** | **-0.036** | **-0.001** | **-0.082** | **-0.002** | **H3a4** | **Supported** |
| Fairness -> R&S -> G_a-HRM | 0.009 | 0.009 | 0.000 | -0.005 | 0.045 | H3b1 | Not sup. |
| Fairness -> EO&D -> G_a-HRM | 0.027 | 0.029 | 0.001 | -0.000 | 0.067 | H3b2 | Not sup. |
| Fairness -> PerfMng -> G_a-HRM | 0.004 | 0.004 | -0.000 | -0.025 | 0.043 | H3b3 | Not sup. |
| **Fairness -> SHRM-> G_a-HRM** | **0.097** | **0.095** | **-0.002** | **0.048** | **0.178** | **H3b4** | **Supported** |
| Explainability -> R&S -> G_a-HRM | 0.007 | 0.007 | -0.000 | -0.005 | 0.038 | H3c1 | Not sup. |
| Explainability -> EO&D -> G_a-HRM | 0.025 | 0.024 | -0.001 | -0.003 | 0.069 | H3c2 | Not sup. |
| Explainability -> PerfMng -> G_a-HRM | 0.013 | 0.012 | -0.001 | -0.010 | 0.056 | H3c3 | Not sup. |
| Explainability -> SHRM-> G_a-HRM | -0.004 | -0.004 | -0.000 | -0.055 | 0.037 | H3c4 | Not sup. |
| Legitimacy -> R&S -> G_a-HRM | 0.040 | 0.041 | 0.001 | -0.002 | 0.095 | H3d1 | Not sup. |
| **Legitimacy -> EO&D -> G_a-HRM** | **0.047** | **0.047** | **0.000** | **0.016** | **0.099** | **H3d2** | **Supported** |
| **Legitimacy -> PerfMng-> G_a-HRM** | **0.050** | **0.052** | **0.001** | **0.016** | **0.114** | **H3d3** | **Supported** |
| **Legitimacy -> SHRM-> G_a-HRM** | **0.078** | **0.078** | **0.000** | **0.025** | **0.160** | **H3d4** | **Supported** |
| Reversibility -> R&S -> G_a-HRM M | -0.009 | -0.010 | -0.001 | -0.041 | 0.003 | H3e1 | Not sup. |
| Reversibility -> EO&D -> G_a-HRM | -0.035 | -0.032 | 0.003 | -0.083 | 0.006 | H3e2 | Not sup. |
| Reversibility -> PerfMng-> G_a-HRM | -0.010 | -0.011 | -0.001 | -0.048 | 0.013 | H3e3 | Not sup. |
| Reversibility -> SHRM-> G_a-HRM | 0.024 | 0.024 | -0.000 | -0.016 | 0.073 | H3e4 | Not sup. |

H2 concerns the direct effects of the normative dimensions on judging the endorsement of the four functional a-HRM domains. As regards the direct effects of accountability (H2a) none of the hypothesized effects received empirical support, thus rejecting H2a. Concerning the direct effects of fairness (H2b), we found a similar outcome but with a statistically significant effect on SHRM (M=0.302, 95%CI [.143; .479] , f2=0.026) thus supporting H2b4 but rejecting H2b1, H2b2, and H2b3. The direct effects of explainability follow the same pattern found for accountability, thus rejecting H2c. As regards legitimacy, findings show it has a direct positive effect on all functional a-HRM domains, namely it has a positive effect on Recruitment & Selection (M=0.430, 95%CI [.257; .599] , f2=0.06), Employee Orientation & Development (M=0.255, 95%CI [.084; .416] , f2=0.019), Performance Management (M=0.348, 95%CI [.139; .559] , f2=0.036) and SHRM (M=0.242, 95%CI [.069; .421] , f2=0.02). This fully supports H2d. As regards reversibility (H2e) none of the hypothesized direct effects was empirically supported, which rejects it.

The hypothesized indirect effects from normative dimensions on general a-HRM endorsement via functional a-HRM domains were also tested. Findings show that accountability has no significant indirect effect to the exception of a negative effect through SHRM (-0.036, 95%CI [-0.082; -0.002] which supports H3a4. In a similar manner, findings show that fairness has no significant indirect effect to the exception of a positive effect through SHRM (0.097, 95%CI [0.048; 0.178]) which supports H3b4. As regards explainability none of the hypothesized indirect effects was found to be statistically significant, thus fully rejecting H3c. In the case of legitimacy, Recruitment & Selection is not a mediator in the indirect effect (0.04, 95%CI [-0.002; 0.095]) while there is a positive indirect effect through Employee Orientation & Development (0.047, 95%CI [0.016; 0.099]), Performance Management (0.05, 95%CI [0.016; 0.114]), and SHRM (0.078, 95%CI [0.025; 0.160]). This rejects H3d1 but supports H3d2, H3d3, H3d4. Finally, no indirect effect was found for reversibility which fully rejects H3e.

It is worth noticing that most of the effects found have a very small effect size where weak effects are only considered from 0.02 upwards and moderate effects from 0.15 upwards (Cohen, 1992). Most the effects reported are indeed very small.

# 4. Discussion and Conclusion

This study was designed to gauge the extent to which normative dimensions are considered in the individual endorsement of deploying AI in HRM both concerning specific functional domains and in a general manner.

Albeit not hypothesized, the first relevant finding from the empirical analysis pertains to the psychometric properties of the scale itself on normative dimensions applied to the functional domains of HRM. Although the confirmatory factor analysis suggests sufficient construct validity, it is worth noting the suboptimal values found for convergent validity in the cases for fairness, legitimacy, and reversibility. This can be interpreted as a yet blurred mental representation of this construct in the participants. Still, the Cronbach alphas were all well above the threshold, thus indicating that their answers were consistent. This goes in line with the relatively modest means found for such ascription to the exception of employee orientation and development but still, it is far from the second highest point in the scale.

Legitimacy was the normative dimension with a lower mean value. The difficulty perceived by individuals of the legitimate use of a-HRM AI applications can be explained by a misalignment between a-HRM AI applications and the values and beliefs of employees and other stakeholders of the organization (del-Castillo-Feito et al., 2022). Acceptance of the use of a-HRM technologies is known to depend on several factors, including subjective norms and individual attitudes (Roh et al., 2023). Thus, the fact that algorithms can silently structure our lives (Martin, 2019a), e.g. decide our salaries (Johnson et al., 2022b) or even determine who is most likely to leave the company (Zhao et al., 2018), may lead individuals to consider AI applications of a-HRM as being intrusive. In addition, legitimacy can be the result of the perceived usefulness shared between HRA teams and all other teams and stakeholders (Cayratt & Boxall, 2022). One of the major difficulties that HRA teams face is their peripheral position in the organizational hierarchy (Angrave et al., 2016). This makes it difficult to gain the support of senior management (Hamilton & Sodeman, 2020), which is of extreme importance for judging the legitimacy of AI applications in HRA teams (Cayratt & Boxall, 2022). From a legal point of view, the illegitimate consideration of the use of a-HRM AI applications by the participants of this study may be related to the lack of clarity in the laws used by organisations that ensure an ethical use of AI in the HRA domain (von Lewinski & Fritz, 2022). Additionally, concerns about employee privacy (Vrontis et al., 2022), employee data privacy (Choi, 2022) and the concrete examples that exist about discrimination and unfairness of algorithm-based decisions (Enholm et al., 2022) may be contributing to individuals considering illegitimate to use a-HRM AI applications.

A-HRM functional domains are not equally endorsed as Employee Orientation & Development (mean=5.01) is quite contrasting with Performance Management (mean=3.81). The rank order of a-HRM functions endorsement ($1^{st}$ “Employee Orientation & Development”, $2^{nd}$ “SHRM”, $3^{rd}$ “Recruitment & Selection”, $4^{th}$ “Performance Management”) suggests individuals tend to endorse less those functions that are more easily depicted while having a stronger impact in their lives (decision to hire or not, decision about performance) with potential to experience more anxiety (as in the job interview or the performance appraisal meeting). The HRM function that receives stronger endorsement is usually taken as benign. Still, one needs to mind that the highest endorsement mean ($mean_{EOD}$=5.01) is still very far from the scale maximum of 7.

Findings regarding how the four HRM functional domain leverage general a-HRM endorsement supported the expected role for Employee Orientation & Development, Performance Management and SHRM but failed to do so for Recruitment & Selection. This can be attributed to the recurrent doubts concerning the effectiveness, or suitability, of automatically selecting people (e.g., Kelan, 2023) associated with its stronger clarity and easier depiction in the mind of employees, since everyone experienced it.

The rejection of H2a shows that the endorsement of any functional a-HRM domain is independent from the individual judgment on how much one can ascertain responsibility, i.e., its accountability. This might be explained by accountability being still a blurred topic in AI ongoing debate as opinions greatly diverge as regards who should be held accountable if any problem occurs. Namely, Martin (2019b) attributes the responsibility to designers, as they are the developers of AI applications. Other authors consider that managers should be held responsible (e.g., Burton et al., 2020). Tóth et al. (2022) consider that the use of AI complexifies the attribution of responsibility, as there are several actors to consider from the AI tool itself to the law maker. So, there is no agreement, nor even a glimpse of convergence, between authors about who should be the prime responsible for any wrongdoing. This lack of agreement hampers any spillover from the academic discussion towards public opinion. We may reasonably expect that it is too soon for the laymen to exact any opinion about this issue of accountability that is still gaining shape into the specialized expert communities.

Findings about the direct effect of fairness on the endorsement of the four a-HRM functional domains only support the anticipated role for SHRM. In line with the interpretation for fairness mean (undistinguished from the scale's neutral point), fairness only relates to a single a-HRM function. Again, this can relate with a certain lack of clarity about what SHRM entails as the other three functions are clearly easier to depict. While Employee Orientation & Development may not raise many issues about fairness; Recruitment & Selection and, especially, Performance Management clearly raise fairness concerns. This joint action of clarity and fairness centrality can be evidenced by the dispersion (in the respective standard-deviations) that is visibly larger. This dispersion can be interpreted as expressing more favorable and unfavorable positions, that can result from individuals, as a whole. having less doubts about what they are judging.

The absence of any association between explainability and the functional domains of a-HRM reinforces the interpretation that what is still lacking clarity can hardly be understood, let alone explained. The mean value for explainability is the highest among the normative dimensions but it is still far from the maximum scale point indicating difficulties relating to it. On the one hand, individuals trust someone can explain it but on the other hand, the complexity and technical nature of AI may be harder to explain in a way that the layman is capable of fully apprehending it. Eventually there is a heuristic-like simplification process that fosters the believe AI can be easily understood.

Although we reasoned that reversibility is an important dimension when judging any action that has the potential for wrongdoing, findings showed no such association with a-HRM domains was found. Eventually, reversibility emerges as a criterion in the cognitive processes only when certain conditions are met pertaining to what exact negative effects can be produced by AI. As such information was not provided in the survey, individuals may still have a blurred preview of what can go wrong. Reversibility should then be salient if such preview is clearly depicted.

Surprisingly, the indirect effect of accountability on the global a-HRM endorsement is found to be negative which means the higher the ability to ascribe responsibility to problems arising from using a-HRM globally, the least individuals endorse it. This may read counterintuitive but there is an important missing information concerning who they believe accountability should be attributed to. We reason that those individuals that have a clear believe about who should be blamed are also those that may be clearer about the possible issues arising from a-HRM accountability attribution targeting human entities, namely the coder or the organizational decision maker. However, if the accountability is conceived as falling upon the algorithm itself or if the respondent has yet not a clear idea about it, the relationship might not be established yet. Fairness, however, has an indirect effect on global a-HRM endorsement, which mimics the direct effect found and discussed. Again, the relatively neutral stance on fairness that is suggested to explain findings, applies here as the indirect effect occurs through SHRM. The absence of indirect effects for explainability, accountability, and reversibility is expectable due to the lack of direct effects between these and a-HRM functional domains endorsement. However, as regards legitimacy and the possible indirect effect of fairness on general a-HRM endorsement via SHRM, it is relevant to ascertain if the magnitude of the respective direct effects adds up into indirect significant effects. Findings showed such is the case for all to the exception of legitimacy via Recruitment & Selection. The most reasonable motive for this occurrence lies in the relatively modest magnitude of associations between these variables. Albeit statistically significant, the confidence intervals are truly close to non-rejecting criteria (lower bound = -0.002; upper bound = 0.095) which could change with a larger sample size also with a stronger presence of IT and HRM specialists.

Overall, although most people would agree that the endorsement of a-HRM is not an irrelevant issue, judging from findings, individuals seem to be still lacking enough clarity so to gain sufficient awareness about the advantages and risks such applications entail. Although normative dimensions are taken as implicit and universally used to make judgments, they can only be effective if the individual holds enough information and conceptual clarity. Such seems not to be the case yet.

Among the normative dimensions considered in this study, legitimacy showed to have a relevant role in the endorsement of the functional domains of the a-HRM. In addition to this result, legitimacy presented the lowest mean value, which may translate a clear opinion about it although we cannot ascertain to which extent participants of this study convergence as to what legitimacy exactly means.

This research has highlighted that the field of HRA is becoming increasingly important as, by empowering HR to make data-driven decisions, it can contribute to the optimization of companies' human capital management. In addition, this research has also highlighted the importance of exploring the various functionalities and responsibilities of a-HRM roles in more detail. By providing greater clarity regarding these roles, it may be easier to ascertain individuals' concerns regarding the adoption of AI in HRM. One of the findings of the present study concerns the significant role of fairness in a-SHRM only. This finding leads us to believe that such relation can be due to the simple fact that it is more difficult to understand SHRM as a function, compared to the others, which are more easily understood.

Thus, organizations can promote a more favorable attitude towards the integration of AI into HRM processes and functions by identifying and addressing these concerns. The clearer these concepts are, the more likely it is to understand the position, for or against, of individuals towards the adoption of AI in HRM. This overall contributes to the SDG 8, decent work and economic growth and the social impact of this topic and research cannot be understated as it brings implications for the design of work itself, for the renewal of relations between people and machines, for the creation and destruction of employment.

## 4.1. Limitations and future research

Despite the relevance of this topic, findings should be interpreted considering the sample size and profile. We chose not to isolate the sample of HR and IT participants as it was not sufficiently large. However, in future studies, it may be interesting to run a separate study on these specific profiles to understand in an isolated way the opinion of these informed populations and to extend the conclusions of this research.

Another limitation of this study is the apparent recency of the topic. Although it is widely known that the use of AI in organizations is becoming increasingly common, we believe there is still a shared ignorance about what it entails in practice and what its possible consequences are. The results of our study point to this, hence it the corroboration of the various hypotheses put forward is but preliminary. There is an urgent need for clarity from top management to junior employees and all stakeholders, on the AI phenomenon and using the normative dimensions (including also reversibility) seems to be the most theoretically sustained option to do it.

Future research may benefit from identifying the degree of clarity individuals hold about the normative dimensions applied judgments about AI applications. What does legitimacy mean for respondents? Are different understandings of legitimacy (e.g. legitimacy as literally expressing lawabiding, or legitimacy as being able to defend on reasonability grounds) linked to different degrees of endorsement? Who were the respondents thinking about when answering the degree of accountability? And what degree of conviction do they hold about it? How is fairness conceived in their minds? As a transaction equilibrium (individuals received equivalent resources to their input) or as a principled-oriented view where fairness is simply the guarantee of universal rights (e.g. the right not be fired due to redundancy with AI-based processes). Lastly, it is important to gauge if normative dimensions would support not only the endorsement but the act of explicitly voting for or against in a “yes or no” format.

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# 6. Appendix

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Português

O meu nome é Carmo Coutinho, estou a tirar o Mestrado em Psicologia Social e das Organizações no ISCTE - Instituto Universitário de Lisboa e estou a estudar o uso de algoritmos de inteligência artificial na Gestão de Recursos Humanos.

Agradecia que me respondesse a este questionário de 9 minutos. A sua participação é anónima e voluntária, e todos os dados e informações recolhidos serão tratados de forma agregada para análises estatísticas.

Se tiver alguma questão, por favor contacte-me em mdcpl@iscte-iul.pt.

Se estiver disposto a participar nesta pesquisa, por favor prima a seta abaixo.

Agradeço desde já o seu interesse e participação.
Carmo

→

Português

Está prestes a ler descrições com exemplos de usos da inteligência artificial na Gestão de Recursos Humanos. Por favor, sinalize o quanto concorda ou discorda com cada uma das frases abaixo, referindo-se à aplicação específica de Gestão de Recursos Humanos descrita. Por favor lembre-se de que em todas as aplicações de Gestão de Recursos Humanos descritas abaixo não há interferência humana.

**Candidaturas a emprego**: São *chatbots* que melhoram a experiência dos candidatos respondendo rapidamente às suas questões, mostrando aos candidatos como funciona a organização, qual será a sua função, com quem irão trabalhar. Este *software* baseado em algoritmos pode identificar candidatos de alta qualidade e fornecer *feedback* a todos os candidatos.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Recrutamento de candidatos:** Assistente Virtual que pré-seleciona autonomamente candidatos de alta qualidade e estima a probabilidade dos candidato aceitarem uma oferta de emprego através da análise dos currículos e de outras informações, e também prevê o desempenho futuro dos candidatos e a probabilidade de estes deixarem a organização após "x" anos.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| Discordo fortemente | Discordo | Discordo ligeiramente | Não concordo nem discordo | Concordo ligeiramente | Concordo | Concordo fortemente |

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

- Discordo fortemente (1)
- Discordo (2)
- Discordo ligeiramente (3)
- Não concordo nem discordo (4)

○ Concordo ligeiramente (5)

○ Concordo (6)

○ Concordo fortemente (7)

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

***Onboarding:*** Assistente Virtual que ajuda os novos colaboradores a tomarem consciência do seu papel e tarefas, ajudando-os a completar a sua formação obrigatória e recomendando competências relacionadas com o trabalho e conteúdos de aprendizagem baseados noutros colaboradores que desempenham funções semelhantes.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

***Employee Engagement:*** Assistente Virtual que proporciona uma experiência personalizada aos colaboradores com base nas suas necessidades e tarefas diárias, horários, compromissos, para facilitar a tomada de decisões, compromisso e colaboração dentro de uma equipa.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Desenvolvimento de Carreira:** Assistente Virtual que identifica para cada colaborador as suas ambições de carreira e identifica oportunidades, competências e formação adequada para maximizar o seu potencial e aumentar a motivação.

| 1 Discordo fortemente | 2 Discordo | 3 Discordo ligeiramente | 4 Não concordo nem discordo | 5 Concordo ligeiramente | 6 Concordo | 7 Concordo fortemente |
|---|---|---|---|---|---|---|
| | | | | | | |

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Avaliação de desempenho do colaborador:** Assistente Virtual que calcula uma pontuação de desempenho para cada colaborador e informa tanto o colaborador como a chefia enquanto prevê e compara o desempenho com os objetivos.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|
| | | | | | | |

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Pacotes remuneratórios:** Assistente Virtual que define uma remuneração salarial inteligente baseada em dados dos colaboradores, tais como o desempenho atual e passado, competitividade, entre outros.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|
| | | | | | | |

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Desenvolvimento de competências dos colaboradores:** Assistente Virtual que mapeia as competências dos colaboradores para identificar necessidades e conteúdos de formação, considerando os seus contributos, cargo, histórico de aprendizagem, equipa empresarial e chefia.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Deteção de risco de saída (*turnover*) dos colaboradores:** Assistente Virtual que prevê a probabilidade de um colaborador sair da organização através de dados sobre o seu perfil, atividades e avaliações de outros colaboradores e dados históricos de outros colaboradores que saíram ou continuam a trabalhar na organização.

| 1<br>Discordo fortemente | 2<br>Discordo | 3<br>Discordo ligeiramente | 4<br>Não concordo nem discordo | 5<br>Concordo ligeiramente | 6<br>Concordo | 7<br>Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Análise de gestão da força de trabalho:** Assistente Virtual que recolhe informação sobre o comportamento dos colaboradores, funcionamento das equipas, para medir o bem-estar, o presentismo e aumentar a motivação e o envolvimento das equipas.

| 1 Discordo fortemente | 2 Discordo | 3 Discordo ligeiramente | 4 Não concordo nem discordo | 5 Concordo ligeiramente | 6 Concordo | 7 Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

**Orçamentação de Recursos Humanos e alocação de recursos:** Assistente Virtual que processa informações de fontes disponíveis para fornecer automaticamente uma alocação eficiente de orçamento para melhor gerir e monitorizar despesas (rastrear gastos) para otimizar custos.

| 1 Discordo fortemente | 2 Discordo | 3 Discordo ligeiramente | 4 Não concordo nem discordo | 5 Concordo ligeiramente | 6 Concordo | 7 Concordo fortemente |
|---|---|---|---|---|---|---|

No caso de alguma coisa correr mal, é muito difícil atribuir responsabilidades.

As decisões não refletem qualquer sentido de justiça.

É muito difícil explicar as decisões tomadas pelo algoritmo.

Não é legítimo deixar um algoritmo tomar decisões tão importantes.

Qualquer erro que envolva tal decisão teria consequências graves e irreversíveis.

Português

Agora, irá responder a breves questões sobre o quão fortemente recomendaria a adoção de Inteligência Artificial (IA) na sua própria organização (se não estiver a trabalhar, considere em termos abstratos uma organização onde gostava de trabalhar).

Por favor, indique a sua opinião de acordo com a seguinte escala.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| Estou totalmente contra o uso de IA autónoma | Estou contra o uso de IA autónoma | Estou ligeiramente contra o uso de IA autónoma | Não tenho posição definida | Estou ligeiramente a favor do uso de IA autónoma | Estou a favor do uso de IA autónoma | Estou totalmente a favor do uso de IA autónoma |

Neste caso ...

| | Estou totalmente contra o uso de IA autónoma (1) | Estou contra o uso de IA autónoma (2) | Estou ligeiramente contra o uso de IA auónoma (3) | Não tenho posição definida (4) | Estou ligeiramen a favor do uso de IA autónoma (5) |
|---|---|---|---|---|---|
| Para gerir administrativamente as candidaturas a empregos. | ○ | ○ | ○ | ○ | ○ |
| Para fazer análise de currículos, analisar entrevistas de recrutamento e prever o desempenho futuro dos candidatos. | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| Para orientar os colaboradores recém-chegados a familiarizarem-se com a organização e o trabalho. | ○ | ○ | ○ | ○ | ○ |
| Para organizar os horários e tarefas dos colaboradores. | ○ | ○ | ○ | ○ | ○ |
| Para identificar oportunidades de carreira para os colaboradores e aconselhar sobre formação necessária e promoções. | ○ | ○ | ○ | ○ | ○ |
| Para avaliar o desempenho dos colaboradores. | ○ | ○ | ○ | ○ | ○ |
| Para definir a remuneração e decidir sobre os bónus. | ○ | ○ | ○ | ○ | ○ |
| Para identificar as competências e necessidades de formação dos colaboradores. | ○ | ○ | ○ | ○ | ○ |
| Para traçar o perfil dos colaboradores, a fim de antecipar a probabilidade de saírem voluntariamente. | ○ | ○ | ○ | ○ | ○ |
| Para medir os indicadores-chave de desempenho de Recursos Humanos. | ○ | ○ | ○ | ○ | ○ |
| Para alocar o orçamento de Recursos Humanos. | ○ | ○ | ○ | ○ | ○ |
| A nível global, considerando todas as funções de Gestão de Recursos Humanos... | ○ | ○ | ○ | ○ | ○ |

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Português

O seu género

- Masculino
- Feminino
- Não-binário/terceiro género
- Prefiro não dizer

A sua idade

Qual é o grau ou nível de educação mais elevado que já completou?

- Até ao 9º ano
- 9º ano ou equivalente
- 12º ano ou equivalente
- Licenciatura
- Pós-graduação: Mestrado ou Doutoramento

A sua área de atuação profissional (Se não está a trabalhar, por favor escolha a última opção)

Recursos Humanos

Tecnologia da Informação

Outro

Neste momento não estou a trabalhar

Se trabalha, por favor indique o tamanho da sua organização (Se não, por favor escolha a última opção)

Até 10 pessoas

10-49 pessoas

50-249 pessoas

250 pessoas ou mais

Neste momento não estou a trabalhar

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Agradecemos a sua participação neste inquérito.
A sua resposta foi registada.