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Leveraging Human Resource Analytics to boost work engagement: exploring its role in Performance Appraisal systems within the IT Sector

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Abstract

Nowadays, it is increasingly clear that digitalization is driving ways of looking at the organizational world. Human Resources Analytics play a crucial role in organizations enhancing their decision-making processes. This concept can have an important impact in the way performance appraisal systems are made and seen by their workers.

The main purpose of this research is to understand the impact of Human Resources Analytics processes on Work Engagement, within the scope of performance appraisal systems, in the IT sector, based on the Job Demands-Resources model.

A survey was carried out among technology workers. A sample of 257 responses was obtained and the results were then analyzed using *SPSS Statistics 29* and *AMOS 29*.

The results of this study were confirmed by four defined hypotheses. Thus, it was possible to verify that the more mature an organization's PA Analytics processes are, the more engaged people are at work, when the employee sees PA Analytics as a resource.

The research contributes to the JD-R model as PA Analytics can now also be considered as a resource (previously not considered in the literature). In addition, it also makes a powerful contribution to human resource management, as it highlights the importance of organizations constantly adapting to new technologies, making their PA Analytics processes more mature, which will have powerful effects on the employee, making them more engaged with the organization and improving their well-being at a professional level.

Keywords: Human Resources Analytics, PA Analytics, Performance Appraisal Systems, Work Engagement

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1. Introduction

Digitalization processes have a noticeable impact on the way organizations manage their resources. Given the growth of this technological aspect in employees' jobs, the influence of the concept on human resources management is notorious.

The term "human resources analytics", also known as "people analytics" or "HR analytics", among others, has become increasingly important. The process refers to "An 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 and Boudreau (2017, p. 13).

One of the objectives of using Human Resources Analytics (HRA), processes is continuously improving decision-making within the organizational environment. In this way, it is possible to use this data as key information, particularly for performance appraisal, allowing human resources professionals to become aware of the patterns in professional performance data (Kiran et al., 2023).

The performance appraisal process has become increasingly digitalized, and this can be seen as a pillar for the success of organizations under strong pressure to innovate (Curzi et al., 2019). According to Gaur (2020), digitalization processes are making businesses increasingly adapt to a more sustainable competitive advantage model, creating new challenges for workers, as there are new tasks and ways of carrying them out.

Nevertheless, regardless of the organization's sector of activity and the degree of digitalization of its processes, employees must be seen as its most important resource (Motyka, 2018). Their motivation and engagement at work are determining factors for improving their performance and, consequently, the company's results.

As the concept of HRA has gained more recognition in this last decade and considering the significant role of work engagement in enhancing a company's competitive advantage, this study seeks to investigate the potential impact of HRA processes in what concerns performance appraisal on work engagement. This document defined four hypotheses to reach a clear conclusion about the topic presented before.

In terms of methodology, a quantitative study will be conducted, using a questionnaire, with the employees of companies in the technology sector. This selection is based on the expectation that these individuals possess a heightened understanding of data analysis and recognize its

significance within the organizational context, particularly in the domain of human resource management.

2. Literature review

2.1 Human Resources Analytics

Human Resources Analytics (or the so-called HR Analytics- HRA) is a term that has only gained recognition in the last 20 years. According to Lawler et al. (2004), there is a big difference between what are considered HR metrics and HRA. The authors state that there are three distinct types of metrics that organizations use to achieve better goals: efficiency, effectiveness, and impact. They have the opinion that the "right HR metrics" don't are enough by themselves, so they explain that HRA, unlike these HR metrics, are not measures but techniques that use statistical data to impact HR activities positively. This type of data is crucial to help the HR departments of organizations make better decisions and help potentiate business growth.

According to a study by McKinsey & Company, (Aminov et al., 2019), today's economy has undergone a major acceleration due to digitalization, "where opportunities and threats instantly and unexpectedly impact an organization's competitive advantage" (Coolen et al., 2023, p. 1).

The fact that organizations increasingly rely on technology to enhance their processes is also evident in human resources management. There has been an acceleration in the use of analytics methods to improve and make more efficient decision-making processes that directly impact employees (Arora et al., 2023).

In this regard, HR analytics has become a rapidly expanding process (Huselid, 2018). Advocates of HRA believe that this process can assist contemporary organizations in defining the direction they want to take to achieve a competitive advantage, leveraging employee data as a valuable resource (McCartney & Fu, 2022).

However, conflicting opinions exist in the existing literature on the practical utility of HRA processes. According to Rasmussen e Ulrich (2015), the concept may become only a fleeting fad that will eventually diminish in importance. On the contrary, Cappelli (2017), argues that there is significant pressure on the Human Resources department to become more analytical, but HR Analytics is not always effective.

Other authors hold different opinions. According to Peeters et al. (2020), the group that benefits most from HRA are the human resources professionals themselves. However, they often fail to grasp the benefits that data can have on their performance and that of the company, and they lack the knowledge to effectively use it, thereby limiting the organization's digitalization process. Dahlbom et al. (2019), state that there are significant gaps in the training of HR professionals in organizations, including aspects of their lack of mathematical proficiency, poor understanding of software and computer systems that already have data that needs to be analyzed. Finally, the

authors claim that there is a tendency to focus on individual data points rather than analyzing them for the benefit of the business. In a quantitative study by Kryscynski et al. (2018), it was possible to conclude that HR professionals who have greater knowledge of analytical processes are more likely to create intrinsic value for their companies.

Given the need for HR professionals to adapt to an increasingly digitalized world of work, the advantages of this knowledge must be applied efficiently to human resources management practices.

2.2 Performance Appraisal Systems

Formal performance appraisals (PA) are a well-known and used practice of Human Resource Management (Cleveland & Murphy, 1995). Much more than a process for evaluating the performance of an organization's employees by defining concrete and measurable objectives for them, PA is also used with a focus on employee development. In this way, it analyzes the skills to be acquired by employees (identified by the system) and reveals their training and development needs (Kampkötter, 2017).

The performance appraisal system is given as a management decision tool. As such, it must be able to reproduce data on employee performance, which determines how accurate the results of this evaluation process are (Poon, 2004). One factor to consider is the feedback given to employees by their superiors when analyzing this data. According to Kampkötter (2017), employees who are aware of and give importance to the feedback provided are more likely to be happy with the appraisal process and, consequently, with their jobs.

Recent studies clarify that employees who have a fair perception of their company's PA, are more likely to accept the process and improve their results through critical appraisal of it (Lyu et al., 2023). When employees believe that an organizational performance evaluation is fair, they will try to maintain a high level of professional performance, with the desire to reward the organization (Siyal et al., 2020). Thus, the level of job performance increases.

Social exchange theory explains that when a worker perceives the way they are treated as fair, then they will have behaviors that positively benefit their relationship with the company. According to Ali et al. (2019), this theory defines that an individual is encouraged to show positive behavior to another when the second one values them. Thus, strong exchange relationships are established when one individual helps another.

Performance appraisal justice promotes work engagement. This concept alludes to “the

degree of employee's perception of fairness in the performance appraisal system, process and results of the organization during the performance appraisal period." (Lyu et al., 2023).

2.3 Work Engagement

In the early nineties Kahn (1990), was a pioneer when he first coined the term work engagement as the individuals' willingness to engage in their work roles from physical, cognition, and emotional sides.

This concept is gaining popularity lately in organizations as it is associated with the performance, motivation, and satisfaction of the employees.

The Gallup Institute, in its 2023 annual report ("State of the Global Workplace"), showed that 23% of global employees are engaged with their companies. Portugal, specifically, was considered one of the countries in Europe with the lowest percentage of engaged employees.

Workers who are engaged with their organizations are more likely to be motivated by their work and experience a feeling of passion for it. On the other hand, workers who have low levels of engagement with their work, perform their duties worse, show no motivation, and end up being resources that could move on to other alternatives. (Penãflor & Juevesa, 2021). This hurts the organization.

According to Schaufeli et al. (2002), work engagement is a concept comprising three dimensions: i) vigor, where an employee demonstrates high levels of energy, puts effort into their work, and exhibits resilience and persistence; ii) dedication, involving a strong commitment to the work, with employees feeling enthusiastic and inspired by their task; iii) absorption, the deep immersion of the person in their work, being thoroughly engrossed in it.

In literature, many theoretical frameworks try to clarify the concept of work engagement such as the self-efficacy theory, the goal-setting theory, the equity theory, the Job demands-resources framework, and the self-determination theory.

The most used in the organizational psychology field is, according to Bailey et al. (2017), the JD-R (Job demands-resources) framework. This theory is commonly used when discussing the influence of work on employees' health, well-being, performance, work engagement, and job performance, among other variables (Knight et al., 2017). Job demands-resources theory is based on the distinction between resources that are correlated with work or personal part (for example, as Knight et al. (2017) states, feedback, social support, development opportunities) and, on the other hand, demands, that are, accordingly to Demerouti and Bakker (2023), delineated as the facets of

a job necessitating sustained physical and/or psychological exertion and are linked with this kind of tool. (for example, accordingly to Knight et al. (2017), workload, emotional and cognitive demands)

Resources are seen as a way of promoting an employee's engagement with their organization, as they encourage higher levels of well-being and performance (Schaufeli, 2014). It refers to the physical, social, and organizational phenomenon of a job. The resources are important as they stimulate employees to seek their professional goals and develop themselves in the labor market (Knight et al., 2017). Demands, on the other hand, can harm the worker because they are based on effort. Thus, in this theory, workers with a higher level of resources are likely to be more engaged in their work (Schaufeli, 2014).

3. Development of the Hypotheses

In this study, HRA was initially widely considered. However, based on the more specific objectives of the research, which only intended to focus on performance appraisal systems, a new variable was created to restrict the scope of the investigation. Thus, the Performance Appraisal Analytics variable (PA Analytics), involves collecting and analyzing data to evaluate and enhance employee performance. This approach combines traditional performance reviews with quantitative data and statistical methods to objectively assess employee contributions. It can involve both simple and complex statistical analyses. The creation of a new variable directs the analysis only to the main focus of the study.

According to Katiyar et al. (2023), HRA in performance management (specifically in performance appraisal) helps businesses and employees achieve their goals. In their article, the authors emphasize the importance of utilizing an HCM (Human Capital Management) system that facilitates great accessibility to performance reviews for employees whose objectives are quantifiable, traceable, and less ambiguous. Performance management tools and employee reviews aim to offer employees a more transparent understanding of their strengths, areas for growth, and actionable strategies for improvement. HR analytics leverages factual data to enlighten both employees and managers, enabling informed decision-making and goal setting derived from such data.

Tyagi and Pandita (2022) carried out a study which concluded that artificial intelligence tools (and more specifically HRA) are probably a way of increasing an employee's engagement with their organization, since they will have more time to focus on the more demanding tasks they have and on their professional goals, which ultimately leads to an increase in their performance.

In this sequence, it is believed that the more people in the organization are familiar with the use of PA Analytics, and the more sophisticated these analyses are, the more they can contribute to employee engagement at work as they provide quick and detailed access to performance information that allows employees to develop their job. So, it is expected that the use of PA Analytics can leverage the job engagement of the employees.

Therefore, a general hypothesis was developed as follows,

H1: The maturity of PA Analytics usage has a positive effect on work engagement.

The JD-Recourses model, as mentioned above, divides the organizational environment into two concepts: demands and resources. The resources refer to elements that help workers deal with demands more efficiently, and thereby increase work engagement. According to Schaufeli (2017), the resources are defined as "the good things".

HRA is an important concept to companies as it generates valuable data that must be interpreted and used carefully. Thus, this data can be used as a decision-making tool, in Human Resources processes such as promotions, compensations, and others (Espinilla et al., 2013).

The analysis of data through HRA demonstrates a clear link between this process and the model described since relevant information can be extracted, such as existing patterns about the demands and resources of an organizational environment. The paper of Ruiner et al. (2022), examines how digitalization affects job demands and resources within digital work environments, with a focus on worker's perceptions and experiences, and highlights the significance of comprehending the equilibrium between job demands and resources in digital work settings, aligning with the concept of HRA, which entails analysing and optimizing the correlation between work demands, resources, and employee well-being.

The data to be analyzed through HRA can be seen as a resource, both by the employees of an organization and by the human resources professionals themselves. It should be noted, however, that perceptions of each piece of data can vary.

In the eyes of employees, the data collected and analyzed by HRA processes can be a resource, if they perceive the data as a way of leveraging their conditions in the organizational environment and giving them access to opportunities, they will not otherwise have such as having some personalized feedback to help to upgrade their work results. On the other hand, if employees feel that the data is somehow intrusive, it can negatively impact their perception of HRA processes (Giermindl et al., 2022), and be perceived as a demand.

From the perspective of human resources professionals, the data obtained by HRA can also be seen as a resource, as it helps them to make decisions in a wide variety of areas, such as recruitment, employee retention, and so on. In addition, it allows them to identify trends and assess the impact their initiatives are having on employees.

This study focuses only on the employee's perceptions of the topic. In this way, it is possible to study the perspective of the end-user of HRA processes and performance appraisal systems, which provides a direct and authentic point of view on the subject. On the other hand, focusing on the employees' perspective also brings insights that can drive the improvement of these practices in organizations, as it provides an in-depth understanding of how these processes can be leveraged in organizations and thus help to create alignment with their objectives at an organizational and strategic level. Finally, it is possible to identify some barriers or challenges that exist when implementing HRA processes or using performance evaluation systems in organizations.

Two hypotheses have been defined. The first one seeks to clarify, within the population to be studied, whether PA Analytics can be perceived by the employees of organizations as a resource. The second hypothesis aims to understand if this correlation between PA Analytics and WE are positive, as it is predictive. Thus, as it follows:

H2: The maturity of PA analytics allows the PA Analytics to be perceived more as a resource than as a demand.

H3: The perception of PA Analytics as a resource has a positive impact on work engagement.

The limited existing literature on the topic of the mediating effect of perception of PA Analytics, viewed as a resource within the JD-Resources framework, underscores a significant gap in current research. Despite the growing recognition of the importance of both HRA and performance appraisal systems in organizational contexts, there is a noticeable absence of studies specifically examining how the perception of HRA influences the evaluation of performance.

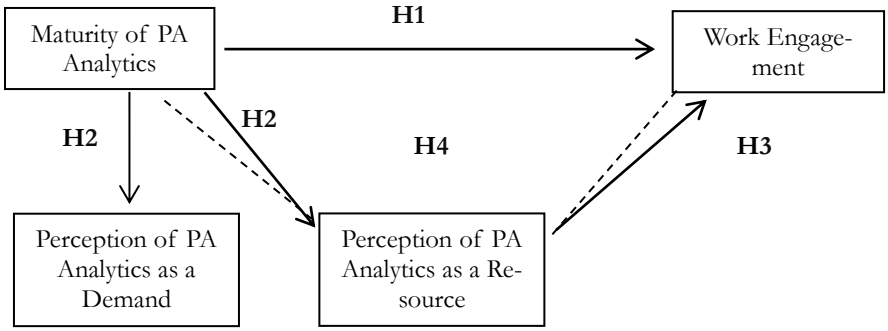
Considering this, studying the mediating effect of the perception of PA Analytics, in the light of the JD-Resources theory, offers a valuable opportunity to understand how organizational resources can influence work engagement and organizational efficiency.

As it follows,

H4: The maturity of PA analytics usage has a positive impact on work engagement, mediated by the perception of PA analytics as a resource.

The **figure 1** represents the conceptual model in study.

Figure 1: Conceptual Model



Source: Own elaboration

4. Methodology

4.1 Research method

The aim of this section is, following on from the previous elaboration of the development of hypotheses, to define the research methodology procedures used in the study.

With the passage of time, primary research methods, such as online questionnaires, are increasingly being used as these methods make it possible for researchers to adapt their methodology to meet the needs and its specific objectives of the research (Kankam, 2020).

Online surveys are gaining popularity recently as recent technologies are changing the way they are made, creating new possibilities of collecting data.(Evans & Mathur, 2018)

The questionnaire survey is most used when conducting studies that require many participants. It also allows data to be quantified in a more simplified way and generalizations and inferences to be made (Batista et al., 2021). According to Holmes (2023), it is a method that costs less than other research methods, can be "self-administered" and allows the participants to answer anonymously, among other things.

However, it should be noted that no research method is 100% effective and reliable, and the collection of primary data through questionnaires also has some disadvantages, such as the fact that the data presented may not be entirely valid for all the population that is being studied and

that there is some subjectivity in the creation and implementation of the questionnaires which can create some biases on the final data collected (Choi & Pak, 2005).

After a careful study of the most common methods to be used, based on the research question, and to evaluate the hypotheses that were described earlier, quantitative research will be conducted, using a questionnaire to obtain data on the subject.

The target population for this study will be restricted to the workers in the technology sector. The study in question involves variables linked to the technological maturity of organizations. The target population was primarily restricted to the technology sector since there is potential in terms of the use of HR Analytics, especially in more advanced technological companies, where the utilization of these technologies is expected. This sector works directly with data to obtain their results. Other sectors were not considered as it is believed that data analysis tools are less likely to be used, as access to and understanding of them can be limited, giving the scope. The data to be obtained at the end of the study could be biased, not demonstrating the feasibility of the possible results. According to the 2023 Portuguese government data, the innovation global index puts Portugal in the 30º place within 132 global economies. This index compares global countries by their propensity for technological innovation. Considering the Portuguese context in the technology sector and the personal ease of data collection in it, this target population was chosen for the study in question.

4.2 Data collection procedures

The survey that gives support to this study was designed on the *GoogleForms,* given the advantages this platform has compared to other online questionnaire tools. According to Vasantha Raju and Harinarayana (2016), this tool is very cost-effective, as it can be used free of charge, allows integration with other *Google* platforms, (which helps to manage the work done), facilitates data collection as it offers basic data analysis, has a very intuitive interface that is simple to customize, among others.

After it was drawn up, given that there was no scale already defined in literature for the PA Analytics variable, a questionnaire pretesting was conducted. As Ikart (2019) states questionnaire pretesting is a widely used technique to see if the questionnaire has been well constructed or if it will cause problems such as unanswered questions from respondents or possible ambiguous questions. This was done in the present study also because, accordingly to the author, it is possible to identify potential errors in the way the questions were previously asked, get a better idea of how long it will take to fill in the form for a participant of the study, test some concepts that may be

difficult to understand, among other things.

The pretesting was conducted in a technology company known to the author of this study which made it a very cohesive environment and easy to get valuable feedback on the survey. Speaking specifically of the pretesting results, it was possible to understand that the question mentioning the length of time the respondents had been in their organization did not initially consider all the possible years (it did not include those who had been in the organization for 3 years, 6 years, 11 years and 15 years, for example, due to the poorly formulated intervals). A better explanation of the concept of PA Analytics was also added later, as it was not clear to the respondents in the pretesting.

Finally, after these corrections, the survey was made available *online*, on platforms such as *Linkedin* and *Instagram*, on a large scale, giving the population under study. To be able to guarantee that the study in question only focuses on workers in the technology sector, this questionnaire was only published to groups in this area. However, there was no specific question regarding the respondents' area of activity, so this limitation was considered and documented at the end of this study. The method of data collection intends to maximize the likelihood of respondents being technology workers, by subdividing them into segments such as software development, data engineers, among others. As a result, the final sample is made up mostly of workers from this area, as expected, even though responses from workers in other sectors were not entirely excluded.

4.3 Measures

To ensure the validity of the questionnaire survey, scales analyzed and discussed in the literature were later utilized and adapted, with full descriptions provided in **Table 1**.

To measure PA Analytics, 3 sub-variables were analyzed, namely the Maturity of PA Analytics Use, PA Analytics as a Resource and PA Analytics as a Demand. As these are sub-variables that don't have specific scales already interpreted in the literature, it was done adaptations and an aggregate of some other questions, based on the JD-R model. In this sequence, to measure the 3 subdimensions, questions ere adapted from articles by Venkatesh et al. (2003) and Popov et al. (2024). Throughout these adaptations, questions were contemplated that tried to capture the simplest analyses of the data, up to more complex analyses.

To measure work engagement, it was used the UWES (Utrecht Work Engagement Scale), described by Schaufeli et al. (2002). The scale has 17 items, 6 of them that measure the Vigor (α is 0,80), 5 measuring the Dedication (α is 0,89) and other 6 measuring the Absorption (α is 0,72).

The items described were drawn up using a Likert scale. The PA Analytics scale has 5 points, with 1 being "Strongly disagree" and 5 being "Strongly agree". The UWES scale, on the other hand, has 7 points, with 0 being "Never" and 6 "Always (Every Day)"

The questionnaire was developed in English as the target population is in general all the workers in the technological sector.

The questionnaire also included socio-demographic questions, as these are important for characterizing the sample. Age, nationality, gender, the country in which the respondent works, how many years they are at that organization, their qualifications, current professional situation, length of time in the organization in question, the size of the organization and the number of human resources professionals in the organization were collected.

Tabel 1: Scales

Variable	Subdimension	Items	Source
PA Analytics	**Maturity of PA Analytics usage**	Incorporating PA Analytics is a practice within my company	(Popov et al., 2024) 0,56<α<0,87 (Venkatesh et al., 2003) 0,79<α<0,94
		My PA feedback involves insights that my supervisor obtains from simple HR data analysis (for example pivot table in Excel)	
		The PA is based on insights that result from HR data obtained through advanced techniques	
		The PA procedures involve advanced tooling, such as statistical or analytical tools.	
		PA processes involves multiple steps such as data preprocessing, the application of techniques and visualization.	
	PA Analytics as a Resource	Using PA Analytics makes my work tasks more interesting	(Popov et al., 2024) 0,56<α<0,87 (Venkatesh et al., 2003) 0,79<α<0,94
		I enjoy dealing with HRA tools for my PA	
		PA Analytics have an influence over how well I will perform my job	
		The PA Analytics allows me to make work-related decisions with great autonomy	
		The feedback I receive from PA Analytics is clear and precise	
		Utilizing PA Analytics helps me identify areas for professional growth and improvement	
	PA Analytics as a Demand	Using HRA within my company is not a good idea	(Popov et al., 2024) 0,56<α<0,87 (Venkatesh et al., 2003) 0,79<α<0,94
		I prefer traditional PA (without the using of HRA)	
		I don't understand the usefulness of PA Analytics for my company	
		I find the idea of using HRA intimidating.	
		I think that the use of PA Analytics is too complex for me	
		It's becoming difficult to keep track of the use of PA Analytics in my organisation	
Work Engagement	Vigor	At work I feel like bursting with energy	(Schaufeli et al., 2002) α=0,80
		At my job, I feel strong and vigorous	
		When I get up in the morning, I feel like going to work	
		I can continue working for very long periods at a time	
		At my job, I am very resilient, mentally	
		At my work I always persevere, even when things do not go well	
	Dedication	I find the work that I do full of meaning and purpose	(Schaufeli et al., 2002) α=0,89
		I am enthusiastic about my job	
		My job inspires me	
		I am proud on the work that I do	
		To me, my job is challenging	
	Absorption	Time flies when I'm working	(Schaufeli et al., 2002) α=0,72
		When I am working, I forget everything else around me	
		I feel happy when I am working intensely	
		I am immersed in my work	
		I get carried away when I'm working	
		It is difficult to detach myself from my job	

Source: own elaboration

4.4 Sample Characterization

Based on the study and its main objective, as previously described, the study was restricted only to one target population, namely current workers in the technology sector. All the answers obtained were validated on this criterion, bearing in mind that the survey was shared within an extremely specific set of contact networks.

The survey in question was designed to have only mandatory responses, so that there would be no missing values when analyzing the data. A total of 267 responses were obtained, 10 of which were not considered, because the current situation of the respondents was "unemployed". Therefore, 257 of the responses were considered to the previous data analysis.

It is possible, in **Table 2**, to verify the characterization of the sample. Concerning the gender of the respondents, there is a significant imbalance, as 14.4% of the respondents are female, and 85.2% are male. Given the area related to this study, this percentage distinction was expected. The average age of the respondents was 32 years.

Regarding nationality, 67.3% of the respondents are Portuguese, 25.3% are Brazilian, and only 7.4% have other nationalities. The majority being Portuguese is expected, given the context in which the survey was conducted.

In terms of the country of employment, 90.3% of the respondents work in/for Portugal, 3.5% in/for Brazil, and 6.2% for another country.

As for the educational qualifications of the respondents, most have completed secondary education (46.7%), followed by 35% with a bachelor's degree, and 17.5% with a master's degree or postgraduate degree. A minority have completed education up to the 1st to 4th year or 7th to 9th year (0.4% for both).

Regarding the type of contract they have, most have a permanent employment contract (73.9%), 18.7% have a fixed-term contract, and only 7.4% are in a service provision regime. There were no respondents who were doing an internship.

As for the length of time the workers have been with their current organization, the majority (43.2%) have been there for 1 to 3 years, followed by those who have been with the organization for less than 1 year (39.3%). Only 11.3% of the respondents have been with their current organization for 3 to 6 years, 3.5% for 6 to 11 years, 2.3% for more than 15 years, and finally, only 0.4% have been with the organization for 11 to 15 years.

Continuing with the topic of the number of employees in the respondents' current organization, 59.1% work in organizations with more than 249 employees, followed by 27.6% who work

in organizations with 50 to 249 employees, and 13.2% of respondents work in a professional environment with 10 to 49 employees. There were no responses from anyone working in an organization with fewer than 10 employees.

Finally, regarding the number of Human Resources professionals in the respondents' organizations, 41.6% reported having more than 10 professionals, 24.9% have 1 to 3 HR professionals, 20.2% have 4 to 6 professionals, and 13.2% have 7 to 10 HR professionals.

Tabel 2: Sample Characterization

Gender	Feminine	14,4%
	Masculine	85,6%
Age (mean)		32 years
Nationality	Portuguese	67,3%
	Brazil	25,3%
	Other	7,4%
Country of employment	Portugal	90,3%
	Brazil	3,5%
	Other	6,2%
Degree of qualification	1st to 4th grade	0,4%
	7th to 9th grade	0,4%
	Secondary education	46,7%
	Degree/Bachelor	35%
	Master's/Postgraduate	17,5%
Contract type	Internship	0%
	Fixed-term contract	18,7%
	Permanente contract	73,9%
	Provision of services	7,4%
Time in the company	Less than a year	39,3%
	Between 1 and 3 years (inclusive)	43,2%
	Between 3 and 6 years (inclusive)	11.3%
	Between 6 and 11 years (inclusive)	3,5%
	Between 11 and 15 years (inclusive)	0,4%
	More than 15 years	2,3%
How many workers have the company	Less than 10 workers	0%
	10 to 49 workers	13,2%
	50 to 249 workers	27,6%
	More than 249 workers	59,1%
How many HR professionals have the company	1 to 3 professionals	24,9%
	4 to 6 professionals	20,2%
	7 to 10 professionals	13,2%
	More than 10 professionals	41,6%

Source: own elaboration

5. Results

The data obtained from the questionnaire was extracted and entered *SPSS software* and then AMOS 29 so that more robust SEM results could be obtained. In a preliminary analysis, it was possible to verify that there was no case in which a response was not obtained. All the items were fully answered.

The first step was to confirm the normality of the data distribution. Thus, the shortness and asymmetry of the data were analyzed, as shown in **Annex 2.** According to Marôco (2014) absolute skewness values (sk) of less than 2-3 are acceptable, as are absolute kurtosis values (ku) of less than 7-10, to confirm the normal distribution of the data in question. As can be seen, the results indicate that all the variables in the model have kurtosis and skewness values within the acceptable limits. There were no variables with asymmetry values above 2 (absolute value) or kurtosis values above 7. This confirms the normality of the data, considering the criteria of Marôco (2014).

Despite this result, to have greater statistical reliability, the Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted. The results can be found in **Annex 3**. According to Marôco (2014), the p-values in this case should be greater than 0.05 to confirm the normality of the data. However, according to the results, the p-values were <0.01, indicating that the variables did not follow a normal distribution, which contradicts the results of the normality tests according to Marôco (2014) criteria, which considered the asymmetry and kurtosis of the data.

Given that there was a slight deviation from normality in the data in this study, it is necessary to carefully pre-select the data analysis method to be considered, as the wrong choice cloud bias the results. Therefore, some alternate methods were considered to carry out the structural equation modeling analysis. This Asymptotically Free Distribution (ADF) method was chosen, as this test is more robust to deviations from the normality of the data (which was the case here), providing the possibility of obtaining more satisfactory and accurate results. Jones and Waller (2015), in their article, studied and supported the idea that ADF is a method that can, theoretically, be used as a good method in the presence of non-normal data (for medium and large samples), leading to more robustness on the results to be presented.

5.1 Factor Analysis

According to Marôco (2014), the factor analyses refer to general linear modeling techniques that can identify latent variables, which play a major role in explaining the behavior of the manifest items. FAs are divided into two subcategories: EFAs (Exploratory Factor Analyses) and CFAs (Confirmatory Factor Analyses).

Based on the measurement instruments used, specifically the PA Analytics measure, which was built from scratch in this study, a factor analysis was first carried out. For the analysis to be considered as robust as possible and out of an abundance of caution, an EFA was done beforehand and then the CFA was studied. However, for the work engagement scale, as changes were not made, an EFA was not necessary, so only a CFA was done.

The EFA was carried out in *SPSS Statistics* (version 29) and the CFA in *SPSS AMOS* (version 29) as Field (2024) recommend considering the size of the sample in question. To have the most robust results possible, in the CFA, it was done an assessment of the existence of outliers, considering the Mahalanobis squared distance (D2), calculated in the *SPSS* software. This is an important step in the analysis of data, because, as Comrey (1985) states, if there is data that is of poor quality, due to some error or some answer that is considered improper, this has negative repercussions on the correlations of the variables and consecutively, in the model. If outliers are eliminated, then the CFA can be handled with more robustness.

5.2 Exploratory Factor Analysis

5.2.1 PA Analytics

A Principal Component Analysis (PCA) was conducted on the 17 items of the PA Analytics scale to see which components were obtained, using the Varimax rotation method.

Firstly, the Kaiser-Meyer-Olkin (KMO) measure was interpreted, since according to Marôco (2014), it shows how adequate the sample in question is so that robust, quality analyses can be carried out. Thus, using his criterion, the data would be adequate from a value of 0.5. As can be seen in **Table 3**, a value of 0.905 was obtained, proving that the sample size is considered interesting enough to proceed with the EFA. Moving on to interpret Bartlett's test of sphericity, which tests the null hypothesis that the original correlation matrix is an identity matrix, if the test is statistically significant, i.e. $p<0.05$ (which was confirmed by **Tabel 3**, where $p<0.01$), it is possible to reject and state that the Factor Analysis is as expected.

Tabel 3: Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity

KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy.		,905
Bartlett's test of sphericity	Approx. Qui-squared	6449,438
	Gl	561
	Sig.	<,001

Source: *AMOS* output

Principal Component Analysis was conducted with Varimax rotation, because according to Comrey (1985), this concept can allow direct comparison in terms of variance and characteristics recovered in the model. So, this step is necessary to understand which factors will be retained for the study.

The PCA showed three main components, which is in line with the theoretical dimension of the study, as can be seen in **Tabel 4**. Component 1 showed very high factor loadings on the variables MPAA1, MPAA2, MPAA3, MPAA4, MPAA5 and PAAR1, PAAR2, PAAR3, PAAR4, PAAR5 and PAAR6, inferring that this component can be seen as a combination of the "Maturity of PA Analytics" and "Perception of PA Analytics as a Resource" dimensions. This suggests that the two dimensions may be interlinked. Component 2, on the other hand, has high factor loadings in the PAAD2, PAAD3 and PAAD4 variables, which suggests that it may be representing the "Perception of PA Analytics as a Demand" dimension, as would also be expected. Finally, component 3, compared to the other two components, does not have such high factor loadings, but there is a specific effect on the variables MPAA3, MPAA4 and MPA55, since they have a moderate loading but with an inverse effect (negative values). This may reflect some aspect that was not previously considered in this study. It may reflect a combination of perceptions, or the Maturity of PA Analytics use itself, which has not been verified in the other dimensions at a theoretical level.

Tabel 4: Principal component analysis of PA Analytics

Component Matrix[a]			
	Component		
	1	2	3
MPAA1	,653	-,114	-,389
MPAA2	,730	,008	-,332

MPAA3	**,797**	**,004**	**-,436**
MPAA4	**,806**	**-,007**	**-,389**
MPAA5	**,817**	**-,072**	**-,335**
PAAR1	**,758**	**-,173**	**,340**
PAAR2	**,771**	**-,113**	**,306**
PAAR3	**,726**	**,001**	**,296**
PAAR4	**,781**	**-,132**	**,410**
PAAR5	**,781**	**-,034**	**,066**
PAAR6	**,745**	**-,179**	**,436**
PAAD1	**,301**	**,689**	**-,069**
PAAD2	**,093**	**,651**	**-,089**
PAAD3	**-,039**	**,730**	**,032**
PAAD4	**,230**	**,764**	**,161**
PAAD5	**,202**	**,779**	**,076**
PAAD6	**,051**	**,711**	**,084**
Extraction method: Principal Component Analysis.			
a. 3 components extracted.			

Source: *AMOS* output

Given that there was an overlap of variables and that it was not clear what the reflection and identification of component 3 was, a Varimax rotation was conducted (the Rotated Component Matrix was obtained) to obtain a more reliable and robust result. As can be seen in **Tabel 5**, there is a great deal of distinction between the components. Component 1 has high factor loadings in all the PAAR variables (above 0.7 in all except the PAAR5 variable where it was 0.607), which leads us to say that it is the representation of the "Perception of PA Analytics as a Resource" dimension, with all the variables having a strong relationship with the dimension. Moving on to component 2, all the MPAA variables had factor loadings above 0.7, showing the strong relationship with the "Maturity of PA Analytics" dimension, contrary to what happened in the component matrix, where there was overlap between dimensions, in this one an isolated effect was observed. Component 3 showed strong factor loadings of the PAAD variables, thus associating the component with the "Perception of PA Analytics as a Demand" dimension, where they were also all above 0.7, except for the PAAD2 variable which was 0.651. It can be concluded, as expected given the theoretical question of the study, that there are 3 distinct components, which confirm the existence

of 3 dimensions of the study ("Maturity of PA Analytics", "Perception of PA Analytics as a Demand", "Perception of PA Analytics as a Resource").

Tabel 5:Principal component analysis of PA Analytics after a Varimax Rotation

Rotating component matrix [a]			
	Component		
	1	2	3
MPAA1	**,215**	**,737**	**-,049**
MPAA2	**,292**	**,743**	**,086**
MPAA3	**,268**	**,864**	**,085**
MPAA4	**,308**	**,837**	**,078**
MPAA5	**,362**	**,808**	**,019**
PAAR1	**,798**	**,283**	**-,046**
PAAR2	**,776**	**,315**	**,013**
PAAR3	**,720**	**,285**	**,119**
PAAR4	**,857**	**,246**	**,003**
PAAR5	**,607**	**,491**	**,077**
PAAR6	**,856**	**,205**	**-,047**
PAAD1	**,069**	**,224**	**,718**
PAAD2	**-,087**	**,097**	**,651**
PAAD3	**-,110**	**-,084**	**,718**
PAAD4	**,166**	**,005**	**,797**
PAAD5	**,085**	**,046**	**,803**
PAAD6	**-,007**	**-,059**	**,715**
Extraction method: Principal Component Analysis. **Rotation method: Varimax with Kaiser Normalization.**			
a. Rotation converged in 5 iterations.			

Source: *AMOS* output

Next, an analysis of the internal consistency of the 3 dimensions present in the study was carried out, calculating Cronbach's Alpha (α). This concept assesses whether the instruments in the analysis consistently show what is being measured.(Field, 2024) According to Marôco (2014), an α

above 0.9 indicates excellent internal consistency and between 0.8 and 0.9 very good internal consistency. Cronbach's alpha was 0.907 for the Maturity of PA Analytics variable, 0.830 for the Perception of PA Analytics as a Demand variable and 0.909 for the Perception of PA Analytics as a Resource variable. Thus, this analysis was successfully validated.

5.3 Confirmatory Factor Analysis

5.3.1 PA Analytics

Considering the Mahalanobis squared distance (D2), it was observed that there is at least one observation with D2 values that suggested the existence of outliers for significance values of 0,001. These outliers were eliminated to continue the study.

Regarding the quality of the overall fit, the $\chi 2/df$ value is 3,5, which is within the acceptable range, according to Marôco (2014). Moving on to the CFI and IFI the value is 0,6 which are not good values, but GFI is 0,8, a reasonable value. The RMSEA is 0.1, so the adjustment is moderate, and the value is at the threshold of adequacy. The ECVI is 1,9, which indicates that this model has an acceptable fit.

About the quality of the local fit, in terms of the standardized factor weights, the items in the model all have weights greater than 0.5 (values between 0.68 and 0.92) Thus, there is adequate factorial validity.

As the model could have better quality of the overall fit, it was analysed the modification indices of this model. This show in which parameters the fit of the model cloud be improved. Thus, it was found that adding some covariances between errors and variables, would improve the model's fit. In addition, the regression weights were quite high for some variables, suggesting the addiction of direct relationships, in this case between the variables PAAR to PAAD3, MPAA to PAAD3 and from PPAD3 to MPAA1. The fit of the model was tested considering all these relationships and their theoretical basis and only the covariances described above and the relationship between MPPAA and PAAD3 were considered to the improvement of the adjustment of the model. Regarding the quality of the overall fit, the $\chi 2/df$ value is now 3, which is within the acceptable range, according to Marôco (2014). Moving on to the CFI and IFI the value is now 0,7 which are not good values but better than before, and GFI is 0,8, a reasonable value. The RMSEA is now 0.09, which was a good improvement from the initial model and the value is at the threshold of adequacy. The ECVI is 1,7, which indicates that this model has an acceptable fit.

About the quality of the local fit, in terms of the standardized factor weights, the items in the model all have weights greater than 0.5 (values between 0.52 and 0.92) Thus, there is adequate

factorial validity.

The new model is shown in **Annex 4.**

As for the individual reliability of the items, all have values above 0.25. So, each of the items is contributing adequately to measuring the PA Analytics. Convergent validity (VEM) is, for Maturity of PA Analytics=0.74; for Perception of PA Analytics as a Resource =0,67 and for Perception of PA Analytics as a Demand=0,55, indicating excellent convergent validity, as VEM > 0.5. The composite reliability is 0,92 for MPAA and PAAR, and 0,85 for PAAD, indicating high composite reliability as FC>0.7.

5.3.2 Work Engagement

Considering the Mahalanobis squared distance (D2), it was observed that there is at least one observation with D2 values that suggested the existence of outliers for significance values of 0,001. These outliers were eliminated to continue the study.

Regarding the quality of the overall fit, the $\chi 2/df$ value is 4,6, which is within the acceptable range, the CFI is 0,6 (which is a little bit below the recommended), IFI and GFI are 0,8, which indicates a moderate adjustment. The RMSEA is 0.1, so the adjustment is moderate, and the value is at the threshold of adequacy, the ECVI is 2,4, which indicates that this model has a reasonable fit.

About the quality of the local fit, in terms of the standardized factor weights, it varies between 0,52 and 0,94 which indicates that most of them are acceptable. In terms of the individual reliability of the items, some of them have values below 0.5 (V1=0,24; V4=0,29; V6=0,27)**.** So, the items in question were removed of the model.

It was analysed the modifications indices as well. Thus, it was found that adding some covariances between errors and variables, would improve the model's fit. Regarding the quality of the overall fit, the $\chi 2/df$ value is now 2.3, which is within the acceptable range, according to Marôco (2014). Moving on to the CFI, IFI and GFI the values are now 0,9 which are good values. The RMSEA is still 0.1 and the value is at the threshold of adequacy. The ECVI is 1,7, which indicates that this model has an acceptable fit.

About the quality of the local fit, in terms of the standardized factor weights, most of the items in the model have weights greater than 0.5 but AB6 was 0,32 and V5 was 0,48. So this two were removed and it was done another analysis to see the benefits of this action.

Regarding the quality of the overall fit, the $\chi 2/df$ value is now 1.8, which is an amazing improvement, and, according to Marôco (2014), it is now a good value. The CFI and GFI are now

0,9 which are good values and AGFI is 0,8, which indicates a moderate adjustment. The RMSEA is still 0.1, so the adjustment is moderate, and the value is at the threshold of adequacy, and the ECVI is 0,6, which indicates that this model has a good fit.

About the quality of the local fit, in terms of the standardized factor weights, the items in the model all have weights greater than 0.5 (values between 0.69 and 0.96) Thus, there is good factorial validity.

The new model is shown in **Annex 5**.

Convergent validity (VEM), for Vigor is 0,73, for Dedication is 0,66 and for Absorption is 0,60, which indicates excellent convergent validity, as VEM > 0.5. The composite reliability is, for Vigor is 0,83, for Dedication is 0,92 and for Absorption is 0,88, indicating high composite reliability for them as FC>0.7

It was done a second order factor model of work engagement as this analysis can help simplify the model, multicollinearity of the factors and getting a better interpretation of the model structure. (Marôco, 2014)

Regarding the quality of the overall fit, the $\chi 2/df$ value is 2.2, which is within the acceptable range, the CFI is 0,8 which is an acceptable value and GFI is 0,9, which indicates a good adjustment. The RMSEA is 0.1, so the adjustment is moderate, and the value is at the threshold of adequacy, the ECVI 0,7, which indicates that has a good fit.

About the quality of the local fit, in terms of the standardized factor weights, it varies between 0,79 and 0,98 which indicates that the items are acceptable. Convergent validity (VEM), for Vigor is 0,715, for Dedication is 0,838 and for Absorption is 0,758, which indicates a good fit as VEM > 0.5. The composite reliability is, for Vigor is 0,834, for Dedication is 0,963 and for Absorption is 0,940, indicating high composite reliability of this variables as FC>0.7.

The model is shown in **Annex 6**.

5.4 Correlation Analysis

To analyse whether there are correlations between the variables under study and, if so, in which direction, it was calculated the mean, standard deviation and correlation between the variables, shown in **Table 6.** In this analysis, the variables were considered: Maturity of PA Analytics; Perception of PA Analytics as a Resource, Perception of PA Analytics as a Demand, Vigor, Absorption e Dedication and also demographic variables, such as age, nationality, gender, country of employment, qualifications, type of contract, how long the respondent has been working in the

organization and how many HR workers there are in the respondent's work organization.

This analysis shows that the Maturity of PA Analytics variable is positively correlated with the Perception of PA Analytics as a Resource variable, significantly ($r=0.746$) for $p<0.01$. The variable Perception of PA Analytics as a Demand, on the other hand, is negatively correlated ($r=-0.133$) with the variable Maturity of PA Analytics and positively correlated ($r=0.121$) with Perception of PA Analytics as a Resource.

Turning to the dimensions of Work Engagement, Vigor is positively correlated with Maturity of PA Analytics and significantly so for $p<0.01$ ($r=0.389$), and with Perception of PA Analytics as a Resource ($r=0.412$) for $p<0.01$. As for the correlation between Vigor and Perception of PA Analytics as a Demand, it is positive, with $r=0.127$. Following for the Dedication, the variable is positively and significantly correlated with Maturity of PA Analytics ($r=0.327$), as it is with the Perception of PA Analytics as a Demand variable, with $r=0.396$ ($p<0.01$). With Vigor, Dedication has an equally positive and significant correlation for $p<0.01$, of 0.086. Lastly, the Absorption variable is positively and significantly correlated, with the Maturity of PA Analytics with a $p<0.01$ and a value of 0,279. The Perception of PA Analytics as a Resource variable is also positively and significantly correlated with the Absorption variable, with $r=0.317$. The variable Perception of PA Analytics a Demand follows the same trend, with a positive and significant correlation (for $p<0.05$) of 0.140. With Vigor, it has a significant ($p<0.01$) and positive correlation with $r=0.698$ and likewise for Dedication with Absorption, with $r=0.767$ (with $p<0.01$).

Finally, regarding the Work Engagement variable, it proved to be positively and significantly correlated with the Maturity of PA Analytics, the Perception of PA Analytics as a Resource, Vigor, Dedication and Absorption variables, with values of 0.366, 0.414, 0.894, 0.926, 0.902 respectively., for $p<0,01$ The correlation with the Perception of PA Analytics as a Demand was positive but not significant (0.129)

The analysis was in line with what was expected in terms of the correlations between the variables of interest to the study.

Tabel 6: Means, standard deviations and correlations

Variáveis	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Age [a]	32,51	9,046																
2. Nationality [b]	1,38	,620	,110															
3. Gender [c]	1,84	,368	,058	-,007														
4. Working Country [d]	1,13	,471	-,042	**,345****	,009													
5. Qualifications [e]	4,67	,818	**,164***	-,099	,037	-,053												
6. Contract Type [f]	2,89	,486	**,311****	-,003	-,019	,107	-,006											
7. Time working in the organization [g]	1,86	988	**,407****	-,010	,128	,018	-,085	**,273****										
8. Workers at the organization [h]	3,50	,690	**,143***	,033	**,160***	-,006	,114	,020	,078									
9. HR Workers at the organization [i]	2,74	1,216	-,078	,041	,093	,059	,063	,025	,003	**,658****								
10. MPAA [j]	3,1126	,94850	-,049	,041	-,110	-,053	-,058	-,017	-,041	,081	,117							
11. PPAR [k]	3,2346	,86921	-,040	,042	-,131	-,070	,004	-,013	-,020	,048	-,010	**,746****						
12. PPAD [l]	2,5882	,80558	,009	,116	-,021	-,013	-,071	,034	,079	-,070	-,134	-133	,121					
13. Vigor [m]	4,5922	1,32471	,003	,007	-,055	-,086	,118	-,045	-,011	-,024	,024	**,389****	**,412****	,127				
14. Dedication [n]	5,0553	1,43212	-,003	,017	-,133	,008	,091	-,015	-,019	-,047	,009	**,327****	**,396****	,086	**,789****			
15. Absorption [o]	4,6427	1,29227	,071	,005	-,049	-,024	,052	-,016	,038	,052	,068	**,279****	**,317****	**,140***	**,698****	**,767***		
16. WE [p]	4,7634	1,22547	,025	,011	-,089	-,036	,096	-,027	,002	-,008	,036	**,366****	**,414****	**,129**	**,894***	**,926****	**,902****	

Source: own elaboration

Notes: n = 257; ** p < 0,01; * p < 0,05.
(a) Age; (b) Nationality: 1- Portuguese, 2- Brazil, 3- Other; (c) Gender: 1- Feminine, 2- Masculine; (d) Working Country: 1-Portugal, 2-Brazil, 3-Other; (e) Qualifications: 1- 1st to 4th grade, 2- 7th to 9th grade, 3- Secondary education, 4- Degree/Bachelor, 5-Master's/Postgraduate; (f) Contract Type: 1- Internship, 2- Fixed-term contract, 3-Permanent contract, 4- Provision of services; (g) Time working in the organization: 1- Less than a year, 2- Between 1 and 3 years (inclusive), 3- Between 3 and 6 years (inclusive), 4- Between 6 and 11 years (inclusive), 5- Between 11 and 15 years (inclusive), 6- More than 15 years; (h) Workers at the organization: 1- Less than 10 workers, 2- 10 to 49 workers, 3- 50 to 249 workers, 4- More than 249 workers; (i) HR Workers at the organization: 1- Less than 10 workers, 2- 10 to 49 workers, 3- 50 to 249 workers, 4- More than 249 workers; (j) Maturity of PA Analytics; (k) Perception of PA Analytics as a Resource; (l) Perception of PA Analytics as a Demand; (m) Vigor; (n) Dedication; (o) Absorption; (p) Work Engagement

5.5 Structural Model Analysis

5.5.1 Path Analysis

The model under study is shown in **Annex 7.** Regarding the quality of the overall fit, the $\chi 2/df$ value is 4,2, which is within the acceptable range, the CFI is 0,9 which is a good value, GFI and AGFI are 1,0 and 0,9 respectively, which indicates a good adjustment. The RMSEA is 0.1, so the adjustment is moderate, and the value is at the threshold of adequacy, the ECVI 0,1, which indicates that this model has a good fit.

According to Marôco (2014), to analyse the structural model, it is important to start by looking at the model's predictive capacity. Therefore, the coefficients of determination were calculated, which allow an assessment to be made of the model's fit, based on the dependent variables. The close the value is to 1, the higher is the predictive capacity of the model.

The variable Perception of PA Analytics as a Resource has a R^2 of 0,4 which means that 40% of the variance of this variable is explain by the Maturity of PA Analytics, so the predictive capacity is moderate. The variable Work Engagement has a R^2 of 0,20, meaning that 20% of the variance of the variable are explained by the predictors of the model (in this case, Perception of PA Analytics and Maturity of PA Analytics), which is also a moderate predictive capacity. Lastly, the variable Perception of PA Analytics as a Demand has a R^2 of 0,01 meaning that only 1% of the variance of this variable is explained by the Maturity of PA Analytics, demonstrating that the predictable capacity of this variable is low.

Secondly, it is important to analyse the regression weight of the variables. This coefficient is 0,03 for the path between the Maturity of PA Analytics to Work Engagement suggesting that there is a weak relationship between the variables. For the Maturity of PA Analytics to the Perception of PA Analytics as a Resource, the coefficient is 0,65, indicating a strong relationship between them. Looking for the path of Maturity of PA Analytics to the Perception of PA Analytics as a Demand, the value is 0,09 which is low. For the relation of the Perception of PA Analytics as a Resource to the Work Engagement, the regression weight is 0,43, indicating a moderate relationship between the variables.

Lastly, the direct and indirect effects were analysed, as shown in **Table 7**.

It is possible to conclude that the hypothesis 1 was not confirmed as the direct effect of the Maturity of PA Analytics on Work Engagement is low and there is no statistical significance. On the other hand, hypothesis 2 was confirmed. The direct effect of the Maturity of PA Analytics on the Perception of PA Analytics as a Resource is 0,65 which is significantly higher than the direct

effect of the Maturity of PA Analytics on the Perception of PA Analytics as a Demand (with the value of 0,01). Following for the third hypothesis, this one was also confirmed, as the direct effect of the Perception of PA Analytics as a Resource on Work Engagement is positive and significant (with a value of 0,43 and a p-value of 0). Lastly, the fourth hypothesis was confirmed. The indirect effect of the mediator, Perception of PA Analytics as a Resource, on the relationship between the Maturity of PA Analytics on Work Engagement was higher than the direct effect of them and significant (0,28 compared to 0,03).

Tabel 7: Hypothesis Results

Hypothesis	**Relationship**	**Direct Effect**	**Indirect Effect**	**Total Effect**	**Bootstrap**	**Significance**
H1	MPAA to WE	0,03	-	0,03	[-0,2;0,3]	p=0,8
H2	MPAA to PPAR	0,65	-	0,65	[0,5;0,7]	p<0,001
H2	MPAA to PPAD	0,01	-	0,01	[0,0;0,2]	p=0,2
H3	PPAR to WE	0,5	-	0,5	[0,2;0,8]	p<0,001
H4	MPAA to PPAR to WE	-	0,2	0,2	[0,02;0,40]	0,0

Source: Own elaboration

6. Conclusions

6.1 Results discussion

Digitalization processes are playing a fundamental role in work environments nowadays. HRA has been an increasingly debated concept in the literature as well as its advantages and practical implications for human resources management and enhancing organization's competitive advantage. It is particularly important as a tool to provide insights into employee data, helping organizations on their decision-making processes (Paul & Khan, 2024).

As the topic of HRA is very current and there are still many gaps in the literature, especially when talking about this tools usage in performance appraisal systems, the main objective of this study is to understand the impact that HRA processes have on work engagement, specifically within the spectrum of performance appraisal systems. The JD-R model was used as the base theory to develop the study's four hypotheses, which were previously analysed and confirmed.

Firstly, it was analysed the effect that the Maturity of PA Analytics usage has on Work Engagement. It was concluded that the effect is positive, which suggests that organizations that have a robust analytics system and integrate it into their employee performance appraisal have employees who are more engaged with their work. In turn, work engagement has a high potential for achieving organizational goals, since it leverages employee satisfaction, reduce factors such as turnover and increase productivity (Parmenas, 2022). Organizations should therefore bear in mind that the maturity of their PA Analytics processes has a positive impact on their employees, and, in this sequence, they should invest in new technologies to potentiate their positive behaviour and well-being. Sharma and Sharma (2017) conclude, in their article, that the use of HRA in performance appraisal systems is positively correlated with employees perceiving their performance appraisal system to be fairer, which, as Gupta and Kumar (2012) suggests, can lead to employee engagement.

Although it is not a topic covered in the analysis carried out in this study, it is important to note that human resources professionals are fundamental on promoting work engagement of their workers, so they should therefore be trained in the technologies (HRA specifically) and practices to be adopted in this regard (Dahlbom et al., 2019).

Looking up to the second and third hypotheses, it was confirmed that the Maturity of PA Analytics usage is more perceived as a resource rather than as a demand by the employees and that this perception of PA Analytics as a resource has a positive effect on Work Engagement. This means that organizations should leverage the maturity of their PA Analytics practises, as they are a noticeable resource to the business, helping in their workers retention, increasing their

productivity and having their loyalty (Better & Decisions, 2018). In the other hand, as the maturity of PA Analytics is not seen as a demand in such a strong way, it can mean that this process helps organizations reducing the stress and burnout effects on their workers as they feel that these tools are helping them on creating a path in their workplace. The maturity of PA Analytics can be adopted as a concept that promotes the well-being of the workers (Pagnozzi, 2022).

Finally, looking at the fourth hypothesis, it was found that the effect of the mediator Perception of PA Analytics as a resource helps to explain the positive effect of the maturity of PA Analytics on Work Engagement. This has practical implications, since the maturity of the process's usage may not directly influence the worker engagement enough. The positive perception they have of the greater maturity of PA Analytics is the key element in making them feel engaged, and not just the maturity of the processes themselves.

6.2 Theoretical and practical contributions to management

This study pretends to help improving and updating the JD-R (Job Demands-Resource) model. After an exhaustive analysis of the model, it was found that the inclusion of PA Analytics as a resource in it would help expanding the existing literature on the subject. Thus, in this study, it was possible to conclude that digital and technological resources such as PA Analytics are concepts that have an impact on increasing employee engagement with their organization. In addition, not only can PA Analytics be seen as a resource for an organization, but it can also be a bridge between those resources and employee engagement itself.

Turning to Human Resources Management, this study also aims to add valuable insights to the field. It is therefore possible to see that PA Analytics can be seen as simplifying work, reducing demands and increasing employee engagement.

6.3 Limitations and recommendations for future research

This study has some limitations, which should be considered in future studies on the subject.

As previously shown, the quantitative method was chosen as one of several methods that could be adopted for this study. Although there are clear advantages on this method usage, there are also disadvantages that must be weighed up. According to Batista et al. (2021), some of the challenges that the quantitative method faces are: the possibility that this method does not represent all the target population; the lacking of intensity, meaning that the depth of the information

that is collected is low when compared to other methods, among others. In this study, 257 responses to the questionnaire were obtained, which, although not exactly a small sample, may not be representative of the total sample, since a convenience sample was conducted. As Stratton (2021) states, the convenience sample can increase the risk of getting limited participant rates and therefore, data that could be significant for the study, can be missed in the previous analysis.

Another limitation of this study is the fact that only one point in time was considered when collecting the data (the design of the questionnaire was cross-sectional), which can bias the results presented. Given that it is studied a causal relationship between variables, it should be possible to collect data at various points in time. However, in this study, cause and effect data were collected all at the same time. Therefore, the data should be interpreted carefully. In the future, potential follow-up studies should consider other methodologies that enhance the results to be presented.

Other limitation presented is the absence of a specific question that directly confirms whether all participants are professionals in the technology field. Although the survey was distributed through networks associated with the technological sector, it cannot be guaranteed that all respondents belong to this field. This limitation should be considered when interpreting the results and generalizing based on this study and it is recommended, for future studies, to include a question that concretely restrict the population to the purpose of the subject.

Data on both dependent and independent variables were collected from only one type of respondent, the technology workers. Thus, it is also considered a limitation: the common method bias. As Kamakura (2010) state in his article, this bias occurs when the measurement of a variable is affected by the method of data collection. In further studies, it is recommended to consider, additionally, other group of respondents so that this limitation can be mitigated. For example, human resources professionals could be surveyed, as they may have relevant knowledge on the subject in question and could bring interesting perspectives to the study. In the present investigation, an attempt was made to reduce bias by anonymizing the results. In addition, the Harman test was carried out, which consists of doing an exploratory factor analysis with all the items in the questionnaire, checking whether the value of the first factor explains a variance of more than 50% (Aguirre-Urreta & Hu, 2019). In fact, in this specific case, the variance was 36,555%, showing that the effect of bias was mitigated.

Finally, it is necessary to mention the non-normality of the data. In fact, in terms of the skewness and kurtosis values, the normality of it could effectively be assumed. However, when the Shapiro-Wilk and Kolmogorov-Smirnov tests were conducted, the result was no longer so satisfactory, showing that the data was not normal. The ML method was subsequently assessed using

AMOS and confirmatory factor analyses were carried out and then compared with the ADF method (Jones & Waller, 2015). However, it is important to bear in mind that although the ADF is a very robust method to use when there are violations of the data normality assumption, it can cause problems depending on the size of the sample in question. It is recommended to use the ADF if there are more than 1,000 responses to be analyzed, which was not the case. In future research, the use of other non-parametric methods which take account of the non-normality of the data should be evaluated in more detail.

Despite all the limitations previously presented, this study can be considered a good starting point for the continued search for knowledge and further study of the subject in the literature. The subject has been little explored, given its topicality, so it is important to redirect efforts towards continuous improvement and robust results within it.

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8. Annexes

Annex 1: Final survey

HR Analytics in Performance Appraisals: Impact on Work Engagement in IT

This survey is being carried out as part of a dissertation for the Master's Degree in Economics and Human Resources Management at the Faculty of Economics of the University of Porto.

The main goal is to study the impact of Human Resources Analytics processes on Work Engagement, based on Performance Appraisal systems, in the IT sector.

The survey will only be used for the dissertation and will be completely confidential. The questionnaire will take approximately 5 minutes to complete. It is only aimed at professionals working in the technology sector.

Section 1:

I declare that I have been informed that my participation in this study is voluntary and that the information collected is confidential. I therefore voluntarily agree to take part in this study.

_ Yes

Section 2: Demographic issues

What is your age?

_____

What is your nationality?

_____

What's your gender?

_ Female

_ Male

_ Prefer not to say

In which country do you work?

_____

What are your educational qualifications?

_ 1st to 4th grade

_ 5th to 6th grade

_ 7th to 9th grade

_ Secondary education

_ Degree/Bachelor

_ Mater's/Postgraduate

_ PhD

What is your current professional situation?

_ Internship

_ Fixed-term contract

_ Permanent contract

_ Provision of services

How long have you been working at your organization?

_ Less than 1 year

_ Between 1 and 3 years (inclusive)

_ Between 3 and 6 years (inclusive)

_ Between 6 and 11 years (inclusive)

_ Between 11 and 15 years (inclusive)

_ More than 15 years

How many workers does your organization have?

_ Less than 10 workers

_ 10 to 49 workers

_ 50 to 249 workers

_ More than 249 workers

How many professionals are there in your company's Human Resources department?

_ 1 to 3 professionals

_ 4 to 6 professionals

_ 7 to 10 professionals

_ more than 10 professionals

Section 3: Performance Appraisal Analytics

Performance Appraisal Analytics involves collecting and analysing data to evaluate and enhance employee performance. This approach combines traditional performance reviews with quantitative data and statistical methods to objectively assess employee contributions. It can involve both simple and complex statistical analyses.

We have abbreviated the following terms in this questionnaire:

Performance Appraisal - PA

Human Resources Analytics - HRA

Performance Appraisal Analytics - PA Analytics

With this explanation in mind, we ask you to answer the following questions:

We ask you to give your opinion on each of the following statements regarding the organization you are currently in, based on the following scale:

1 - Strongly disagree

2 - Disagree

3 - Neither agree nor disagree

4 - Agree

5 - Strongly agree

	1	2	3	4	5
Incorporating PA Analytics is a practice within my company					
My PA feedback involves insights that my supervisor obtains from simple HR data analysis (for example pivot table in Excel)					
The PA in my company is based on insights from data obtained through advanced techniques.					

The PA procedures in my company involve advanced tooling, such as statistical or analytical tools.					
PA processes in my company involve multiple steps such as data preprocessing, the application of techniques, and visualization.					
Using PA Analytics makes my work tasks more interesting.					
I enjoy dealing with HRA tools for my PA					
PA Analytics have an influence over how I will perform my job					
The PA Analytics allows me to make work-related decisions with great autonomy					
The feedback I receive from PA Analytics is clear and precise					
Utilizing PA analytics helps me identify areas for professional growth and improvement					
Using HRA within my company is not a good idea					
I prefer traditional PA (without the using of HRA)					
I don't understand the usefulness of PA Analytics for my company					
I find the idea of using HRA intimidating.					
I think that the use of PA Analytics is too complex for me					
It's becoming difficult to keep track of the use of PA Analytics in my organisation					

We ask you to give your opinion on each of the following statements regarding the organization you are currently in, based on the following scale:

1 - Never

2 - Almost never (A few times a year or less)

3 - Rarely (Once a month or less)

4 - Sometimes (A few times a month)

5 -Often (Once a week)

6 - Very often (A few times a week)

7 - Always (Every day)

	1	2	3	4	5	6	7
At work I feel like bursting with energy							
At my job, I feel strong and vigorous							
When I get up in the morning, I feel like going to work							
I can continue working for very long periods at a time							
At my job, I am very resilient, mentally							
At my work I always persevere, even when things do not go well							
I find the work that I do full of meaning and purpose							
I am enthusiastic about my job							
My job inspires me							
To me, my job is challenging							
I am proud on the work that I do							
Time flies when I'm working							
When I am working, I forget everything else around me							
I feel happy when I am working intensely							
I am immersed in my work							
I get carried away when I'm working							
It is difficult to detach myself from my job							

Annex 2: Coefficients of skewness (sk) and kurtosis (ku) of the data

	N	**Skewness**		**Kurtosis**	
	Statis-tics	**Statistics**	**Standard error**	**Statistics**	**Standard error**
MPAA1	**257**	**-,537**	**,152**	**-,228**	**,303**
MPAA2	**257**	**-,212**	**,152**	**-,870**	**,303**
MPAA3	**257**	**-,002**	**,152**	**-,649**	**,303**
MPAA4	**257**	**-,076**	**,152**	**-,874**	**,303**
MPAA5	**257**	**-,077**	**,152**	**-,852**	**,303**
PAAR1	**257**	**-,389**	**,152**	**-,294**	**,303**
PAAR2	**257**	**-,181**	**,152**	**-,338**	**,303**
PAAR3	**257**	**-,445**	**,152**	**-,605**	**,303**

PAAR4	**257**	**-,271**	**,152**	**-,508**	**,303**
PAAR5	**257**	**-,270**	**,152**	**-,397**	**,303**
PAAR6	**257**	**-,405**	**,152**	**-,208**	**,303**
PAAD1	**257**	**,193**	**,152**	**-,593**	**,303**
PAAD2	**257**	**,013**	**,152**	**-,166**	**,303**
PAAD3	**257**	**,239**	**,152**	**-,512**	**,303**
PAAD4	**257**	**,161**	**,152**	**-,789**	**,303**
PAAD5	**257**	**,249**	**,152**	**-,413**	**,303**
PAAD6	**257**	**-,019**	**,152**	**-,558**	**,303**
V1	**257**	**-,245**	**,152**	**-,574**	**,303**
V2	**257**	**-,277**	**,152**	**-,512**	**,303**
V3	**257**	**-,466**	**,152**	**-,564**	**,303**
V4	**257**	**-,337**	**,152**	**-,627**	**,303**
V5	**257**	**-,663**	**,152**	**-,408**	**,303**
V6	**257**	**-,697**	**,152**	**-,145**	**,303**
D1	**257**	**-,547**	**,152**	**-,446**	**,303**
D2	**257**	**-,502**	**,152**	**-,563**	**,303**
D3	**257**	**-,431**	**,152**	**-,715**	**,303**
D4	**257**	**-,545**	**,152**	**-,578**	**,303**
D5	**257**	**-,828**	**,152**	**,004**	**,303**
AB1	**257**	**-,560**	**,152**	**-,234**	**,303**
AB2	**257**	**-,310**	**,152**	**-,633**	**,303**
AB3	**257**	**-,467**	**,152**	**-,421**	**,303**
AB4	**257**	**-,471**	**,152**	**-,433**	**,303**
AB5	**257**	**-,318**	**,152**	**-,637**	**,303**
AB6	**257**	**,019**	**,152**	**-1,122**	**,303**

Source: *AMOS* output

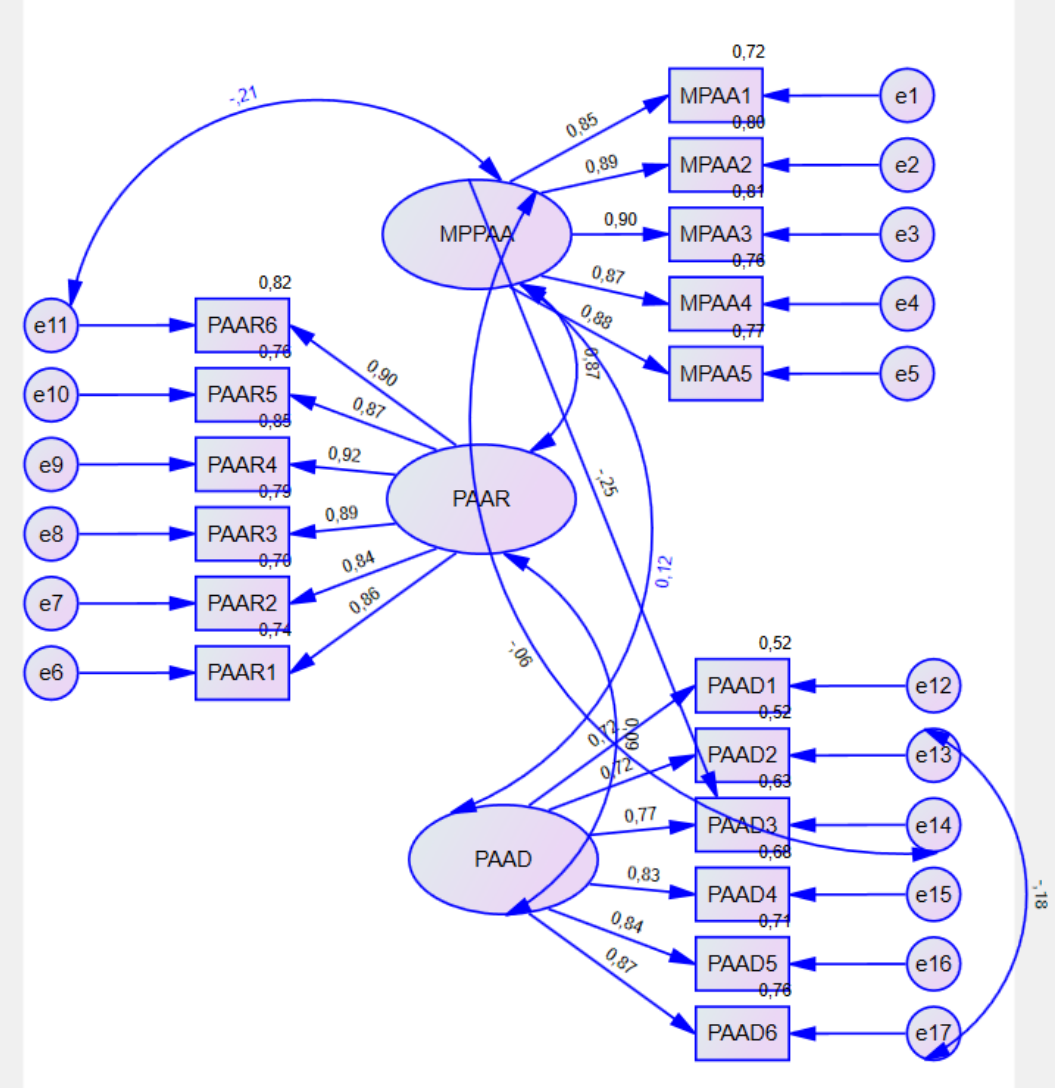
Annex 3: Normality test: Kolmogorov-Smirnov and Shapiro-Wilk

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistics	gl	Sig.	Statistics	gl	Sig.
MPAA1	**,216**	**257**	**<,001**	**,891**	**257**	**<,001**
MPAA2	**,185**	**257**	**<,001**	**,904**	**257**	**<,001**
MPAA3	**,191**	**257**	**<,001**	**,914**	**257**	**<,001**
MPAA4	**,175**	**257**	**<,001**	**,911**	**257**	**<,001**
MPAA5	**,173**	**257**	**<,001**	**,913**	**257**	**<,001**
PAAR1	**,232**	**257**	**<,001**	**,885**	**257**	**<,001**
PAAR2	**,223**	**257**	**<,001**	**,903**	**257**	**<,001**
PAAR3	**,212**	**257**	**<,001**	**,885**	**257**	**<,001**
PAAR4	**,216**	**257**	**<,001**	**,903**	**257**	**<,001**
PAAR5	**,215**	**257**	**<,001**	**,905**	**257**	**<,001**
PAAR6	**,195**	**257**	**<,001**	**,898**	**257**	**<,001**
PAAD1	**,204**	**257**	**<,001**	**,897**	**257**	**<,001**
PAAD2	**,250**	**257**	**<,001**	**,891**	**257**	**<,001**
PAAD3	**,188**	**257**	**<,001**	**,904**	**257**	**<,001**

PAAD4	**,217**	**257**	**<,001**	**,880**	**257**	**<,001**
PAAD5	**,215**	**257**	**<,001**	**,882**	**257**	**<,001**
PAAD6	**,245**	**257**	**<,001**	**,890**	**257**	**<,001**
V1	**,141**	**257**	**<,001**	**,941**	**257**	**<,001**
V2	**,161**	**257**	**<,001**	**,936**	**257**	**<,001**
V3	**,161**	**257**	**<,001**	**,927**	**257**	**<,001**
V4	**,174**	**257**	**<,001**	**,933**	**257**	**<,001**
V5	**,244**	**257**	**<,001**	**,882**	**257**	**<,001**
V6	**,239**	**257**	**<,001**	**,886**	**257**	**<,001**
D1	**,160**	**257**	**<,001**	**,914**	**257**	**<,001**
D2	**,181**	**257**	**<,001**	**,915**	**257**	**<,001**
D3	**,164**	**257**	**<,001**	**,921**	**257**	**<,001**
D4	**,195**	**257**	**<,001**	**,911**	**257**	**<,001**
D5	**,214**	**257**	**<,001**	**,878**	**257**	**<,001**
AB1	**,164**	**257**	**<,001**	**,922**	**257**	**<,001**
AB2	**,153**	**257**	**<,001**	**,942**	**257**	**<,001**
AB3	**,161**	**257**	**<,001**	**,933**	**257**	**<,001**
AB4	**,162**	**257**	**<,001**	**,930**	**257**	**<,001**
AB5	**,158**	**257**	**<,001**	**,936**	**257**	**<,001**
AB6	**,129**	**257**	**<,001**	**,932**	**257**	**<,001**
a. Lilliefors Significance Correlation						

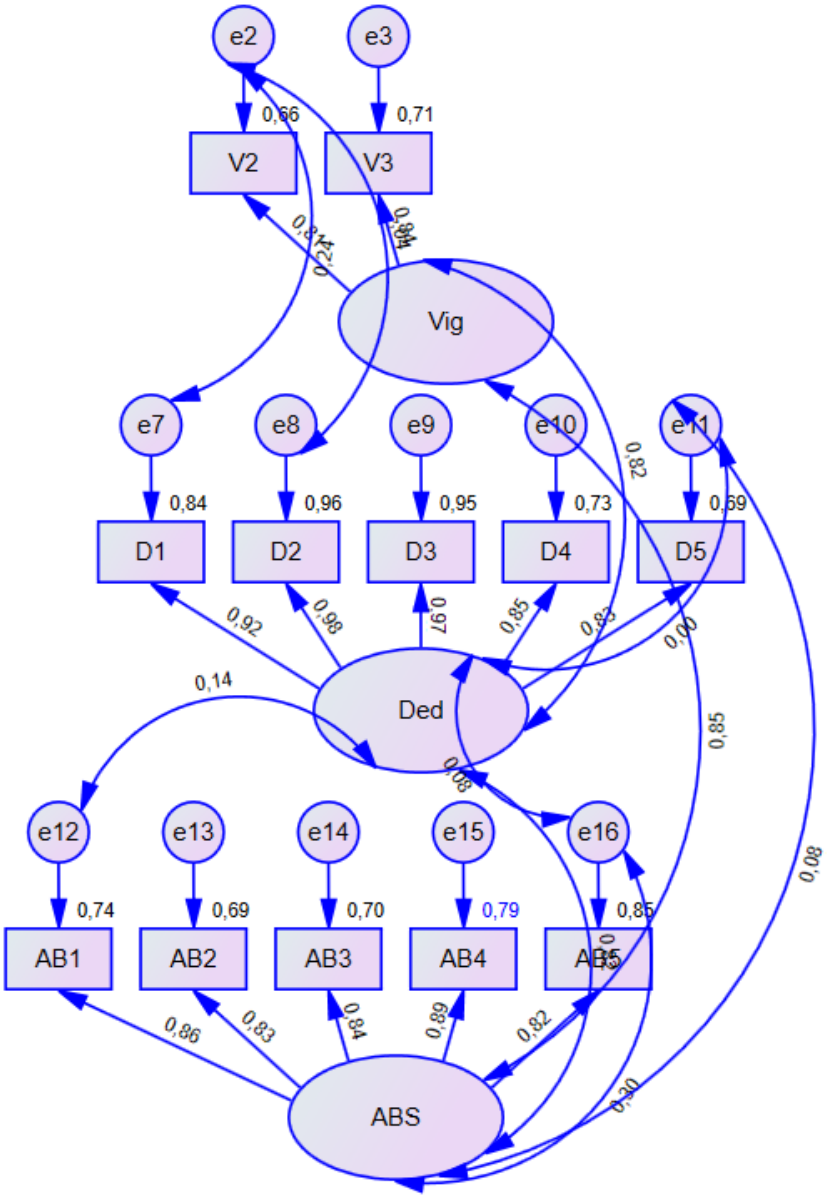
Source: *AMOS* output

Annex 4: Confirmatory Factor Analysis - PA Analytics



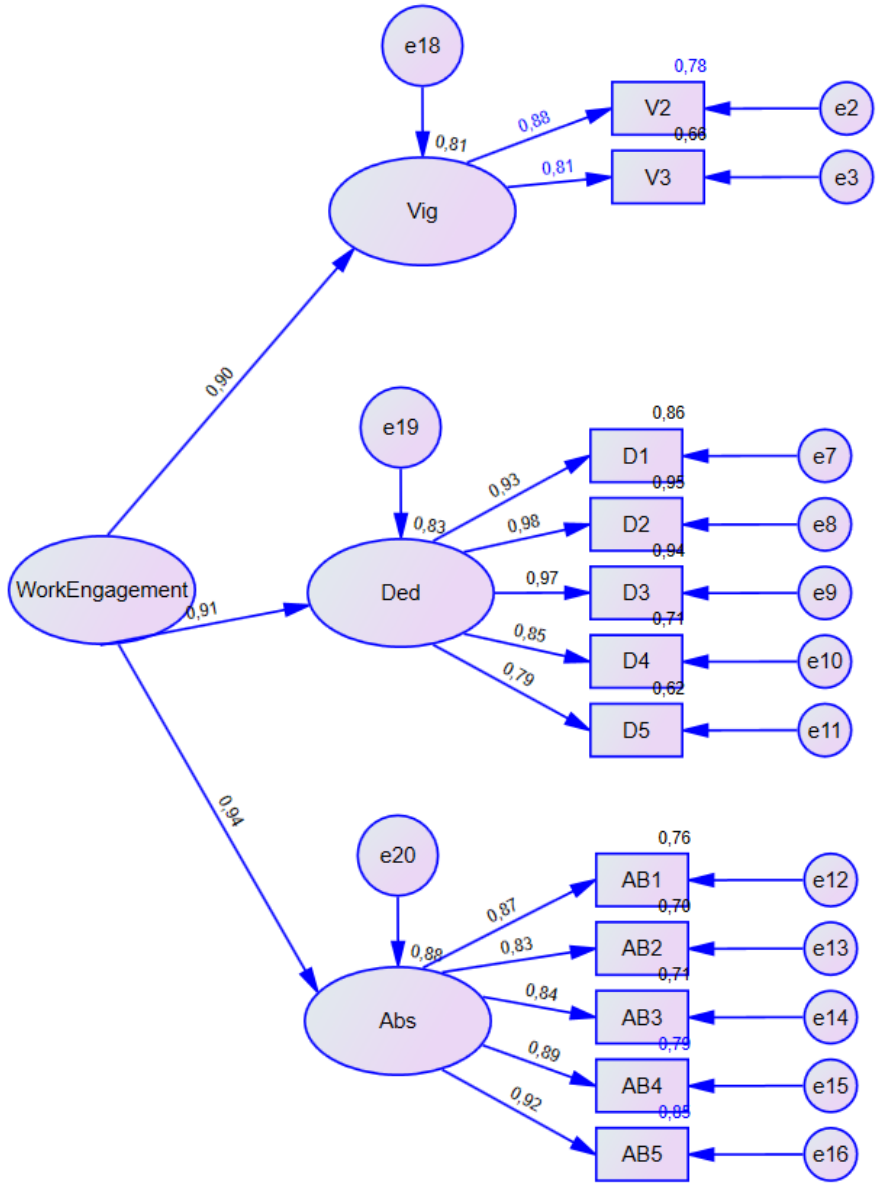
Source: *AMOS* output

Annex 5: Confirmatory Factor Analysis – Work Engagement

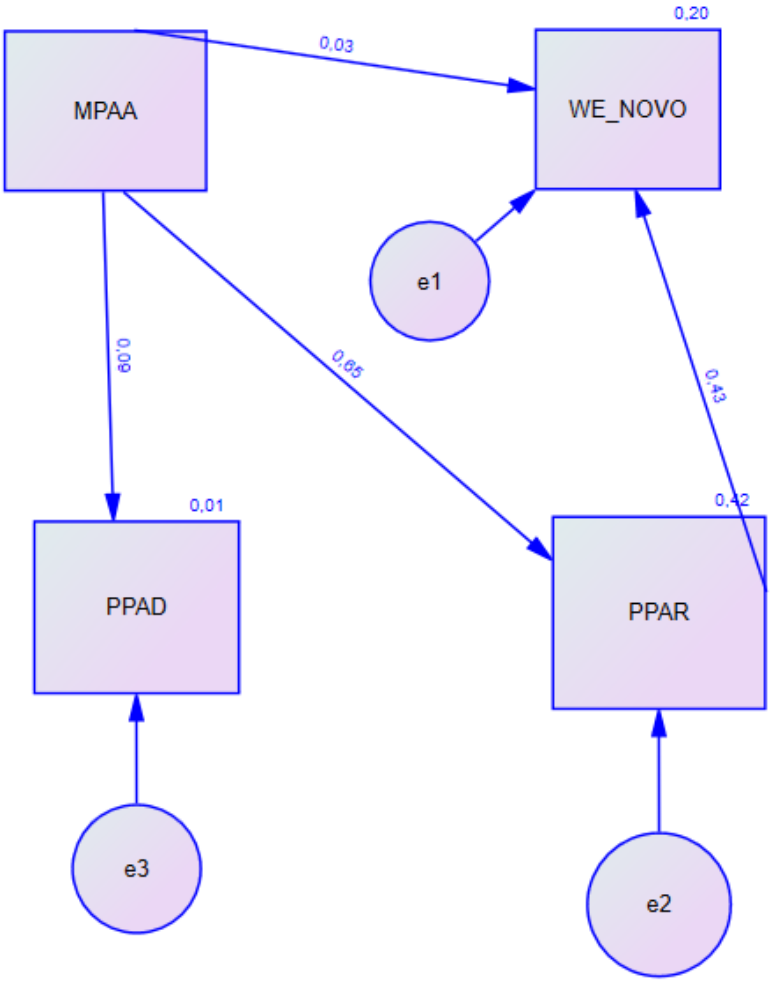


Source: *AMOS* output

Annex 6: 2nd order factor model of Work Engagement



Annex 7: Structural model



Source: *AMOS* output