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HR Analytics in the commercial airline sector in Portugal: a mixed method/ case study analysis.

António Pimenta de Brito

PhD in Management, specialization in Human Resources Management.

Supervisors:
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“Ce qui sauve, c’est de faire un pas. Encore un pas. C’est toujours le même pas que l’on recommence…”
Antoine de Saint Exupery, 1939.

“After close to 20 years of hopeful rhetoric about becoming ‘strategic Partners with a ‘seat at the table’ where the business decisions that matter are made, most human-resources professionals aren’t nearly there. They have no seat, and the table is locked inside a conference room to which they have no key.” (Hammond, 2007). Today, HR finally has the key and is seated at the table, but everyone else has left the room (Cappelli & Tavis, 2017)” (Minbaeva, 2021).

Acknowledgements

I start by thanking the women who were crucial for this PhD project. Firstly, I would like to thank my family, especially my wife Marta, a great woman, mother, and wife who is also a PhD in Psychology. She understands the challenges of a PhD candidate and has been my main pillar throughout this process. Without her support, patience, advice, continuous encouragement, and understanding, the hours spent writing, researching, and away from family would not have been possible. Secondly, I want to thank my dear daughters, Marta and Maria, who were born in the middle of this PhD journey, for their patience and the joy they bring, which continuously encourages me to pursue future endeavours.

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Finally, as Harold Bloom once said, there is always the “anguish of the influence” of others in our work. For me, it’s not an anguish but an honour. I would like to thank all the authors cited in this PhD Project without whom the work would not have been possible.

Resumo

HR Analytics (HRA), um campo em crescimento dentro da Gestão de Recursos Humanos, utiliza IA, ciências sociais e estatística para analisar dados da empresa e facilitar a tomada de decisão. Apesar da sua proeminência, a HRA enfrenta ceticismo quanto à sua eficácia. A HRA progride através das fases descritiva, preditiva, prescritiva e autónoma. A maioria dos departamentos de RH permanece na fase descritiva devido a vários desafios, incluindo falta de conhecimento especializado e altos custos de TI. No entanto, aplicações empresariais bem-sucedidas de HRA, permitem decisões baseadas em dados e previsões, como o employee churn. Este estudo emprega uma abordagem de métodos mista num case study, para determinar a eficácia da HRA no setor do transporte aéreo comercial em Portugal. Entrevistas semiestruturadas qualitativas identificam os principais desafios na gestão de pessoas, enquanto a análise quantitativa utiliza regressão linear múltipla em dados de um questionário a 369 profissionais de companhias aéreas portuguesas para explorar os fatores que influenciam as intenções de saída. As principais conclusões incluem a desvalorização dos RH nas companhias aéreas, o desalinhamento entre estratégias de negócios e de RH, e altas intenções de saída entre pessoal de terra, exacerbadas pela pandemia. O estudo confirma que a satisfação com a carreira, liderança, equilíbrio entre vida pessoal e profissional e remuneração afetam significativamente as intenções de saída. Este estudo contribui validando uma nova escala de satisfação laboral para o setor do transporte aéreo português, destacando o valor das metodologias mistas e fornecendo recomendações práticas para políticas de RH.

Palavras-chave: #hranalytics #casestudy #companhiasaéreas #métodosmistos #IA #employeechurn

Abstract

HR Analytics (HRA), a growing field within Human Resource Management, uses AI, social sciences, and statistics to analyze company data and facilitate decision-making. Despite its prominence, HRA faces skepticism about its effectiveness. HRA progresses through the descriptive, predictive, prescriptive and autonomous phases. Most HR departments remain in the descriptive phase due to several challenges, including a lack of specialized knowledge and high IT costs. However, successful enterprise applications of HRA enable data-driven decisions and predictions, such as employee churn. This study employs a mixed methods case study approach to determine the effectiveness of HRA in the commercial air transport sector in Portugal. Qualitative semi-structured interviews identify the main challenges in people management, while quantitative analysis uses multiple linear regression on data from a questionnaire to 369 professionals from Portuguese airlines to explore the factors that influence turnover intentions. Key findings include the devaluation of HR at airlines, misalignment between business and HR strategies, and high turnover intentions among ground staff, exacerbated by the pandemic. The study confirms that career satisfaction, leadership, work-life balance, and pay significantly affect turnover intentions. This study contributes by validating a new scale of job satisfaction for the Portuguese air transport sector, highlighting the value of mixed methodologies and providing practical recommendations for HR policies.

Keywords: #hranalytics #casestudy #airlines #mixedmethods #AI #employeechurn

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CHAPTER 1

Introduction

HR Analytics

Often, a problem encountered in the HR analytics approach is that it is not only detached from business problems but also too confined within the human resources department (Green, 2020; Rasmussen & Ulrich, 2015). There should be contact and dialogue with the different departments of the company, from the commercial area to operations, so that an HR Analytics strategy will be successful. It is equally important not to conduct an uncritical or random investigation of the data but to adopt an approach based on business problems, namely customer experience (Green, 2020; Minbaeva, 2021; Rasmussen & Ulrich, 2015). Thus, with this dialogue, the strategic alignment of human resources with the business strategy is adopted, embedding a strategic perspective of HR analytics management. This can be a true tool in decision-making and in creating value not only for people but also for the business (Gabanová, 2012).

From the administrative perspective to the strategic perspective, HR departments are increasingly evolving. In the age of complexity, there is a growing demand on human resources departments to demonstrate their effectiveness and utility. In recent years, the field of HR Analytics has grown significantly, not only in practical applications within companies but also in the number of academic studies. Since 2015, studies on HRA have exploded (Bahuguna, Srivastava & Tiwari, 2023; McCartney & Fu, 2022). Whenever digitalization in human resources is discussed, "People Analytics" is mentioned. The problem is that the topic is more complex than a simple trend. HR Analytics, as it is more commonly known (Margherita, 2022), is the area of human resources that uses techniques from artificial intelligence, social sciences, and innovation to collect, process, and analyse people data for decision-making. Through data, a more analytical approach is sought, moving away from "I think" towards concrete data analysis, with the aim of providing managers with not only information but also valid and value-adding knowledge for people and the business.

However, despite the buzz around the topic, the implementation of HR analytics in companies has not met expectations, and doubts about the effectiveness of its techniques are frequently raised in various literature reviews, including the most current ones (Arora et al., 2022; Isson & Harriott, 2016; Margherita, 2022; Marler & Boudreau, 2016;

McCartney & Fu, 2022a; McCartney & Fu, 2022b; Minbaeva, 2021; Peeters, Paauwe & Van De Voorde, 2020; Shet et al., 2021; Tursunbayeva et al., 2018). Despite several case studies and applications (Buttner & Tullar, 2018; Harris et al., 2011; Green, 2017; Isson & Harriott, 2016; Kane, 2015; McCartney & Fu, 2022b; McIver et al., 2018), there are still doubts and many challenges regarding the use of people data for decision-making. The literature suggests several factors that may explain the still weak implementation, according to the authors. These include infrastructure costs, lack of sponsorship from leadership, common misconceptions about data quality, a non-strategic approach focused on business problems, poor data analytics skills in HR, weak internal communication, limited "data" mindset, etc. (Marler & Boudreau, 2017; Minbaeva, 2021).

Paradoxical findings in the literature on the topic are faced: on one hand, a trend everyone talks about, present in all HR reports, and expressed desires of companies to join—of the largest companies and consultancy firms. On the other hand, especially in academia, plays its role by questioning many assumptions and measuring the level of implementation and effectiveness of HR analytics practices as below expectations. On one side, practice showing multiple proofs that there are companies benefiting from this strategy for self-knowledge of their workforce and improving financial results; on the other, some sceptics questioning these practices and pointing to several challenges not sufficiently addressed, particularly issues related to data privacy and security and the reliability of algorithms. On one side, an HR practice boasting of being more practical than theoretical but focusing little on customer experience and still tied to HR "processes" and applying strategies instead of being part of strategic decision-making. HR remains a poor relative in companies. On the other hand, academia claims to be the critical spirit but sometimes overly concerned with creating theories and problems rather than revisiting established HR theories and assumptions and questioning them (Minbaeva, 2021).

Research Questions

Amidst this controversy, the research questions that still need answering and are posed by this study are:

1. Is HR analytics effective as a strategic decision-making tool?
2. How can HR Analytics be useful for the business?

This topic is important because companies want to know if the large investment in time and resources, they will have to make in the HRA strategy will be compensated in tangible results. These results include:

1) Getting to know the company's employees more deeply.
2) Acting on the most pressing problems based on data.
3) Predicting phenomena.
4) Improving the employee and customer experience.
5) Reducing costs through the most reliable determination of causes and effects in the most pressing HR and business issues.

Likewise, the most recent literature in the area has concluded that the efficacy of HRA is still a topic to be explored and in need of more empirical studies and case studies. HRA will be effective in using the tools of AI, social sciences, and innovation to create value for people. It is effective when it allows for a deeper knowledge of the workforce, identifies the reasons for problems, and can anticipate more harmful consequences. All through data.

To answer these questions, a case study was chosen to demonstrate the effectiveness or not of HR Analytics practices. A specific economic sector was chosen for this: the aviation sector and the subsector of "commercial air transport" (ICAO, 2019) companies commonly named "Airlines". Starting from the literature review and how it points to business problems as the starting point for any analytics strategy (Quinn, 2020; Rasmussen & Ulrich, 2015), choosing a specific sector facing concrete challenges seemed the most appropriate methodology.

First, in this PhD Thesis, a review of the literature on HR Analytics to date will be made. It will focus on the most mentioned subjects in academic and industry literature, such as conceptualization, applications in business, most addressed research topics such as the strategic component of HRA, technology and methodologies, and the controversy around the topic, namely issues of privacy, security, data preparation, and bias. To make the empirical evidence sought through the case study methodology more robust, a mixed methods approach was chosen, executing both qualitative and quantitative methodologies together.

Employee Churn was found to be relevant to study in HR in airlines in the first part of this PhD project, the qualitative part. Semi-structured interviews were conducted with

HR experts in commercial airlines and experts in AI (artificial intelligence). AI can be a tool that helps to measure these indicators and find solutions for decision-making.

The aim of the quantitative part is:

1. To validate a job satisfaction scale to predict employee churn in airlines.
2. To create a predictive model that helps to understand and solve professional loss in the commercial airline sector in Portugal.

This is possible by:

1. Identifying the factors that influence turnover intentions in the commercial air transport sector and their relative contribution.
2. Issuing practical recommendations for human resource management in airlines.

The methodology used in the quantitative part is a questionnaire to 369 professionals in commercial airlines in Portugal and company data. An EFA (Exploratory Factor Analysis) and CFA (Confirmatory Factor Analysis) will be performed to test the prediction capabilities of the variables that influence employee churn. Multiple linear regression and other inferential and descriptive statistics techniques will be used to test the influence of the factors and their relative contribution and, lastly, to test the relationship between the sociodemographic variables and the satisfaction variables.

Other areas of business analytics are more developed in practice than HR Analytics, namely marketing and customer analytics (e.g., Davenport & Harris, 2017; Holsapple et al., 2014). A problem that the commercial airline industry faces is professional turnover, more specifically employee churn. The customer churn indicator is widely used in the marketing field to measure the loss rate of customers in the purchase process (Hassouna et al., 2015; Saradhi & Palshikar, 2010).

The PhD study is about the effectiveness of HR Analytics to measure people management outcomes and drive valuable business decision-making. Employee churn will work as an example/ case to test this effectiveness in retention analytics. The study of the factors that influence employee churn in the commercial airline sector in Portugal and a predictive model for employee churn, job satisfaction, and job performance. However, there are other areas in HR in airline management; this is one of the "pains" addressed by the experts in the qualitative part of this study, the interviews. So, the thesis is not about Employee Churn but about HR Analytics' effectiveness, and a case study will be the way to test the practice. The outcome is to prove whether HRA is or isn't useful for decision-making and how it is effective.

The Employee Churn indicator studies commonly the phenomenon of voluntary job loss and measures how people leave a company for their own reasons. Unlike turnover, which measures the ratio of people who leave to those who enter a company, regardless of the reason they do it, whether voluntary or involuntary. The employee churn indicator commonly measures the level of voluntary departure of workers and that does not necessarily involve replacement. This is a big problem for organizations because a worker is valuable and replacing them is costly. This area is little, or nothing studied with the proper methodology in HR Analytics and specifically in the airlines sector in Portugal.

1.1. Research Objectives of the PhD

The research objectives of this PhD Study are therefore constituted of two General Objectives (GO) and six specific objectives (SO):

GO1 – Qualitative Study: Test the effectiveness of HR Analytics in business and in the commercial airline sector

SO1: Understand the challenges in human resources management in the commercial airline sector

SO2: Understand the application of HR Analytics in human resources decision-making in the commercial airline sector

SO3: Enumerate the indicators/dimensions of measurement useful for HR in airlines

SO4: Identify what are the theoretical implications and practical recommendations for science and business

GO2 – Quantitative Study: Figure out how HR Analytics can be effective and implemented in the commercial air transport sector

SO1: How can HR indicators/dimensions help measure and predict HR phenomena?

SO2: What are the theoretical implications and practical recommendations for science and business?

In summary, the qualitative part serves as an exploratory study of HRA's main problems to address in business and HRA indicators/dimensions in HR in airlines. Secondly, with the results of the qualitative study, namely indicators to measure in HR in aviation, a quantitative study will be carried out, using a specific indicator – employee churn – and testing HRA techniques in a specific professional sector, the airline industry. The last part of the study, namely the "discussion and results" will serve to wrap up all results and respond to the main questions of this PhD: "Is HRA effective? How? What theoretical implications and practical recommendations does this study have?"

1.2. Research Contributions of the PhD

The main contributions of this PhD Study to science and practice are:

1. There is no scale of job satisfaction created or validated to date to predict employee churn in the commercial airline sector in Portugal.
2. There is no predictive employee churn model with these predictive capabilities in the commercial aviation sector to date.
3. While most churn predictive models try to figure out the factors that influence churn, there are few studies that delve into the relative contribution of the variables to the model (Srivastava & Eachempati, 2021).
4. Few churn predictive models concentrate on the phenomenon of churn as the most reliable predictor of turnover intentions: job satisfaction.
5. Few or none of the models use the dependent variable "turnover intentions" as the most reliable antecedent of actual churn.
6. Few models of churn/HRA use a qualitative method and especially mixed methods research methodology – quantitative and qualitative.
7. A complete and systematic literature review of HRA and employee churn to date.
8. Theoretical implications are drawn on the effectiveness of HR Analytics in business in general and airlines specifically.

9. Useful and practical recommendations are provided to the airline sector in Portugal and other countries on the area of HRA implementation and HR policies in general.

This PhD study aims to address critical questions about the effectiveness of HR Analytics in strategic decision-making and its utility for businesses, particularly in the commercial airline sector. By employing a mixed methods approach, the study seeks to provide comprehensive insights into the challenges and opportunities of implementing HR Analytics, ultimately contributing valuable knowledge to both academic and business practices.

CHAPTER II

Theoretical Framework

2.1. HR Analytics, the concept

Human resources management (HR) has evolved from a merely administrative discipline to one where people management is now regarded as an essential business strategy partner. Individuals are now a source of competitive advantage for the company rather than just resources. Today's knowledge societies place a high value on human resources as a business strategy. Organizational performance has been demonstrated to be impacted by human resources policies (Delaney and Huselid, 1996; Guthrie, 2001; Fu et al., 2017 cited by McCartney & Fu, 2022b).

HR have come under increased demand to demonstrate how their work affects corporate success since the year 2000. Methods of assessing performance and practical indicators that might measure different people development indicators emerged in order to determine this performance (Ergle Ludviga and Kalvina, 2017). These are approaches for measuring HRM-related activities (Bassi, 2011; Fitz-Enz, 2010). Metrics comprise items like retention rates, employee turnover, and the cost of recruitment. While these are valuable data for analysis, they are only a small portion of analytics. That data is descriptive; the goal and breadth are greater with analytics. Business and decision-making can benefit greatly from insights which are not always apparent from straightforward raw data outputs. The addition of a predictive element is known as analytics. By means of data and additional information, comparisons and correlations, models that forecast a certain phenomenon from the data can be created. Accordingly, analytics is more about forecasting the future than it is about the past (Ergle Ludviga and Kalvina, 2017).

There are several terms that are used interchangeably for HR Analytics (Yahia Hlel & Colomo-Palacios, 2021). "People Analytics" (Green, 2017; Kane, 2015), "human resources analytics" (Lawler, Levenson & Boudreau, 2004; Levenson, 2005; Rasmussen & Ulrich, 2015), "workforce analytics" (Hota & Ghosh, 2013; Simón & Ferreiro, 2018), "talent analytics" (Davenport, Harris & Shapiro, 2010), and "human capital analytics" (Andersen, 2017; Minbaeva, 2017, 2018; Levenson & Fink, 2017; Schiemann, Seibert & Blankenship, 2017). "Human resources analytics" is the most used term (Margherita, 2022; Marler & Boudreau, 2016). The term "People Analytics" was made popular by Google's case study (Marler & Boudreau, 2016). For our study, the term "HR Analytics" will be used because it is the most used terminology in the academic literature (Margherita, 2022).

Research and academic production in this field exploded since 2015 and quadrupled between 2015 and 2021 (Bahuguna, Srivastava & Tiwari, 2023; McCartney & Fu, 2022). When it came to the total number of publications, the most productive nations were the United States, Canada, China, India, and the United Kingdom. Human Resource Management Journal, Human Resource Management, International Journal of Manpower, and Journal of Organizational Effectiveness-People and Performance are the top four scholarly publications in HRA (Bahuguna, Srivastava & Tiwari, 2023).

A Google Trends search presented in Figure 2.1. indicates that from 2004 to 2023 more people have been looking for the term "HR analytics" online. This output, which expresses the most common search terms used by internet users worldwide, has shown a precise increase over time.

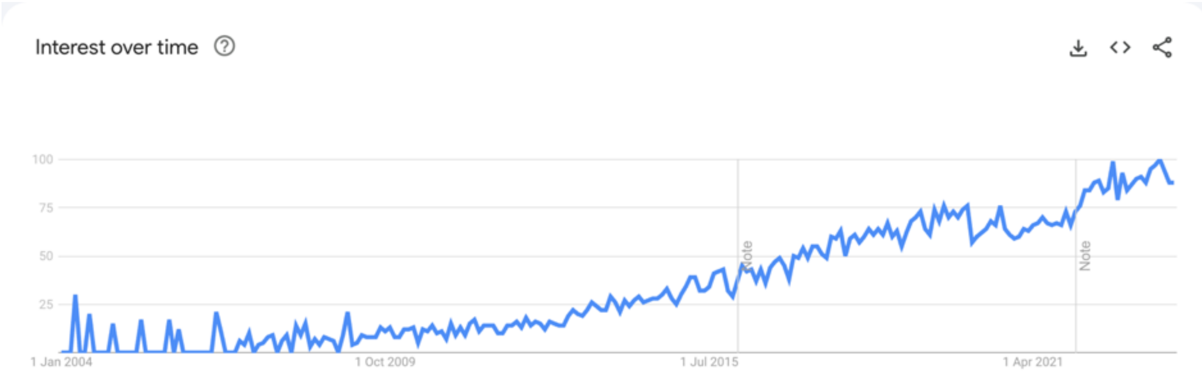

Figure 2.1: Google Trends output of the search term "HR Analytics" worldwide, in the period between 2004 and 2023 (author)

The term "HR Analytics" is relatively new. "Human Resource Analytics" was first mentioned in 2003–2004 in published HR literature (Marler & Boudreau, 2016). 'HR Analytics' is distinguished from 'HR metrics' by Lawler, Levenson, and Boudreau (2004). HR metrics, which are categorized as effectiveness, impact, or efficiency, are measurements of important HRM outcomes. Lawler et al. (2004), in contrast, assert that HR Analytics are experimental methods and representative statistical techniques that can be utilized to demonstrate the impact of HR activities rather than metrics (Marler & Boudreau, 2016). As a result, the field of HR Analytics combines corporate strategy and statistics. It's about getting useful business insights out of the data, not only about metrics as they might be misinterpreted. It involves making predictions about the future, not merely analysing data at random but also posing pertinent questions and using the data to create value for the firm and its workers in the long run. It is imperative to begin with the organization's challenges or the most urgent issues pertaining to its members (Green, 2020).

Terminology changes in HR Analytics point to new and changing requirements in HRM. Administrative duties, the use of technology to get insights, HR strategy, privacy concerns, and other difficulties relating to the application of algorithms to human behaviour (Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Tursunbayeva et al., 2018).

Marler & Boudreau (2016, p.13) define HR analytics 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."

According to Tursunbayeva et al. (2018, p. 231), HR Analytics or "People Analytics" "is an area of HRM practice, research, and innovation concerned with the use of information technologies, descriptive and predictive data analytics, and visualization tools for generating actionable insights about workforce dynamics, human capital, and individual and team performance that can be used strategically to optimize organizational effectiveness, efficiency, and outcomes and improve employee experience." However, these authors don't mention an important tool and revolution data science has already had, which is the democratization of the use of artificial intelligence.

Margherita (2022), in one of the most recent comprehensive reviews on HRA, cites 12 definitions derived from the existing academic literature in the last 10 years, and in none is the term "artificial intelligence" mentioned. Also, McCartney & Fu's (2022a) definition and view of HR analytics, another recent literature review on the subject of HRA, lack this dimension in their definition. Arora et al. (2022) points out this limitation in HRA studies: the use of artificial intelligence in the models. These definitions don't include explicitly the input of artificial intelligence and the more recently democratized techniques of Generative AI. Artificial intelligence, as well as the use of machine learning to analyze and extract insights for decision-making from data, are not new realities, but more recently, in November 2023, the company Open AI with the creation of ChatGPT and the development of LLMs (large language models) came to democratize the use of generative AI in the generation of knowledge and content through a conversational platform. This creation was a significant disruption in the utilization of this software in various contexts. This accelerated the use of generative AI in human resources. The HRA area is also no exception (Budhwar et al., 2023; Margherita, 2022).

Margherita (2022), besides elaborating on the new capabilities of artificial intelligence in HRA, addresses the topic of the various stages of HRA maturity, namely descriptive, predictive, and prescriptive. Recently, a fourth level was added related to generative AI, which is autonomous analytics (Giermindl et al., 2022), which is beyond the predictive capabilities of HRA. This dimension opens several revolutionary possibilities in the application of artificial intelligence but poses other thorny implications.

2.2. The HRA trend, uses and context

Numerous HR analytics strategies centre on employee lifetime values, performance evaluation and development, gender pay disparities, onboarding, cultural fit, and engagement. Workforce planning, which includes studies on novel scheduling models or recognizing and assessing staff competence, is another prominent category in the literature. Additional research focuses on the application of HRA in sourcing and acquisition/hiring, wellness, health and safety, and attrition/churn and retention (Tursunbayeva et al., 2018).

HR Analytics is the second most significant HR trend, with 84% of respondents ranking it as important or very important in the Global Human Capital Trends survey (Deloitte Insights, 2018; Tursunbayeva et al., 2021). Advanced HR Analytics are still being implemented in few businesses, nevertheless. Only 16% of businesses have advanced HR analytics installed even though some are making use of the technology (Sierra-Cedar, 2018). In a survey conducted by NTT Data in 2023 in Portugal, the study found that just 4% of the 70 organizations surveyed had a high degree of HR Analytics maturity. The report defined maturity as applying the predictive component to generate HR decision-making insights. This study's findings follow the same percentage of HRA maturity but in 2013. According to a study from Bersin by Deloitte, only 4 percent of Fortune 1000 companies were using predictive analytics, but in doing so, this group's stocks outperformed their peers on the Standard and Poor's 500 by 30 percent.

The big data revolution also has echoes in people management. In a modern approach to HRM in which people are the competitive advantage of the organization (Sullivan, 2013), similarly to marketing which aims to put the customer first, in the HR area the internal customer is the one the company wants to serve. To serve the company needs to know who it serves.

There are parallels between the big data revolution and human resource management. Similar to marketing, which strives to put the customer first, a modern approach to HRM places the emphasis on serving the internal customer as the organization's competitive advantage (Sullivan, 2013). To be of service, the business must understand its clientele. Within the realm of commerce and society, an instance of this can be found in the consumer goods distribution industry, where a supermarket serving thousands of clients every day must process and store the volume of data produced by millions of transactions in one spot, including buyer profiles, transaction times, amounts spent, and the goods bought. All valuable data for one-to-one marketing through CRM (Customer Relationship Management) systems, all the way up to the most recent Big Data concept that incorporates artificial intelligence and predictive models. How can managers predict the new spending trend using patterns and associations? One of the queries a big data strategy may bring up is this one. Managers can use this data to forecast what the consumer will buy next, what psychographic profile can be created, and other information depending on the type of goods they have already purchased.

The data revolution emerged alongside the growth of the internet. The so-called Web 1.0 was read-only throughout its initial phase, requiring users to participate passively and unable to create or publish anything. The Web 2.0, a revolution in social networks with high levels of interaction and user participation in content creation, emerged in the second phase (Almeida, 2017). The content revolution of Web 2.0 brought with it a lot of data, most of it unstructured. Web 3.0 and Web 4.0, in particular, have led to the development of tools and processes that transform this data from unstructured to structured, from raw data into valuable knowledge to produce insightful findings for business and scientific research, whether in the natural sciences or in other fields.

Big Data is defined as "huge in volume, high in velocity, diverse in variety, exhaustive in scope, fine-grained in resolution, relational in nature, and flexible in trait" by Kitchin (2014, p. 68). The necessity of using evidence-based decision-making and going beyond common sense cannot be overlooked in people management. HRM can benefit from big data's sophisticated capabilities, which provide access to an entirely new range of evidence sources.

As an illustration, the National Bank of Australia (Green, 2020) has shown how a highly engaged and driven employee affects the client and increases his level of satisfaction. The inquiry that followed was "What causes this?" It was determined to choose better leaders and give them better assistance and training once it was discovered that the leaders were the ones responsible. As a result, the National Bank of Australia is confident that it will accomplish these goals. This value chain is designed with both customers and employees in mind. This illustration demonstrates that a company can only implement policies and make choices based on validated insights from the data.

According to Jones (2014, p.43), the field of HR analytics is "hotter than hot" because the current time is of digital transformation and the "gold rush" of data (Kennedy et al., 2015, p. 172). In HR circles, the claim has become more and more common (Deloitte, 2017). The bulk of research on HR analytics originates from the business world rather than academic institutions, mostly from the fields of organizational psychology and psychometrics. However, more and more, the field of computers and data sciences is following suit (Tursunbayeva et al., 2018). The field with the most representation in HRA scientific articles is business management and accounting.

Despite this attention to the subject, especially in practice, it is encountered in the academic field a more sceptical approach and some areas more developed and elaborated than in the industry, namely the concept and definition of HRA (Fernandez & Gallardo-Gallardo, 2021; Margherita, 2022; Marler & Boudreau, 2016; McCartney & Fu, 2022a; Tursunbayeva et al., 2018), the business effectiveness of HRA (Arora et al., 2022; Isson & Harriott, 2016; Margherita, 2022; Marler & Boudreau, 2016; McCartney & Fu, 2022a; McCartney & Fu, 2022b; Minbaeva, 2021; Peeters, Paauwe & Van De Voorde, 2020; Shet et al., 2021; Tursunbayeva et al., 2018), and especially the perils and risks of HRA such as privacy, security, and bias (Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Tursunbayeva et al., 2018). These subjects are going to be covered ahead in this study.

2.3. The effectiveness and best practices in HR Analytics

In the dynamic realm of modern businesses, HR analytics has emerged as a crucial tool for organizational success. To navigate the intricacies of this field, adopting best practices is essential. The effectiveness of HRA is a significant topic of discussion among academics, contributing to several studies (Arora et al., 2022; Isson & Harriott, 2016; Margherita, 2022; Marler & Boudreau, 2016; McCartney & Fu, 2022a; McCartney & Fu, 2022b; Minbaeva, 2021; Peeters, Paauwe & Van De Voorde, 2020; Shet et al., 2021; Tursunbayeva et al., 2018; Wang et al., 2024). This literature review presents several contributions on determinant factors for the successful implementation of HRA.

2.3.1. Green's 16 key practices

Green (2017) elaborates a framework of best practices in HRA Analytics (Figure 2.2):

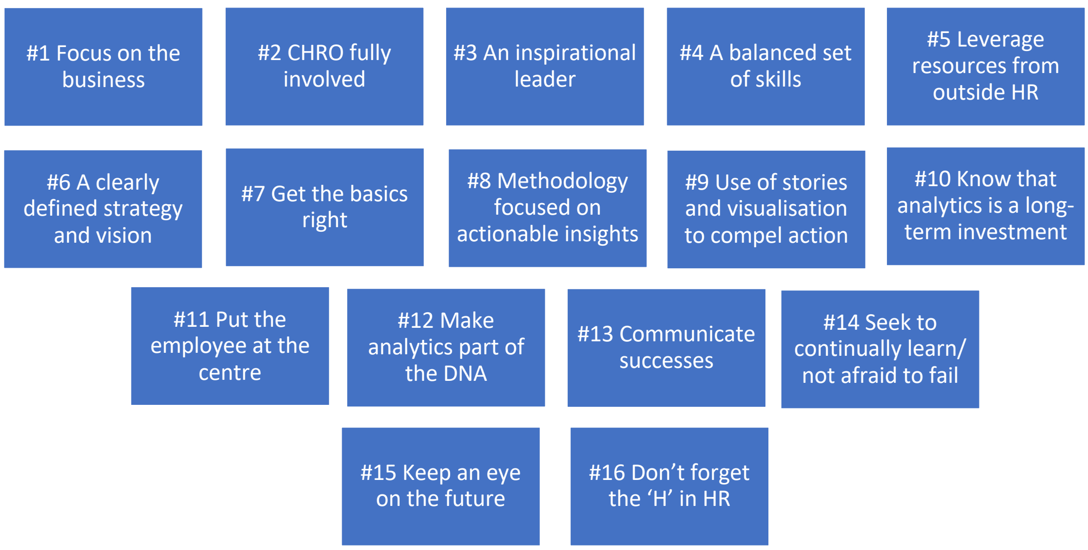

Figure 2.2: 16 Best Practices for Succeeding in People Analytics (Green, 2017, adaptation from the author)

1. Focus on the Business: successful HR analytics teams prioritize understanding and contributing to the overall business strategy (Figure 2.3). They align their efforts with organizational goals, ensuring that HR decisions are in harmony with broader business objectives.

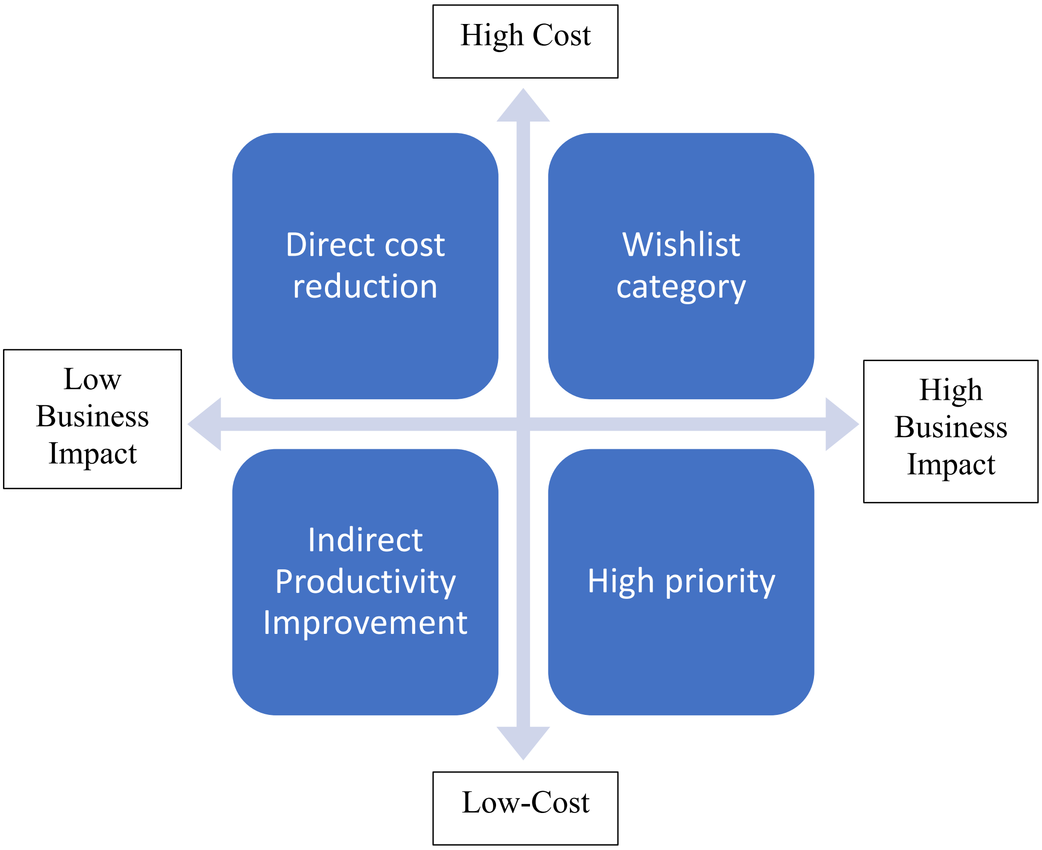

Figure 2.3: matrix to prioritize HR analytics projects (figure adapted by the author from Chakrabarti (2016).

2. Involve a Fully Engaged CHRO**:** the Chief Human Resources Officer (CHRO) plays a principal role in the success of HR analytics. The involvement of top HR and business management is crucial, with the HR Director (HRD) possessing seniority, a clear understanding of business challenges, and having a direct reporting line from the HRA management to the HRD.

3. Inspirational Leadership: leadership in HR analytics requires more than just technical expertise. The HRA leader should be an inspirational figure with a keen understanding of both people and business, possessing a specific skill set and strong coordination capabilities.

4. Balanced Skill Set and Capabilities: a successful HR analytics team possesses a diverse skill set, including change management skills. They act as consultants, defining business problems, developing hypotheses, problem-solving, and effectively managing projects.

5. Leverage External Resources: to enhance their capabilities, successful HRA teams leverage resources from outside HR and the company when necessary. Collaboration with

external experts and different functional areas of the company can bring fresh perspectives and insights.

6. Clearly Defined Strategy and Vision: a well-defined strategy and vision guide the HR analytics initiatives. This clarity ensures that efforts are aligned with organizational goals and contribute meaningfully to the company's success.

7. Get the Basics Right: paying attention to foundational elements such as data cleaning, governance procedures, data privacy policies, and prioritization mechanisms lays the groundwork for effective HR analytics.

8. Actionable Insights Methodology**:** adopting a structured methodology such as the eight-step model proposed by Guenole et al. (2017) (Figure 2.4) ensures that HR analytics efforts lead to actionable insights, driving positive organizational outcomes.

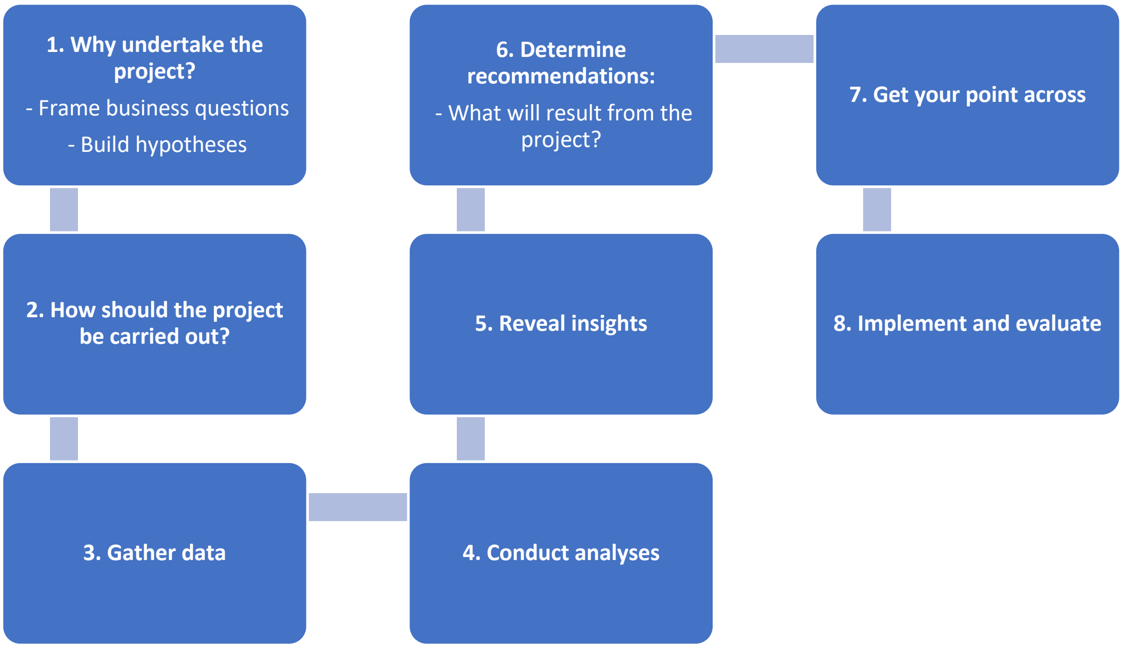

Figure 2.4: Eight-step practical methodology of HRA implementation (Guenole et al. (2017)

9. Use Stories and Visualization**:** effective communication through storytelling and visualization is key to compelling action. HR analytics professionals must answer critical questions: "What do you want your audience to know? How do you want them to feel? What do you want them to do?"

10. Long-Term Investment Perspective: recognizing that analytics is a long-term investment is crucial. Success in HR analytics is not immediate, and organizations must commit to continuous improvement over time.

11. Employee-Centric Approach: Placing the employee at the centre of analytics efforts is paramount. Legal expertise can be integrated to prevent situations that might lead to employee dissatisfaction.

12. Make Analytics Part of the DNA: Embedding analytics into the organizational culture ensures that data-driven decision-making becomes a natural part of the business processes.

13. Communicate Successes: Transparently communicating successes helps build trust and enthusiasm for HR analytics initiatives within the organization.

14. Embrace a Learning Culture: Successful HR analytics teams are not afraid to fail. They continually learn from both successes and failures, fostering a culture of innovation and improvement.

15. Future-Focused: Keeping an eye on the future ensures that HR analytics initiatives evolve in tandem with changing business landscapes and technological advancements.

16. Don’t Forget the ‘H’ in HR: Amidst all the data and analytics, the human element remains paramount. Successful HR analytics teams never lose sight of the ‘H’ in HR, understanding that the goal is to enhance the human experience within the organization.

By adhering to these best practices (Green, 2017), organizations can unlock the full potential of HR analytics, driving informed decision-making and fostering a thriving, people-centric workplace culture.

2.3.2. People Analytics effectiveness Wheel

There is a need for a framework that allows companies to implement an effective strategy of HR analytics and have a go-to strategy daily. In practice, the HR analytics department should be a service in the company that is used by several areas and requests for data or insights should be answered quickly and effectively, as this is what decision-making requires (McCartney & Fu, 2022a).

Peeters, Paauwe & Van De Voorde (2020) delves into the intricacies of HR Analytics effectiveness, offering a comprehensive framework known as the “People Analytics Effectiveness Wheel” (Figure 2.5). This framework is designed to guide organizations in optimizing their HR Analytics strategy for maximum impact.

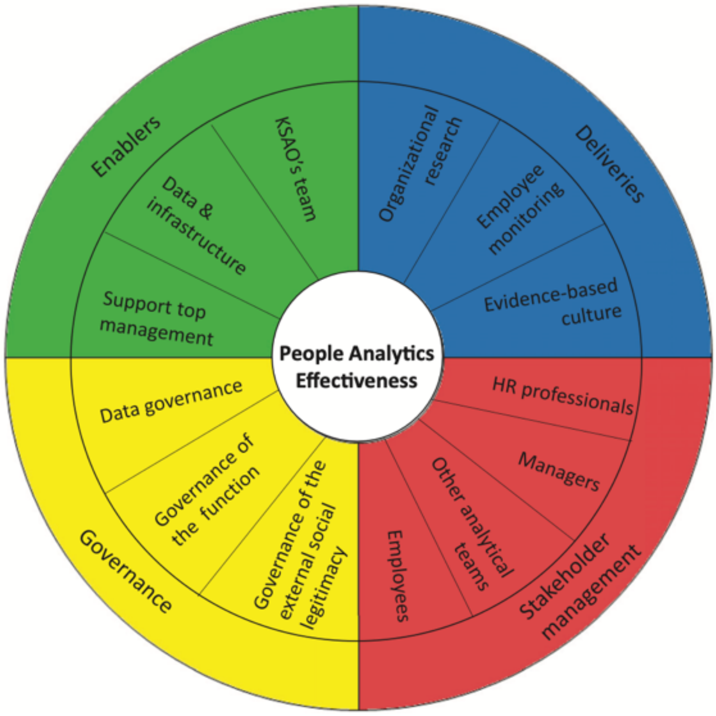

Figure 2.5: Peeters, Paauwe & Van De Voorde's (2020) "People Analytics Effectiveness Wheel"

The first dimension of the wheel, labelled as "Enablers," underscores critical factors that pave the way for effective HR Analytics implementation. This involves securing senior management support, establishing robust data and infrastructure, and cultivating the necessary knowledge, skills, abilities, and other characteristics (KSAOs) within the HR Analytics team. Drawing on insights from Andersen (2016), Green (2017), and Marler and Boudreau (2017), the enablers lay the foundation for a successful HR Analytics initiative.

Moving to the second dimension, termed "Deliveries," the focus shifts to tangible outcomes derived from HR Analytics efforts. This includes the development of sophisticated employee monitoring tools, engagement in organizational research, and the establishment of an evidence-based culture. Angrave et al. (2016) and Marler and Boudreau (2017) contribute to this dimension by emphasizing the importance of practical, impactful deliverables in shaping an effective HR Analytics strategy.

Governance emerges as the third dimension, encompassing critical aspects such as data governance, which involves meticulous management and ethical considerations. Additionally, governance of the HR Analytics function itself is examined, encompassing organizational positioning, reporting structure, internal team structure, and delivery channels. The authors stress the significance of building and maintaining social legitimacy as an integral part of governance.

Stakeholder Management, the fourth and final dimension, acknowledges the diverse players involved in the HR Analytics process. This includes HR professionals, various levels of management (senior and line management), employees and their representatives, and collaboration with other analytical teams. This dimension emphasizes the importance of effective communication and collaboration across different organizational levels (Guenole et al., 2017; Van den Heuvel & Bondarouk, 2017).

In essence, Peeters, Paauwe & Van De Voorde's (2020) "People Analytics Effectiveness Wheel" provides a comprehensive and integrated framework ensuring that organizations not only possess the necessary foundations and capabilities but also deliver tangible outcomes while maintaining ethical governance and fostering positive stakeholder relationships. By addressing each dimension of the wheel, organizations can navigate the complex landscape of HR Analytics with a strategic and effective approach.

2.3.3. The 7 pillars of HRA

The seven most crucial talent management pillars that leaders believe are essential for generating business value from their talent data are:

1. Workforce planning
2. Sourcing
3. Acquisition/hiring
4. Onboarding, culture fit, and engagement
5. Employee churn and retention
6. Performance assessment and development, and employee lifetime value
7. Employee wellness, health, and safety

These findings are based on a comprehensive survey conducted with companies and published in a work about HR Analytics by Isson & Harriott (2016). The characterization of each of the pillars will be developed below except for "Employee churn and retention," which will be portrayed later in this work and will have a central place in this doctoral thesis.

2.3.3.1. Workforce Planning

A key component of HR analytics is workforce planning. According to Isson and Harriott (2016, p. 129), this planning "helps organizations to identify the target segment of employees needed in order to achieve business goals." The organization creates a plan and specifies the type of worker it wants and where it will look for them, as opposed to responding to what the labour market has to offer. This profile relates to both technical and non-technical talents, and the organization then develops a plan to draw in, hire, and keep these workers. Throughout the entire process, top management and the entire organization are involved in this workforce planning, which is done in support of corporate strategy. Organizations can save human expenses associated with hiring and developing talent by implementing workforce planning. The organization anticipates hiring requirements and balances excess and shortage of human resources when executing workforce planning.

2.3.3.2. Sourcing

Talent has traditionally been in high demand in businesses and organizations. Both dozens and hundreds of hires may be the subject of this search. However, a new world has emerged thanks to the internet, big data, social media, mobile devices, and cloud computing, which has caused data volumes to soar and made connectivity previously unthinkable possible.

The volume of data made it possible to employ analytics to maximize sourcing tactics and operations. The workforce of today is composed of several generations. Businesses must plan how they will draw in, evaluate, develop, and keep job seekers and current employees considering this fact.

The STEM fields—science, technology, engineering, and mathematics—have the highest hiring needs; therefore, businesses must adjust and employ cutting-edge, unconventional strategies to address the talent gap in these fields. Reaching applicants who are actively and passively looking for work can be accomplished through social networks, talent communities, and other Big Data solutions and service providers. To find out which channels they prefer to communicate with, a conversation is necessary.

Referrals (word of mouth) are the most efficient way to find new hires; thus, it's important to take advantage of this channel. However, it's important to divide up the market and figure out which distribution methods work best for each.

Big Data analytics allows for the integration of data from many sources, including employee recommendations, job boards, social media, applicant tracking systems, and talent management systems, to provide an overall picture that can expand the talent pool and the range of demand. The applicants are here, which is where the company should be. Like a marketing approach, the recruiter may draw in, engage, promote, develop content, and keep applicants in these settings—the only difference being that the employee is the product or service.

2.3.3.3. Analytics for Talent Acquisition

As previously mentioned, HR Analytics for Talent Acquisition uses the same customer-acquisition strategies as marketing, namely those that are designed online, like SEO (Search Engine Optimization). Again, a major factor in this is how relevant the companies are online. Here, both online interaction and a content strategy are essential. How the potential hire interacts with others online and how they are regarded in professional communities and networks like Stack Overflow, GitHub, Glassdoor, and X. Decisions are better supported by evidence and the "finding" effect is lessened thanks to HRA prediction models. It can be applied as an initial screening filter for hiring, such as automatic curriculum screening. As Google's Eric Schmidt said, "hiring is the most important thing you do" (Schmidt & Rosenberg, 2014, p. 510).

The recruitment process also has a cost-cutting effect, as fewer people apply after a set of criteria are applied to the data. Otherwise, HR efforts were distributed, and the choice's dependability was compromised, whether by a manual search or a bare-bones assumption. Additionally, if the hiring process is "tailor-made," as in marketing, there is less chance that the individual won't be dependable and skilled, which lowers expenses down the line. Because HRA lowers turnover costs, the loyalty component is crucial.

Companies today should use their intelligence and cunning when recruiting personnel; managers who have an HRA mindset know that a smart hire is a combination of experience, gut feeling, facts, and data (Isson & Harriott, 2016).

2.3.3.4. Onboarding and Cultural Fit

The moment a candidate starts working for the company is crucial. Since first impressions are so important, the company must work hard to establish its culture and organizational vision from the outset in addition to trying to generate a positive first impression.

The company’s goal is to find talent that aligns with its values and behaviours; if not, the employee may be highly skilled but not yet accustomed to “the way things are done around here.” The candidate will stick around more readily if the organization acts and behaves authentically since it fosters retention and trust.

The multi-phase onboarding process takes several months to complete. It is imperative to seek out early wins (Watkins, 2013) in the process of introducing the new candidate to the vision and values in order to involve him from the outset and support his work. OPEN (orient, provide, engage, and next) is a model that was developed to track the onboarding procedure (Isson & Harriott, 2016).

2.3.3.5. Analytics for Talent Engagement

The essential employee involvement with the business follows the employee’s attractiveness and recruitment. This involvement has to do with performance. As previously mentioned, this connection needs to be genuine and grounded in the company’s distinctive qualities. Although questionnaires are frequently utilized, they are insufficient to try to figure out what drives an employee. These employee engagement surveys ought to both anticipate and impact the achievement of the company’s goals. One organization should look for engagement-related trends and metrics through data collection.

To be effective, there must be congruence between the company’s executives and the intended business goals. Maintaining direct contact with the employee is a more successful approach since it enables the measurement of the employee’s departure risk indicators.

2.3.3.6. Performance Management

Performance evaluations are conducted along the employee’s route within the organization, and these are necessary for the business to stay competitive. These performance evaluations are predicated on the benefits that follow and the effect that is created for the business. This examination needs to be conducted internationally and pro-actively. Performance metrics must align with both the workforce’s demands and preferences and the company’s plan. Analytics technologies ought to aid in forecasting and staff promotions.

2.3.3.7. Employee lifetime value (ELTV) and cost estimation

To gauge a role’s impact inside an organization, three key metrics are used. Information for decision-making is provided by performance, cost, and attrition (“churn”). These measurements support metrics like ELTV. Such measures evaluate an employee’s tenure and output. Again, this KPI was originated from the marketing field, the “customer lifetime value” (CLTV), the same concept applied to the customer. It is primarily employed in jobs with high turnover and volume. The organization is continuously learning and responding in areas like performance, engagement, and recruitment according to the study of these variables (Isson & Harriott, 2016) to measure and act upon data.

2.3.3.8. Safety, well-being, and health of employees

There is proof today that an organization will have a more productive staff if it prioritizes employee wellness in its strategy. To quickly return to the statistics following the 2008 financial crisis, businesses aggressively engaged in boosting productivity; nevertheless, these efforts are difficult to achieve without a robust and motivated staff. Employer branding, a value proposition that encourages a positive work environment and a strong work-family balance, will all be added benefits that entice candidates. The finest places to work have demonstrated a causal relationship between profitability and organizational well-being, including health and safety.

These firms’ wellness departments’ analytics tools attest to the connection between productivity and well-being. This is crucial because, contrary to popular belief, individuals who are happier at work tend to produce more. However, by employing analytics tools, these indicators can be measured precisely and, as Peter Drucker stated, “if you can’t measure it, you can’t manage it.”

Employee Wellness: What Is It? In terms of health and lifestyle modifications, workplace wellness promotes employees to adopt preventive measures like increasing physical activity, developing healthier eating habits, lowering stress levels, quitting smoking, receiving lifestyle counselling, and more. These preventive actions result in a rise in employee morale, a reduction in absenteeism, and an increase in involvement. Programmes for workplace wellness include a range of education and behaviour modification activities.

2.3.4. Google case-study

Google set out to establish a team devoted to HR Analytics when it launched the “Oxygen” research project, which eventually evolved into a strategy (Sullivan, 2013). Employees are their most valuable asset, so by gathering data about them, they hoped to better understand their characteristics and design better HR policies. It has been demonstrated that implementing these strategies has raised worker satisfaction, retention, and performance. Given that Google is seeking the greatest talent possible who aspires to stay with the company, this viewpoint is not out of the ordinary. It pursues the objective of talent retention using data and research tools.

Google invested in this HR domain for two reasons. Serving employees who are the company’s most valuable asset comes first. Secondly, cost savings are achieved because hiring new employees accounts for 60–70% of overall costs (Isson & Harriott, 2016, p. 69). HRA models enable the prediction of behaviour and consequently potentially unwanted, unanticipated events. For instance, significant savings could result from the ability to forecast an employee’s retention rate. If the person hired left the company, money would need to be spent on hiring, training, and keeping a new employee.

Google developed the “Oxygen 10 behaviours for great managers” as part of the project to support leaders’ recruitment. According to Sullivan (2013), Google remains at the forefront of HR Analytics thanks to ten practices that shape the company’s policy:

1. Improvement of leadership: Google discovered through the analysis of vast volumes of internal company data that great leaders possess not only technical skills but also a regular feedback system and a period of one-on-one coaching with employees.

2. The PiLab is a special subgroup at Google that creates experiences for employees to learn what motivates productivity, performance, job satisfaction, health, and well-being.

3. An algorithm that Google has created predicts which employees will pose a retention problem. This strategy enables managers to take preventative action.

4. Google’s approach to people management is predictive, utilizing models and “what if” analysis.

5. Google also makes use of algorithms to increase diversity and inclusion within the organization. By analysing data on hiring and promotions, Google can identify and address potential biases, ensuring a more diverse and equitable workplace.

6. A powerful algorithm: Google determines the likelihood that a candidate won't be hired when it comes to recruiting. This feature made it possible to drastically cut down on the recruiting time. After four interviews, their investigation revealed that not much value was added. Additionally, since decisions regarding hiring are made by a group rather than an individual, personal preferences—such as the propensity to hire people for short-term goals—are avoided, making strategic recruitment autonomous and safer.

7. Google has devised a method to distinguish high achievers within the organisation from mediocre ones. It values talent in this way and makes investments to find, hire, and nurture exceptional talent.

8. Google's workplace design fosters greater collaboration among staff members in various roles, with innovation emerging from discovery (learning), teamwork, and enjoyment.

9. Instead of being done in a classroom, on-the-job training is done practically. self-directed continuous learning and adaptability through project rotations, errors, and event promotion with celebrities are two skills that Google promotes.

10. Making recommendations to managers and executives is the last crucial element in the Google Team HRA's success, not research. It convinces with facts and data before enforcing. Because all executives have an analytical perspective and are aware of the data-driven mindset and performance, this is an easy task to complete.

Three insights emerged from Google's "Oxygen" experience to help with effective HR Analytics management: 1) To make data infrastructure investments; 2) To find the answers to the important issues. The HRA Google team initially attempted to respond to every inquiry, which proved to be time-consuming and unproductive. In the end, concentrated on the crucial inquiries; 3) There are multiple Social Science research teams within Google. The "Google People Analytics Ecosystem" consists of the following departments and a network: business partnership insights team, people operations, voice and people innovation lab teams, business intelligence group, and so on (Nicol, 2019).

2.3.5. CRISP-DM approach

As stated in our study, it is crucial to focus on a final goal when analysing data from an analytics and data science perspective, particularly in the predictive aspect that is the object of our study. This goal is to ensure that data contributes to management decision-making. In the case of HR analytics, this pertains to decision-making in people management. Beyond insights or dashboards, recommendation tools or visualizations, what ultimately matters in an analytics project are calls to action and behaviour change. In this sense, as already argued in this study, starting with business problems can be a strategic and effective approach to business (Rasmussen & Ulrich, 2015). The most popular methodology for initiating and developing an analytics project in this context is the CRISP-DM methodology. During the research for this PhD study, the researcher invariably found this approach to data science to be the most effective and the one that promotes behaviour change in organizations. This evidence is supported not only by the literature review but also by the qualitative research – semi-structured interviews – conducted later in this study. The AI experts interviewed invariably recommended the CRISP-DM methodology to bring a data analytics project to a successful conclusion and to ensure the project has an effective impact rather than just being a reflective exercise (see chapters 3.2 and 4.1).

“Cross Industry Standard Process for Data Mining” is referred to as CRISP-DM. When the methodology was first developed in 1996, the term “data mining” was frequently used to refer to the applications that would later be connected to the broader definition of predictive analytics (Shearer, 2000). A methodology like CRISP-DM is useful for two main reasons. First, it provides a clear, simple, and coherent overview of the steps involved in creating a predictive analytics program. This is particularly helpful for any non-technical stakeholders in the project. Second, it offers a set of checkpoints that project participants are required to attend to as a process model. This reduces the possibility that a crucial detail will be missed and ruin the project.

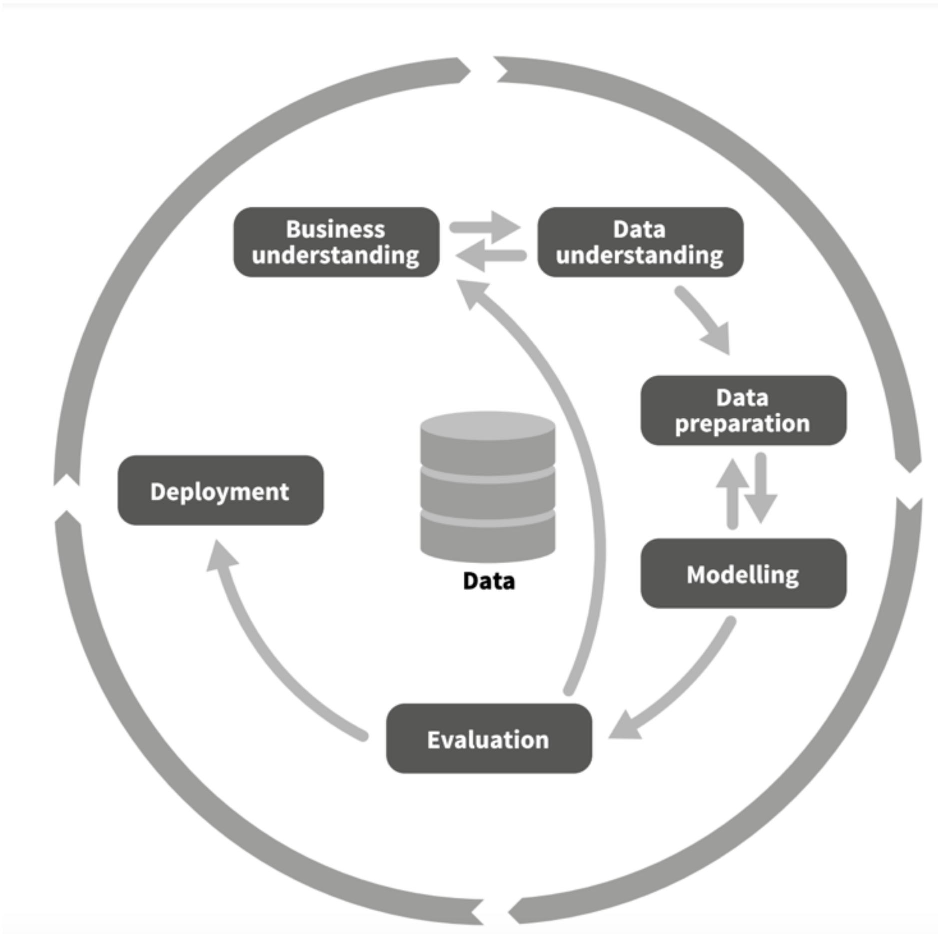

Figure 2.6: CRISP-DM process (Quinn, 2020)

Figure 2.6 shows a circular schematic of the CRISP-DM process. This scheme reflects that the CRISP-DM methodology is a six-major phase iterative process. This framework draws attention to the fact that the modelling part is only one part of the success of good data analysis. Business understanding is equally important and crucial and, as we have already discussed, summoning knowledge from various business areas of the organization and specially the main stakeholder of the business area is a sine qua non condition for the success of an analytics project.

2.3.6. More contributions on the effectiveness of HRA practices

McCartney & Fu (2022b) sought to understand whether there is a correlation between HR Analytics practices and organisational performance. The authors concluded that there is indeed a correlation, with technology acting as the enabler. Technology triggers HR Analytics, which in turn facilitates evidence-based management (EBM), consequently impacting organisational performance.

Shet et al. (2021) identifies key aspects related to technological, organisational, environmental, data governance, and individual factors that influence the adoption of HR Analytics (Figure 2.7). Furthermore, their research determines 23 sub-dimensions of these five factors as crucial for successfully implementing and practicing HR Analytics within organizations (Figure 2.7).

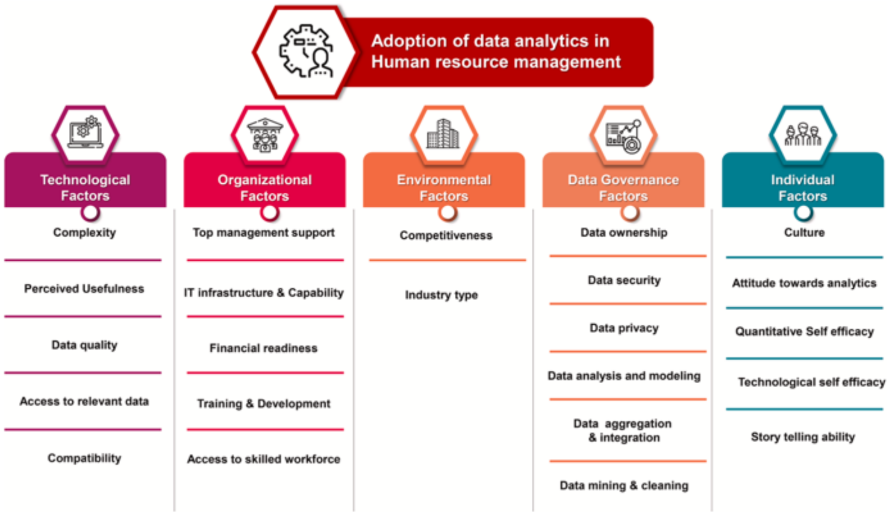

Figure 2.7: Framework for adoption of data analytics in HRM (Shet et al., 2021)

Fernandez and Gallardo-Gallardo (2021) explore the challenges and potential solutions related to HR digitalisation, with a specific focus on the factors and barriers influencing the adoption of HR Analytics in companies. The study identifies 14 barriers grouped into four categories: data and models, software and technology, people, and management.

Under Data and models, issues such as lack of data integration and sharing, insufficient data and metrics, and lack of standards for data and HR metrics are highlighted. Software and technology barriers include the low quality of HR data and a lack of strategic HR focus in complex models. People-related barriers involve a lack of knowledge, skills, and competencies related to analytics, a lack of strategic business view, and insufficient storytelling skills. Finally, Management barriers encompass keeping HR analytics within the HR department, underestimating the impact of organizational culture, replacing management discussions with HR analytics, and focusing on interesting problems instead of business problems.

To overcome these barriers, the authors propose key factors falling into four categories: preparation, development, dissemination, and team.

In preparing for the adoption of HR analytics, organizations must recognize the unique challenges and distinctions from big data processes (Figure 2.8). The initial phase sets the stage for a thoughtful and tailored approach to integrating analytics into HR practices. Starting with business problems is the best approach (Green, 2017; Harris et al., 2011; Quinn, 2020; Rasmussen & Ulrich, 2015). This approach implies a connection with the various functional areas of the company. Here, the HRA area must move beyond the human resources department (Rasmussen & Ulrich, 2015) and seek to understand the "pains" of the company's areas, but above all, be aligned with the strategy outlined by top management. Thus, HRA becomes a business partner and not just an area that investigates "interesting subjects" but "important issues" (Fernandez and Gallardo-Gallardo, 2021) that have an impact on the business. This is why HRA may be the last chance for HRMs to become truly strategic and crucial in value creation, if they have not already been considered so, in Favor of the operational areas.

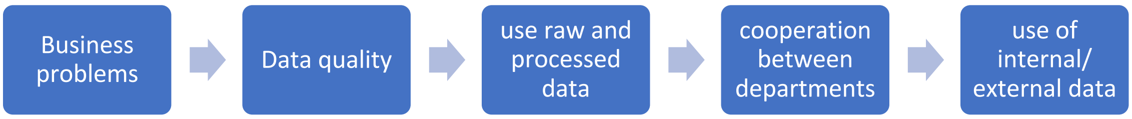

Figure 2.8: Preparation for the adoption of HR Analytics (adaptation of Fernandez and Gallardo Gallardo (2021) by the author)

After this focused approach aligned with the company's strategy, it is necessary to analyse the quality of the data (Figure 2.8). If there has never been an HRA practice, it is common to find the information fragmented, in various formats, and often disaggregated, duplicated, and decontextualised. It is necessary to clean up and process this information so that it can be used effectively. A concrete example is attempting to answer a set of people management questions without having reliable and structured data readily available (Fernandez and Gallardo-Gallardo, 2020; Jeske and Calvard, 2020; McCartney & Fu, 2022a).

Furthermore, several problems have arisen due to the absence of structure and a centralised site for data storage, including data duplication, erroneous and inaccurate entries, and missing data (King, 2016; Boudreau and Cascio, 2017; Levenson and Fink, 2017; Minbaeva, 2018; Shet et al., 2021).

Both raw and processed data can be utilised. The next step involves cooperation between various departments to obtain this information, either in response to specific requests or for integration into a data lake. Finally, this data can be internal or external (Figure 2.8).

During the development stage, it is crucial to avoid direct comparisons with big data processes. Instead, organisations should employ contextual models and prioritise the creation of standard HR metrics to establish a common language within the organisation. Incorporating HR academic theoretical frameworks provides a solid foundation for analytics efforts, ensuring a nuanced understanding of the discipline.

The dissemination phase marks a shift from focusing solely on individual people skills to cultivating collective team skills. A balanced approach, incorporating business acumen, analytical capabilities, and effective storytelling skills, becomes paramount for communicating findings and insights. Locating the analytics team outside of the HR department can facilitate cross-functional collaboration and offer a broader perspective, enriching the analytical process (Rasmussen & Ulrich, 2015).

Lastly, in building the analytics team, increasing managers' understanding of analytics results is vital. This understanding fosters trust and credibility in the outcomes generated by HR analytics, ultimately enhancing the overall effectiveness of the function. By emphasising trust-building among managers, organisations can ensure that analytics insights are not only accepted but actively inform strategic decision-making across the entire organisation.

By addressing these key factors, organisations can navigate the complex landscape of HR analytics adoption, mitigating barriers and unlocking the full potential of data-driven decision-making in the realm of human resources.

2.4. Stages of maturity in HRA

There is a consensus among researchers and industry participants regarding the several stages of HR Analytics development maturity and value creation in organizations (Davenport, 2013; Margherita, 2022; NTT Data, 2023; Roy et al., 2022). These phases reflect the complexity and maturity of data processing, analysis, and value extraction. As previously mentioned, analytics encompass more than just the past; future prediction is crucial. According to difficulty, complexity, and value created, the stages of development are descriptive, prescriptive, predictive, and autonomous analytics (Davenport, 2013; Giermindl et al., 2022; Roy et al., 2022).

The simplest level of HR analytics management is called descriptive analytics, and it focuses on "what happened, why it happened, and what is happening." It refers to metrics related to human resources, including headcount, employee age, salary, gender, and geographic origin. Resolving queries like "what will happen and why will it happen in the future" is the goal of predictive analytics. This method allows specific workforce trends and behaviours to be predicted using data, statistical analysis, and artificial intelligence techniques. This is the most valuable and challenging approach to implement, and it is the one that HR departments use less frequently because it demands the highest level of expertise and nuanced data handling. Prescriptive analytics seeks to provide answers to queries like "what should I do and why should I do it?" (Margherita, 2022; NTT Data, 2023; Roy et al., 2022; Davenport, 2013). Lastly, autonomous analytics, a new level of maturity and complexity that goes beyond HRA's predictive capacity, is connected to generative AI (Giermindl et al., 2022). Although this dimension presents some challenging consequences, it also opens innovative possibilities for the application of artificial intelligence.

There is also the perspective that the descriptive approach is not necessarily low in maturity or least valuable for decision-making. A study reported that most HRA techniques used in companies are descriptive analytics (Cayrat & Boxall, 2022). The complexity of analysis does not always correlate with its value. Shell reported that 80% of their descriptive statistics analysis was very useful (Van der Togt and Rasmussen, 2017). Peeters, Paauwe & Van De Voorde (2020) pointed out that this hierarchy of analytics maturity stages is incorrect when considering the added value of the team. Additionally, an analytics team requires various skills and abilities, including stakeholder knowledge, not just statistical and computer programming skills. A team can be highly expert in the most advanced machine learning technologies, for example, but if it lacks strategic vision and business knowledge, predictive models will fail miserably. In short, a multidisciplinary HR analytics team needs a set of skills to be effective in its analysis. To begin with, a good demographics descriptive structure of the company, with its most relevant data, integrated into a single database, where the information is clean and of high quality, is already a very powerful HR Analytics strategy and a foundation for more complex analysis.

2.5. Business problems

Starting from the premise of Rasmussen & Ulrich (2015), Harris et al. (2011), Green (2017), and the CRISP-DM approach (Quinn, 2020), which propose an effective HR Analytics approach that focuses on business problems, the sectoral analysis of the implementation of HR Analytics becomes essential because each professional sector has different problems and specificities. What are the most pressing business concerns of top management? Where there's the pain, there's the way.

As proposed by this study, the choice of a specific sector to test HR Analytics may initially seem to be a limitation due to the supposed lack of ability to generalise the results to other sectors. On the other hand, testing a certain strategy in real circumstances and with specific problems can establish standards and show patterns not only relevant to the specific sector but also serve as a case study for other industries.

2.6. HRA technology and skills

The following characteristics, as stated by the Nesta Global Innovation Foundation (2014), describe the ideal data analyst profile: competencies (analytics attitude, creativity, and curiosity); soft skills (storytelling and teamwork); domain and business knowledge (understanding of corporate goals and procedures); and core skills (analytical or technical). For HR professionals to effectively conduct HRA, Levenson (2011) highlights the various analytical competencies required. These include root cause analysis, data preparation, basic and intermediate data analyses, basic and advanced multivariate models, study design, survey design, and quantitative data collection and analysis.

Minbaeva (2021) offers an interesting recent insight related to autonomous analytics propelled by AI. Data analysts risk losing their jobs due to new language models and automated systems. However, a crucial role remains: the critical thinking needed by a researcher, stakeholder knowledge, and the ability to formulate problem statements that refine algorithms and guide machines.

The HRA approach draws from several areas of knowledge, not only from human resources. Artificial intelligence is crucial for HRA's functionalities to be effective. Human resources management significantly benefits from the influence of human resources strategy. Without an interdisciplinary approach to HRA, companies risk losing the full capabilities that this strategy offers. These areas include AI and statistics, strategic human resources, and the sector-specific business area and respective functional business areas.

Thakral et al. (2023) highlight in a recent literature review the most used algorithms in HR Analytics: neural networks, sentiment analysis, MCDM, deep learning, artificial intelligence, and fuzzy logic. Although it is somewhat general to mention "Artificial Intelligence" generically, it points out the main techniques utilized in most HRA studies.

Access to HR technology is a key factor in the adoption of HR analytics and serves as a prerequisite and enabler of HR analytics (McCartney & Fu, 2022b). Access to this technology is crucial to utilise the capabilities that analytics resources offer. In turn, these resources cannot be used without resorting to an Evidence-Based Management (EBM) methodology. Organizations must, for instance, formulate an issue or problem into a question that can be answered (asking), systematically seek out and collect the best available evidence (acquiring), critically assess the reliability and applicability of the evidence (appraising), weigh and compile the evidence (aggregating), incorporate the evidence into the decision-making process (applying), and assess the decision's outcome (assessing) (Barends et al., 2014; McCartney & Fu, 2022b). Finally, EBM is positively associated with organisational performance (Figure 2.9).

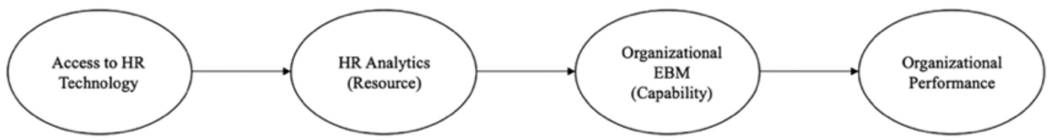

Figure 2.9: McCartney & Fu's (2022b) theoretical model

The most popular suppliers of HR Analytics consulting services conducted research as part of a recent comprehensive academic review of HR Analytics (Tursunbayeva et al., 2018). Links to the IBM HR Analytics home page were found on the most of search results pages for vendors. Additionally, other results were retrieved, along with their frequency: News (Forbes), Research (Harvard Business Review), HRA-related Communities (Kaggle), Organizations/Platforms offering access to educational materials on HRA (HCA Group webpage - Copenhagen Business School HRA research group, Coursera), specific training programmes (Human Resources MBA), and Conferences (Wharton HRA conference) (Tursunbayeva et al., 2018).

Typically, the suppliers provide consulting services for businesses looking to implement and manage an HR analytics strategy. They typically present various value propositions. The most comprehensive value propositions were found to be provided by Accenture, IBM, Kronos, and Cornerstone, and they included:

(A) Better access to accurate information and analytical tools facilitates more effective strategic decision-making.

(B) More creative approaches to data collection, combination, analysis, and interpretation enhance data handling processes.

(C) More efficient HR decision-making and increased efficiency in people management.

(D) New technological solutions for HR data collection, storage, or analysis, including process automation.

(E) Direct effects on HR or strategic business outcomes, such as optimising human resource assets to increase income relevant to payroll.

(F) Benefits targeted at employees, like better work conditions or increased job satisfaction (Tursunbayeva et al., 2018).

2.7. Generative AI and HRA

Over the past ten years, artificial intelligence technologies and digital platforms have become essential components of commercial organisations and society. This technology can analyse large amounts of data, extract insights and predictions from it, and use artificial intelligence to perform day-to-day functions, whether in knowledge-based tasks, physical tasks, or even conversational tasks (von Krogh, Roberson and Gruber, 2023). Artificial intelligence can perform various tasks such as robotic automation, speech recognition, sentiment analysis, network analysis, machine and deep learning, and natural language processing. All these forms of AI have created a host of opportunities and achievements in solving certain problems and performing functions more efficiently, reshaping business models, and creating business solutions and applications like never before. However, there is the challenge of separating hype from substance in AI, with varying degrees of success in different applications (Budhwar et al., 2023).

Generative AI has an impact on various fields, and human resources management (HRM) is no exception (Budhwar et al., 2022; Chowdhury et al., 2023; Edwards et al., 2022; Malik, Budhwar & Kazmi, 2022). There has been recent growth in HRM scholarship on AI, with studies emphasising the benefits of AI-based machine learning tools in areas like diversity promotion, employee recruitment, and enhancing workplace experience (Budhwar et al., 2023).

The introduction of Generative AI is exemplified by ChatGPT, which can generate human-like responses to questions and create new content based on prompts. This technology goes beyond predictive algorithms, although the quality of training data is crucial for the relevance and timeliness of the generated content. Large Language Models (LLMs) present in the well-known ChatGPT are not new, nor is Generative AI, but ChatGPT has democratized conversational chatbots based on LLM algorithms, which are continuously improved in their learning and predictive capacity. Generative AI integrates machine learning to generate new content like text, sound, image, software code, and simulations based on large datasets used to train the model (Budhwar et al., 2023). There has been an evolution of LLMs, including GPT models, which have progressively improved in terms of dataset size and the number of parameters to provide more accurate responses. However, the quality, relevance, and consistency of the training dataset will determine how contextually relevant the newly generated information is (Boston Consulting Group Generative AI, 2023; McKinsey & Featured Insights, 2023). For instance, until 2021, approximately 45 terabytes of data were collected from the internet to train GPT-4 (OpenAI GPT-4 Technical Report, 2023). As a result, it is doubtful that the responses will include current and accurate information (Budhwar et al., 2023). Therefore, there are challenges associated with early models, including incorrect outputs and offensive content, leading to the incorporation of human feedback to improve the alignment of responses with users' intent.

In summary, Generative AI, exemplified by ChatGPT, represents a significant advancement in AI technology, with applications in various fields, including HRM. Its development has been marked by the need for larger and better training datasets and safety measures to produce more accurate and contextually relevant outputs.

2.7.1. Implications of Generative AI in HR analytics

There are some important implications of Generative AI for HR analytics. Generative AI can significantly enhance the processing of HR data. HR analytics often involve the collection and analysis of large datasets related to employee performance, engagement, and other HR-related metrics. Generative AI can assist in the faster and more efficient processing of this data, enabling HR professionals to gain insights more rapidly (Budhwar et al., 2023). Secondly, with the availability of Generative AI, HR professionals can make more data-driven decisions. AI algorithms can analyse HR data to identify trends and patterns that might not be immediately evident to human analysts. This can lead to more informed decision-making in areas such as recruitment, talent management, and performance evaluation.

Generative AI can also facilitate predictive analytics in HR. AI algorithms can analyse historical HR data to make predictions about future HR trends and outcomes. For example, predictive analytics can help HR professionals anticipate turnover rates (Choudhary, 2020; Ekawati, 2019), identify employees at risk of leaving, or forecast staffing needs. Generative AI can automate routine HR analytics tasks. HR analytics often involve generating reports, charts, and graphs to present findings. AI can automate the creation of these materials, allowing HR professionals to focus on interpreting the results and acting. Generative AI can support HR professionals in adopting evidence-based HR practices (McCartney & Fu, 2022b). By providing quick access to research-based information and insights, AI can help HR teams make decisions grounded in empirical evidence.

HR analytics often involve sensitive employee data. The use of Generative AI for HR analytics may raise concerns about data privacy and security (Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Tursunbayeva et al., 2018). HR professionals and organisations need to ensure that data used in analytics is properly protected and that AI-generated insights do not compromise data security.

The introduction of Generative AI may require HR professionals to acquire new skills related to data analysis and AI technology (Daugherty, Wilson & Michelman, 2019). HR teams might need to undergo training to effectively use AI tools and understand the insights generated by AI algorithms (Levenson, 2011; Marler & Boudreau, 2016; McCartney & Fu, 2022a; Nesta Global Innovation Foundation, 2014).

Despite the benefits, HR professionals must exercise quality control over AI-generated insights (Budhwar et al., 2023). Ensuring the accuracy and relevance of AI-generated analytics is crucial to making sound HR decisions: a “trust but verify” approach to working with ChatGPT (Budhwar et al., 2023; Purcell & Hutchinson, 2007). Critical thinking has become one of the most needed soft skills of modern times.

In summary, Generative AI can play a significant role in enhancing HR analytics by providing faster and more data-driven insights for HR professionals, although critical data curation is highly recommended.

2.7.2. Examples of Gen. AI in HRA

Generative AI can help automate and enhance certain HR tasks and policies. For instance, a multinational corporation faces the challenge of attracting top talent in a competitive job market. The HR team believes that crafting compelling job descriptions is essential but time-consuming. By adopting Generative AI to assist in creating job descriptions, the AI tool analyses the skills and qualifications needed for a position and generates engaging, tailored job descriptions automatically. It also helps identify relevant keywords to improve the visibility of job postings. As a result, the company can experience an increase in the number of qualified applicants by implementing AI-generated job descriptions. The HR team can also save hours of work per week, which can be redirected towards strategic HR tasks. Another possible outcome is that the quality of candidates can improve, leading to a reduction in the time and resources needed for interviewing and onboarding.

Another example is predicting employee turnover. Tech companies frequently struggle with high employee turnover. The HR department aims to proactively address this issue but lacks a clear predictive strategy. A tech company can employ Generative AI for HR analytics to predict employee attrition/churn. The AI model analyses historical data, including employee performance, engagement, and survey feedback, to identify attrition/churn risk factors. It then generates a predictive model. If the model is robust, the AI-generated attrition/churn model can correctly identify a high percentage of employees at risk of leaving, allowing HR to intervene with retention strategies. The company can see a percentage decrease in employee turnover within a period, resulting in cost savings and improved team stability. The HR team shifts from a reactive approach to a proactive one, focusing on retaining key employees based on AI-generated insights.

A third example is a healthcare organisation determined to invest in the professional development of its staff. However, creating personalised development plans for each employee is resource intensive. This hospital implements Generative AI for HR analytics to create personalised employee development plans. The AI system analyses each employee's skills, performance history, and career aspirations. It then generates customised development plans that include training courses, certifications, and mentorship opportunities. As a result, employees report higher job satisfaction as they perceive that their career development is a priority. The hospital can experience an increase in employee retention and internal promotions, reducing recruitment and onboarding costs. Finally, HR professionals can focus on coaching and monitoring employee progress rather than creating development plans from scratch.

These examples illustrate how Generative AI can be applied in HR analytics to address real HR challenges, including improving recruitment, predicting employee attrition/churn, and personalising employee development. The technology provides valuable insights, saves time, and leads to more data-driven HR decision-making.

2.8. HRA controversy

2.8.1. Concept

Despite all the proofs of success and the buzz around the topic of HR Analytics (HRA), the notion and definition of HR Analytics are subject to significant debate, particularly in the most significant and current literature reviews on the topic (Fernandez & Gallardo-Gallardo, 2021; Margherita, 2022; Marler & Boudreau, 2016; McCartney & Fu, 2022a; Tursunbayeva et al., 2018). The variety of ideas, features, and tasks assigned to HRA is at the root of the issue. It is occasionally mistaken for "metrics" or the simple application of demographic information to decision-making (McCartney & Fu, 2022a; Ergle, Ludviga, & Kalvina, 2017).

The inclusion of artificial intelligence and deep learning as necessary tools to maximise HR Analytics' potential has begun to be introduced into practice in companies and scientific research (Yahia, Hlel & Colomo-Palacios, 2021), but these advanced techniques are still a minority in HRA practice (Arora et al., 2022).

2.8.2. Effectiveness

There are still many unanswered questions regarding the efficacy of HR Analytics practices, despite the hype and buzz surrounding them (Arora et al., 2022; Isson & Harriott, 2016; Margherita, 2022; Marler & Boudreau, 2016; McCartney & Fu, 2022a; McCartney & Fu, 2022b; Minbaeva, 2021; Peeters, Paauwe & Van De Voorde, 2020; Shet et al., 2021; Tursunbayeva et al., 2018). The most recent literature reviews on HRA still address this issue (Espegren & Hugosson, 2023; Wang et al., 2024). Espegren & Hugosson (2023) conclude that the literature on HR Analytics is very conceptual and lacks empirical studies, especially qualitative ones, that can prove the effectiveness of HRA practices. In this sense, their review maintains the conclusions of the latest literature reviews on the subject (Arora et al., 2022; Espegren & Hugosson, 2023; Marler &

Boudreau, 2017; Margherita, 2022; McCartney & Fu, 2022; Wang et al., 2024). They conclude that more than guidelines on how an HR strategy can work, there is a lack of demonstrations of HRA "as a practice," because the success factors for implementation often reside in contextual factors rather than those more commonly highlighted. A qualitative or mixed-methods approach could detect these factors, which are sometimes hidden in the more traditional methodologies used.

The application of HR Analytics is likewise controversial, and the reasons behind the lack of adherence are manifold (Fernandez & Gallardo-Gallardo, 2021; McCartney & Fu, 2022a; Peeters et al., 2020). Several factors contribute to this, including the deficiency of technical expertise in artificial intelligence and social sciences within HR departments, a lack of managerial support and interest, privacy and data security risks, and high expenditure on IT infrastructure and HR resources (Marler and Boudreau, 2016; Minbaeva, 2017; Minbaeva, 2021). Mainly, the principal problem is not HRA adoption but how it is adopted. There are organisational problems, cultural factors, and methodological weaknesses. One common mistake in implementing HRA is to overlook the data preparation phase of analytics. Without data quality, the input inserted into the analytics process is flawed, resulting in "garbage in, garbage out" (Ribeiro, 2024).

Nevertheless, several case studies have already demonstrated the value of HR Analytics (Buttner and Tullar, 2018; Harris et al., 2011; Green, 2017; Isson & Harriott, 2016; Kane, 2015; McCartney & Fu, 2022b; McIver et al., 2018). HR Analytics is proven to be effective, but further research and evidence are still needed to show that its methods and resources can boost organisational output and enhance the HR decision-making process. There is still much room for research in this area as it is in its infancy (Arora et al., 2022; Fernandez & Gallardo-Gallardo, 2021; Margherita, 2022; Marler & Boudreau, 2017). Above all, the most valuable contributions in academic research that are still lacking are case studies, empirical studies, predictive analytics studies, and demonstrations of HRA praxis (Arora et al., 2022; Espegren & Hugosson, 2023; Margherita, 2022). However, despite all the excitement surrounding HR Analytics, the idea remains somewhat hazy, and businesses may adopt this technology more quickly than anticipated.

2.8.3. HR Analytics: a temporary trend?

Even with all the hype around the subject, a more thorough study of the literature concludes that HR Analytics (HRA) is not being used in businesses to the extent that is anticipated (Espegren & Hugosson, 2023; Marler & Boudreau, 2017; Margherita, 2022; McCartney & Fu, 2022; Minbaeva, 2017; Minbaeva, 2021; Wang et al., 2024). The notion that HR Analytics will be associated with improved organisational performance appears to be challenged by certain data. Falleta (2014) conducted a survey to find out how HR Analytics was used by Fortune 1000 companies. Falleta (2014) found that just 15% of respondents, using a sample of 220 organisations, said HR Analytics played a key part in developing or implementing HR strategy. According to the HR Technology Market 2021 Report, 42% of HR technology projects prove to be either partially successful or fail after two years, indicating a considerable gap between projected and realised value (Bersin, 2021). Moreover, the primary focus of HR Analytics was limited to the examination of employee survey information. According to surveys conducted among over 100 Fortune 500 organisations, less than one-third have HR Analytics that gauge the connection between HRM procedures and people and business impact (Lawler et al., 2004; Lawler & Boudreau, 2015). According to Marler & Boudreau (2016), the primary reasons for this might be the following: teams' deficiency in analytical abilities, supervisors' limited ability to make decisions, and, lastly, the HR department's lack of IT capability.

There are distinctions between gathering information through surveys and data extraction, and even using certain standards to guide decisions. HR Analytics is a social science activity that involves gathering a lot of data, analysing relationships, and drawing conclusions. It is challenging to be successful in these activities without the usage and expertise of social scientific research methods. According to Marler & Boudreau (2016), HR teams are not typically known for being analytics driven.

The case study of Google (see chapter 2.3.4.) demonstrates unequivocally that HR Analytics is a field of "research," and the literature makes a distinction between analytics and metrics. Companies will therefore find it difficult to use the immense power that data has if they do not employ data analysts or other specialised staff. It's also not a requirement to own the software and hardware to claim to have an HR analytics system. Ownership of the data is not as important as what you do with it.

Another theory proposed is that companies are still embracing HR Analytics in its infancy, and the most inventive and daring are the ones who will advance. The marketing product lifecycle model states that when a product receives consistent positive feedback from consumers, more customers who are less risk-averse will follow the innovators and support the product's growth in adoption until it reaches the next stage, maturity.

Rasmussen & Ulrich (2015) identified four recommendations to prevent HRA from becoming a management fad: emphasising business concerns in HRA work, removing analytics from HR, keeping human resources in mind, and preparing HR professionals for an analytical mindset. Within the essay, the authors contended that there exists a genuine risk that HR analytics personnel may grow somewhat estranged from the functional domains of the organisation and might be examining data unrelated to the actual issues facing the company. The suggestion, then, is to take HR Analytics out of HR and integrate them into other business functional areas. This includes operations, finance, marketing, customer service, and other departments, to comprehend the problems facing each area. The question addressed by these authors concerns HR Analytics ownership (McCartney & Fu, 2022a). This question has been raised by recent research: should HR Analytics stay within human resources or outside of it? (Rasmussen & Ulrich, 2015; Andersen, 2017; Marler & Boudreau, 2017; van den Heuvel & Bondarouk, 2017; Minbaeva, 2018; Fernandez & Gallardo-Gallardo, 2020). Some argue that if HR Analytics seeks to create value for people and deals with human resources issues, it should stay within the human resources department because it is, in principle, the one that will best defend people's interests and handle these issues effectively. Others argue that HR departments lack the necessary skills to deal with HR Analytics, particularly the technical and infrastructure skills and capabilities required. This quarrel seems to recall the old misalignment between people and business strategy (Minbaeva, 2021), which is very common in many sectors of activity, including the commercial airline industry analysed in this study. In the research carried out through semi-structured interviews (see chapters 3.2 and 4.1), many commercial airline experts stated that a common problem is the divorce and misalignment between HR departments and the operational areas of commercial airlines. If the goal of HR Analytics is to create value for people and ultimately for the business, as it must start from business problems (Rasmussen & Ulrich, 2015), this alignment is essential. If HR Analytics is a company-wide service, it must be involved with all functional areas of the company and understand their problems. HR Analytics, therefore, in addition to the challenge of skills and abilities, must also interact with, know, and understand the specific problems of the business and "speak the language of the business," quoting a commercial airline executive interviewed in the qualitative research of this PhD project.

Since many HR departments are often seen as merely passive executors of a company's strategy and not very interested in or knowledgeable about the business in which they operate, it is equally important for the operational area to empathise with the needs of the people areas. Namely, the focus of business on people, and Google's claim that "hiring is the most important thing you do" (Schmidt & Rosenberg, 2014, p. 510).

Human resources professionals are often seen as those who show up when it is necessary to receive a salary and schedule holidays. This time, HR Analytics may be the last opportunity for the human resources area to finally play a truly relevant and decisive role in the management of the company. People are no longer just a means to an end, but they are the end in themselves. If businesses know their people better and can serve them better, if they can attract the best talent with a strategic approach, people can be the essential asset for the pursuit of business goals. Again, Porter can come to the conversation. The real competitive advantage? People.

Beginning with the problems of the business rather than the information, Rasmussen (Green, 2020) continues to argue that the real business problems should be addressed first. However, he retreats from the idea that HR should leave the department, concluding that certain specialised techniques are actually required, such as applied social sciences, automation, machine learning, and specialised metrics. He comes to the final conclusion that proximity to decision-makers and commercial issues is essential, but this should not come at the expense of the specialised aspect of the role. Finally, the author supports a "hub & spoke" system where data resources are centralised in the HRA but can be accessed by other areas in a centralised "data lake" that is connected to the company's functional areas (Green, 2020). Once more, the manager tackles a crucial issue raised in the HRA literature: the requirement for HR Analytics experts to possess more specialised training and understanding (Marler & Boudreau, 2016).

2.8.4. The dark side of HR analytics

The goal of HR Analytics is to boost an organisation's performance and effectively manage its staff with data. It is a tool for improving worker performance and wellbeing, but it can also pose a threat. There are several problems and difficulties associated with HR Analytics practice. Probably due to the marketing around HRA, particularly in the industry realm, the dark side of HRA is not sufficiently addressed and discussed. However, science has done its job of questioning all assumptions, and there is substantial evidence indicating serious dangers and risks that can jeopardise the success of HRA, and the wellbeing of the people involved. Interestingly, this is a topic that is underexplored and needs further contributions from research (Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Tursunbayeva et al., 2018; Tursunbayeva et al., 2021).

2.8.4.1. Ethical risks

2.8.4.1.1. Algorithmic opacity

Algorithmic opacity means that employees may not always know what data is collected about them, how it is handled, how it is collected, and who accesses the information (Gal, Jensen & Stein, 2020). Data science thrives on analysing large amounts of data and looking for patterns and associations. The predictions and insights drawn from this data can result in outcomes that are not understood or transparent to the employee. Unclear algorithms may also be used. For example, if an algorithm is established to help the company decide who to dismiss using certain criteria, it may not be clear whether the final decision is made by a machine or a person, or what criteria underpin the decision. Additionally, there is the danger of bias and subjectivity in this algorithm, potentially causing injustice. A practice that can be employed in this case, without limiting the help of technology and while respecting the dignity of the employee, is to use this technology as support for decision-making and then inform the employee of the criteria that underpinned the decision to dismiss someone, ensuring the interests of both the company and the employee are safeguarded.

As the architecture behind algorithms is sometimes opaque and unclear, some decisions made using HRA can create unfair, non-transparent situations or biased results (Giermindl et al., 2022). For example, the case of false positives caused by drug testing in recruitment can prevent a hiring that would be advantageous for both parties and make future recruitment impossible or more difficult for the candidate (Calmes, 2016). In the case of HR Analytics' descriptive and predictive methods, the variables and models are still somewhat transparent, but when generative AI is concerned, using machine learning algorithms, the decisions made by machines can become incomprehensible and unclear regarding what method and reasons led to such a decision by the system. This can create not only injustices but also a perception of anxiety and distrust among employees, which can reduce their commitment and performance and ultimately lead to them leaving the company or litigating against it. In such conflict situations, HR Analytics would have to be held accountable. Can a company hold computers and algorithms accountable for decisions based on assumptions that even software engineers sometimes do not understand? (Burrell, 2016).

2.8.4.1.2. Datafication

Datafication is a danger incurred when decisions are dehumanised because they are made by technology, rather than using data as a mere tool (Gal, Jensen & Stein, 2020). Instead of a final human decision supported by technology, decisions are made by technology. When the actions of employees are quantified and HRA creates “personas” through machine patterns and categorisations, the system can fail to see the personal idiosyncrasies of human beings, which are not captured in the models of algorithms. Furthermore, it denotes a behaviouristic cause-and-effect theory of human behaviour that fails to consider the unique motivations and meanings that drive each member’s activities. One analytics tool, for instance, uses member activity on business social networks to categorise users into one of five predefined personas: “the engager,” “the catalyst,” “the responder,” “the broadcaster,” and “the observer.” To conduct this study, the frequency with which members engage in various predetermined behaviours (such as starting conversations, commenting, and liking) is counted. After being categorised, members can be treated according to the presumptive traits of their persona (Gal, Jensen & Stein, 2020). From an ethical standpoint, such a strategy presents significant difficulties. Initially, a data-driven understanding of members and their tasks runs the risk of oversimplifying both. In this example, a small amount of secondary data is used to classify persons, while the immense variety of human variation is reduced to five pre-specified models. Members may find it challenging to recognise themselves in oversimplified representations of their conduct (Gal, Jensen & Stein, 2020).

HR Analytics has the danger of reducing employees’ autonomy. In principle, HRA is designed to increase job satisfaction, improve productivity and work motivation rates, and enhance worker autonomy by prescribing certain KPIs that measure performance and evaluate human resources policies to optimise the employee experience. In practice, there is evidence that by using its measurement techniques, it can transform a policy aimed at improving satisfaction into an automated process that eliminates the human factor, transforming it into an action of vigilance and pressure on the employee (Giermindl et al., 2022). Some companies place sensors and measure all kinds of human resources indicators, such as the level of sales achieved by the employee, the number of hours worked, even the level of motivation and health indicators that can predict the risk of employee burnout. In theory, HRA is done for the benefit of both parties, company and employee; in practice, it can vitiate and predetermine the employee’s behaviour, which was intended to be spontaneous and autonomous (Burton et al., 2019). If the employee knows that the company is constantly measuring their indicators and, on top of that, acting through an autonomous computer that learns from the measurement process (machine learning) and improves its process to be more effective not only in measurement but also in decision-making and alignment with the company's strategic objectives, the employee may feel like an object and not a person and lose their autonomy and freedom, even to make mistakes. Moreover, with the emergence of recent autonomous analytics software created by generative AI, this risk rises with possible effects of alienation and dehumanisation. The dematerialisation of the leader-employee relationship, an essential factor in labour motivation and productivity, can increase these risks (Giermindl et al., 2022). For example, a boss's feedback given by an automatic sales report and work scheduling determined by a robot based on the employee's sales level, without any further explanation or reasoning, can be demotivating (O'Connor, 2016).

HRA can marginalise human reasoning and erode managerial competence (Giermindl et al., 2022). HR Analytics has the potential to reduce the necessity, importance, and value of true human decision-making abilities (Gal et al., 2017; Mayer et al., 2020). Employees may trust HR Analytics more than their own assessment of present situations or their distinctive qualities such as intuitive judgement, reasoning, and critical reflection due to the perceived superiority of analytics. As a result, human characteristics like problem-solving and creativity may progressively give way to calculation, efficient predictability, and control. Employees' strength of judgement and thinking atrophies over time, like untrained muscles, and their capacity to make independent decisions can gradually deteriorate (Giermindl et al., 2022). Finally, the use and dependency on learning algorithms and AI as utilised in autonomous analytics is likely to exacerbate the erosion of managerial competencies and may even reduce their function to that of a puppet for the machine (Faraj et al., 2018; Schildt, 2017).

2.8.4.1.3. Nudging

Cybernetics is where the term "nudge" and its guiding concepts were originally coined (Gal, Jensen & Stein, 2020). The concept gained attention in the 2008 book "Nudge: Improving Decisions about Health, Wealth, and Happiness" by economists Richard Thaler and Cass Sunstein (Cai, 2020; Giermindl et al., 2022). It is the process of behavioural economics that leads the user to act in a way that appears convenient for them but can also be intrusive and manipulative, serving the interests of a third party. Based on the employee's information, the system can suggest products, options, and services related to the employee's preferences that also align with the company's people management strategy. However, like social networks, the HRA system can exploit people's vulnerabilities to its advantage rather than in their own interest. For example, corporate social networks (Slack, Yammer) recommend colleagues with common interests to employees, thereby influencing future interactions and associations (Gal, Jensen & Stein, 2020). Social media tech companies admit that this is common practice and claim they do not use the data for purposes other than platform performance and user interests, anonymising the data to prevent identification. We must trust this is the truth.

Gal, Jensen & Stein (2020) cite a well-known Facebook case published by the newspaper "Australian" (Armstrong, 2017). The case concluded that Facebook advertisers could target their ads at teenagers when they were particularly vulnerable psychologically. Facebook assisted advertisers in identifying times when kids felt stressed, insecure, apprehensive, or overwhelmed to persuade them to purchase products by tracking posts, images, and interactions in real-time. Facebook issued a statement to this news, calling it misleading and denying that it would target people based on their emotional state. They guaranteed that it "was never used to target ads and was based on data that was anonymous and aggregated" (Meta, 2017). Additionally, this case needs further clarification to understand what services would actually be suggested to adolescents by advertisers, whether they would enhance these negative emotions or offer services or content that contradict these emotional states.

There are claims in literature and among practitioners that the use of "nudging" in HRA can make users addicted to technology or provide them with false information, leading them to make decisions they might not want if they thought about them more carefully. This makes the process unethical. In HR Analytics, it can lead the employee to become a slave or pawn in the hands of the company. "Nudging" is used every day, for example in marketing and the customer experience, but also in the employee experience. It can be seen as part of the customer/employee experience service but also as manipulation (Green, 2020).

2.8.4.1.4. Privacy concerns

The privacy of employees may be compromised when data about users, including their personal information, performance, or actions, is extracted. Despite this, neither literature nor business have tackled this subject sufficiently. The latter hardly discusses the negative aspects of HRA and essentially just highlights its positive aspects (Tursunbayeva et al., 2018; Tursunbayeva et al., 2021). Recent literature reviews on HRA even omits this important discussion. For example, Thakral (2023) fails to mention the several perils, challenges, and questions about HR Analytics pointed out by the most relevant recent discussions on the topic (Arora et al., 2022; Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Minbaeva, 2021; Tursunbayeva et al., 2021) and addressed in this PhD study. In the COVID-19 pandemic context, privacy was found to be one of the hot topics in HRA by well-known practitioners, despite receiving little attention (Brito, 2024).

A legal framework and corporate transparency policies are also essential if employers want their employees to believe that their data is their own. If not, the investment in these technologies may be compromised, the employment-employer social contract may be jeopardised, and eventually the organisation's sustainability may be at risk.

Furthermore, as there is a higher danger of surveillance and monitoring when working remotely, these issues grew more pressing during the COVID-19 pandemic, which caused a significant portion of the workforce to work from home. Given that the pandemic has altered the nature of employment and sped up societies and businesses' digital transformation, the need for addressing these issues will only grow in the future.

Analytics make it feasible to keep an eye on staff emails, social media accounts, and interactions with smartphones, wearables, and apps. For instance, the email system can be used to determine if an employee is at their desk or not. Wearable technology is also occasionally used to measure health indicators, although it can also be manipulated and surveilled. These approaches have the potential to be used as a justification for enhancing the work experience for employees as well as a means of continuously tracking their whereabouts, activities, mental health, and social lives. Specifically, through work gamification (Cardador et al., 2017) and productivity and wellness apps (Ajunwa et al., 2017), technologies aim to increase motivation and productivity at work through the use of games and interactive tasks.

Despite the privacy dangers that HRA poses to both individuals and businesses, there is a gap in relevant legislation. Although it leaves some space for interpretation, the European General Data Protection Regulation (GDPR) is widely applicable throughout Europe and aims to raise awareness of certain risks and vulnerabilities associated with certain developments (Politou et al., 2018). When it comes to this matter, the United States resembles the "wild west". According to reports, businesses frequently monitor their employees without following any rigid or definite legal guidelines (Ajunwa et al., 2017; Tursunbayeva et al., 2018; Tursunbayeva et al., 2021).

Tursunbayeva et al. (2021) list the following six possible consequences of privacy breaches when using HR Analytics: operationalising bias and discrimination, psychological or social profiling, behaviour shaping, reducing performance/people to statistics, generating annoyance or insecurity, and endangering privacy or autonomy through tracking and surveillance.

To help with effective decision-making, companies continue to gather workforce data from a variety of sources, including text messages, emails, social media, microphones, motion sensors, and wearable technology. As a result, protecting employee privacy poses a significant HR challenge (Kane, 2015; Khan and Tang, 2017; Chatterjee et al., 2021).

There is some evidence that most employees consent to being observed (Mann et al., 2018), although this seems insufficient evidence. One suggestion might be to improve internal communication by effectively educating employees about monitoring, as this will be the best way to obtain their consent (Kim, 2017).

2.8.4.2. Bias and reliability

Another type of risk that exists in the use of advanced machine learning models is the questioning of the reliability of the algorithms and the bias they can create. HRA can lead to an unquestioning belief in predictions and prophecies (Giermindl et al., 2022). The fact that HRA techniques deal with predictive models does not mean that the models predict everything that will happen; rather, they indicate a probability of an event occurring. The famous case of Google Flu Trends illustrates this (Lazer & Kennedy, 2015). In 2008, researchers at Google announced that they could predict flu trends by analysing and applying predictive models to users' searches. The result was disastrous and failed to predict flu trends accurately. The subsequent conclusion of several researchers was that it does not mean we should stop believing in the potential of Big Data, but rather that the way models are built, and not just their mere application, guarantees meaningful results.

HRA can foster path dependencies (Giermindl et al., 2022); HRA models make predictions based on the analysis of historical data, so the results are mere extrapolations based on what has already happened but can ignore new patterns and parameters (Pachidi & Huysman, 2018).

Another dark side of HR Analytics is that it can bring an illusion of control and be reductionist (Giermindl et al., 2022). Because HRA's tools and tasks are mathematical and algorithmic, they are assumed to be so accurate that they don't fail in their insights and predictions. By analysing large amounts of data and using machine learning methodologies and advanced artificial intelligence, one might think that the patterns found, and results are almost unquestionable, but humans are complex. There is also the danger that human beings will be reduced to mere numbers, overlooking the fact that behind statistics are people, who are much more complex than machine learning models. The unquestionable belief in "exact sciences," namely quantitative methods, overshadows the importance of considering other variables, including qualitative ones.

HR Analytics solutions are designed with the goal of operationalising bias and discrimination in favour of an organisation by employing objective data rather than just common sense. However, as algorithms are created by humans, who are inherently biased, the outcomes may also be biased. One well-known example is the case of Amazon, where a software engineering hiring algorithm thoroughly reviewed a large number of resumes and concluded that men were more qualified than women for the position. Because this approach did not fulfil Amazon's stated diversity policy, the company chose to abandon it.

The previously discussed "nudging" approach to behaviour modification can be viewed as manipulative and invasive. It is possible to reduce groups and individuals to simple machines while ignoring the variety and complementarity of each person's skill set. It is said that many HRA programmes overlook teams and individuals in favour of groups and organisations.

Additionally, there's a chance of causing discomfort or unstable income. Sometimes data analysis results in abrupt and unpredictable changes to employees' work schedules. For instance, Starbucks used a variety of data sets, including pedestrian patterns and weather information, in its scheduling software, which led to ambiguity around the availability of shift labour (Tursunbayeva et al., 2021).

2.8.4.3. Conclusion

One problem with evaluating Business Analytics, HR Analytics (HRA), or Social Media Analytics (SMA) practices is that the researcher can only describe the evidence of both sides if the work is to portray the state of the art of a research topic impartially. It is not objective to naively defend digital platforms, but it is also not scientifically objective to describe the cases incompletely and without mentioning the other party involved. As information and data from big tech platforms are difficult to obtain, the most a scholar's work can provide for research is the evidence of both sides.

Organisations may run the risk of undertaking HRA projects. As a new era of "consent" dawns, whether it be in data or relationships, businesses run the risk of endangering their work and suffering more harm than benefit from these tools if they do not adopt moral, responsible, and user-focused behaviour. Because of this, HRA initiatives are beginning to consider the business's risk in addition to their return on investment.

It is important to note that experts in human behaviour and ethics, rather than only technicians, computer scientists, or HRA suppliers, should be working on this problem (Calvard & Jeske, 2018). The CEO of Google, Sundar Pichai (2023), also emphasizes the inclusion of "philosophers and social scientists."

Some dangers and risks of HR Analytics limit people's ability to cultivate their virtue and flourish (Gal, Jensen & Stein, 2020). The solution to mitigate these challenges is to humanize HR Analytics. One solution is for organizations to be honest and transparent about the functions and implications of HR Analytics. They should communicate the risks and act transparently in the policies they will follow, creating practices that do not cause harm to workers (Gal, Jensen & Stein, 2020).

2.9. Employee churn/ retention analytics

Within the workforce, some individuals emerge as high-value creators and top performers, while others may grapple with performance challenges. The departure of an employee, whether voluntary or involuntary, is termed churn or turnover. Voluntary churn occurs when an employee opts to leave for more favourable conditions elsewhere, possibly with a competitor, while involuntary churn pertains to position termination. Harnessing the power of employee churn analytics becomes imperative in creating business value from attrition/churn knowledge. By analysing internal and external talent data intelligently, organisations can address critical attrition/churn questions, such as identifying employees at risk, predicting performance issues, and understanding the motivations of top performers who are considering leaving.

The key questions addressed by employee churn analytics are:

1. Identification of at-risk employees.
2. Anticipation of performance issues.
3. Retention of top performers.
4. Understanding departure motivations.
5. Timing of departure.
6. Factors influencing churn.
7. Proactive retention strategies.
8. Cost of losing top performers.

Employee retention revolves around identifying and comprehending employees at risk and predicting when and why they might leave. Analytics facilitate the fusion of employee data, company data, and market data, offering predictive insights into the behaviours of top performers. This pillar provides essential components for forward-looking organisations, enabling them to retain top talent, stay competitive, and proactively create value through an engaged workforce. Many sectors face this problem with serious consequences on their bottom line, such as the technology sector. In this PhD study, the commercial airline sector is tested—one that deals with this issue and is not as extensively studied as the banking and technology sectors.

Traditional approaches no longer produce effects, often based either on intuition or on the assumption of the problem when it no longer has a solution, often when the worker has already decided to leave. Furthermore, assuming that these motivators to churn are recognised prior to the decision to leave (time is critical, as most studies indicate that workers begin considering leaving nine to twelve months prior to their resignation) (Isson & Harriott, 2016).

The advantage of analytical approaches is that they allow for timely knowledge of turnover intentions. Turnover intention precedes the action, which no longer has a solution. If this phenomenon can be prevented by analysing data and acting on that data, many financial consequences of loss of value and employee dissatisfaction can be avoided. What often happens is that employees have their resumes always present online, constituting a passive job search and bringing another factor that is difficult to measure and predict to influence departure. However, this factor can also be considered in the model, as will be seen below.

Employee exit interviews are often an important tool for evaluating the process. These interviews usually aim to understand why the person leaves, what failed, and to create actions and policies that can prevent such exits in the future. However, in practice, the reliability of this instrument is questionable for measuring the causes or factors that lead to professional abandonment. On one hand, it deals with privacy issues; on the other, the sincerity of the departing employee is not always high. Finally, we learn the reasons when the event we wanted to avoid has already happened. With predictive analytical approaches, there's the ability to know in advance the probability of a person leaving, and thus, with time, the company will be able to create and offer conditions to prevent this exit. This is yet another example of HRA's usefulness. It is the data that raises questions and provides answers, and this information forms the basis for decision-making in people management.

It might come as no surprise that the two largest obstacles in HR are attrition/churn and retention. More than 70% of participants in a recent Deloitte study indicated that they were "highly" or "very highly" concerned about keeping key talent over the next 12 months, and 66% were similarly concerned about keeping high-potential personnel (Isson & Harriott, 2016).

According to Isson & Harriott (2016), the essential pillars of analytics in talent retention are the same as in any other area of analytics. They consist of:

1. Data: the raw material of any work of collecting information, processing, and generating insights from this data. Without data, there is no Analytics, and its existence and quality are critical success factors for HRA to be effective. The corpus of data to study churn/attrition should be composed of data from employees both who left and stayed in the company, so that it is possible to know what factors employees value in leaving/staying in the organisation. In this way, the model can be trained to discern the differences between situations and learn the patterns underlying each reality. Only then can an analysis generate predictions based on these patterns. This employee data should be as extensive, fast, and varied as possible to ensure reliable forecasts. There are also mechanisms, rules, and ethical assumptions that must be followed so that the collection, processing, and presentation of this data respect privacy and security.
2. Intelligence: the generation of value through data. From the data, several actions can be developed. First, the formulation of the problem facing management and using the data to generate insights for decision-making. People are essential to using this data strategically and with value for the business and people. It is important for an HRA

team to be multidisciplinary. Composed of experts in statistics, IT, but also HR, it must have contributions from various stakeholders and knowledge of the company's business. Only in this way can the use of data be truly useful in decision-making.

3. Technology: the software used to collect, process, and utilise this data. This ranges from software that is used to host the data (Microsoft Office, text and calculation files, etc.) to data mining and predictive analytics applications (SPSS, SAS, KNIME, R, PYTHON).

What can be concluded from the research in this study (namely the qualitative part) is that the most critical factor in the success and effectiveness of the HRA strategy (and any type of analytics) is the availability and quality of the data. Without this factor, no other factor will be useful or necessary. After using all these pillars of success in an HRA approach and the insights generated, recommendations can be issued to management, which are the real useful output in the HRA strategy.

The issue of retention is essential in people management because the departure of an employee means not only a financial loss, expressed in investment in training and qualification of the person, but also the loss of knowledge and experience to a competitor, a decrease in productivity, and a possible drop in employee motivation. "The cost of losing one employee is 1.5 to 2.0 times the person's annual salary," according to Josh Bersin, principal of Bersin (Isson & Harriott, 2016, p. 288). And this expense rapidly rises above double if the company is talking about a senior executive or highly skilled professional. This is due to the limited number of potential replacements for this individual, says the same executive.

A study by Deloitte concluded that for certain workers, excessive travel causes fatigue and demotivation, which is related to turnover intentions. But for younger workers, it's precisely the opposite; they value travelling as a driver of motivation for work (Isson & Harriott, 2016). To conduct an effective retention analysis, it is important to start by studying the factors that impact turnover intentions. The same Deloitte study concluded that it is important to study the evidence over time to act on it; otherwise, it will already be too late, and the employee will eventually want to leave. Today's workforce is very agile and adaptive, so if an employee is dissatisfied, they quickly look for alternatives and change. Another important conclusion of this study is that there is a strong reaction effect to extremes. Excessive travel, long hours, and little vacation time can all lead to voluntary departures; the more severe these circumstances, the more departures they will cause—and more quickly (Isson & Harriott, 2016).

Social media is another important source of information for HRA. Through the permanently generated data on social media networks, sentiment analysis and network analysis can create valuable insights about the workforce. Examples of social media data include posts, contributors, and content. Are users unhappy with their work? With work conditions? What connections are established at the level of published posts? Who likes, who retweets, who interacts, how many people and with what topics. There is an endless set of analyses that can be done with social media analytics, providing added value for many purposes, including HRM (Brito, 2021; Isson & Harriott, 2016).

These HRA models look perfect and can make automatic results, but is that really the case? There is evidence to suggest that it does. As identified in the previous Deloitte case study, statistical models with a broad range of data sources have been found to detect in the top decile (10 percent) those individuals who have a likelihood of departing from the company 330 percent more than the average. Furthermore, concentrating on the top two deciles (20%) of the workforce may enable retention of 65 percent or more of the departing workforce. These astounding figures demonstrate the predictive ability of these models, which draw from a multitude of data sources, years of expertise, and thousands of data points.

It is also very useful to link the churn models with the ELTV ("employee lifetime value") models (See "Effectiveness of HRA", Chapter 2.3.). It allows HR to know the different financial and strategic values of employees and shape human resources policies and practices directed at these audiences. On the other hand, it allows the use of resources in a strategic and focused way, directing most of the talent management investment to those employees who will give a greater return on that investment. If the company obtains this data, it will seek to act against the employees who cause the greatest negative impact if they leave the company.

When the company identifies the individual reasons for an employee to leave or the reasons that make them stay, it can implement policies and measures to retain the employee. This talent retention strategy involves first analysing the drivers of retention via HRA, followed by programming and designing retention initiatives at the individual level. The next step is to prioritise the implementation of these initiatives for individuals most at risk of leaving and those with higher impact. The final step is to quantify and monitor KPIs, updating them as they change and evolve (see Figure 2.10).

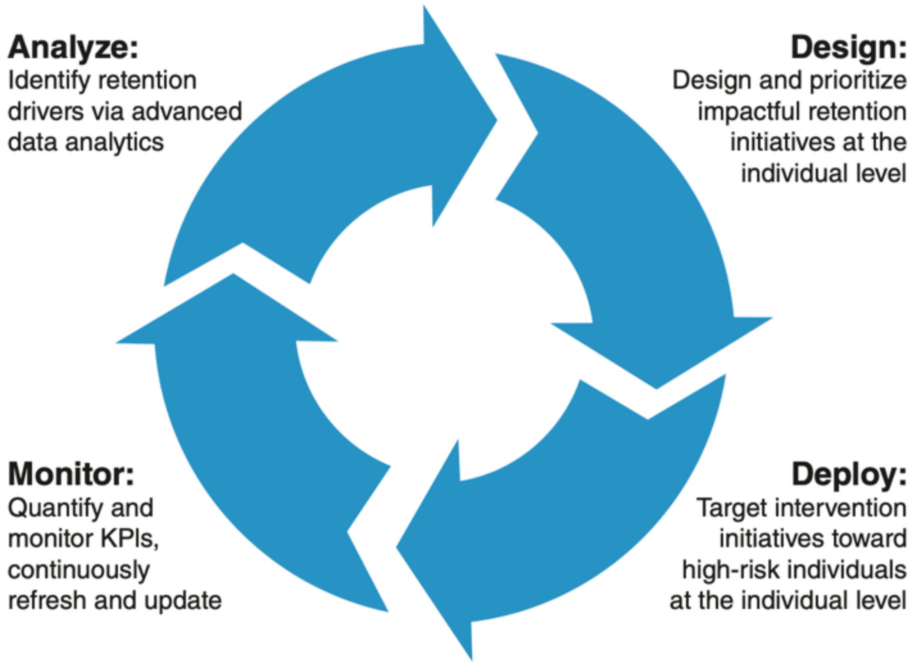

Figure 2.10: talent retention framework (Isson & Harriott, 2016)

A practical and numerical example of the effectiveness of an HRA approach to churn/retention involves an organisation with 50,000 employees and an average voluntary turnover rate of 5%, resulting in 2,500 employee losses annually. The organisation loses $500 million annually due to churn, which costs twice the yearly wage at an average salary of $100,000. Predictive algorithms might save $200 million if they can reduce the 5 percent churn rate to 3 percent (Isson & Harriott, 2016).

Price's Law (De Sola Price, 1965) states that the square root of the group's total number of members completes roughly 50% of the work in any group of people. For instance, the top 10 performers in a group of 100 oversee 50% of the production. If a retention strategy based on these powerful analytics is applied to the top performers in a company, the company may save millions of dollars with minimal effort while proactively seeking the best conditions for the workforce.

According to Isson & Harriott (2016), HR professionals and managers can proactively implement initiatives and strategies to fulfil company business objectives by using predictive models, which offer actionable information. Possible questions that can guide this research strategy include:

- Which talent issues are the most significant to the company?

- Which workers are most likely to leave the company? When and why?
- What kind of workers are most likely to quit?
- What danger does the company face from departing employees?
- How are the company staff doing right now? What are the trends?
- What are the organisation's primary causes of churn?
- How are they mapped by different employee subsets?
- Which staff are the company's key players and top performers? In the upcoming three to six months, which ones are most likely to depart, and why?
- What is the impact/risk?

Predictive models include two different kinds of variables together with an equation that unifies them:

1. Independent variables: These are included in the model to test and evaluate their link with the outcome event. The impact of these variables in outcome prediction is also provided.
2. Dependent variables: These are the components attempted to forecast. The churn/attrition status in this instance would be 1 = attrition and 0 = no attrition. These could also be referred to as responses.

There are three types of data that can be used in predictive models in general, and in churn/attrition models: company data, publicly available employee data, and labour market data. According to Arun Chidambaram, director of global workforce intelligence, only looking at internal data misses a big picture about talent retention (Isson & Harriott, 2016).

Data from tracking systems, training systems, and HR compensation data are examples of internal data. Financial performance, revenue, growth, customer base, brand, social media scores, online reputation, and evaluations and rankings of the company on Glassdoor and opinion sites are all examples of corporate statistics.

Data on the labour market comes from a wide range of sources and covers topics like GDP by industry location and company size, rate of unemployment by industry and size of organisation, cost per hire, turnover rate, indicators of the company's stock market trend, and stock market indicators, such as Standard & Poor's 500. It is important to compare internal turnover to industry standards; otherwise, the real picture can be missed. There is no "high" or "low" turnover, only one relative to the industry's levels.

Regarding publicly available data, it is the digital footprint of employees on the internet, namely on social networks. Facebook, Instagram, TikTok, LinkedIn, X accounts, published content and interactions can be accessed and analysed through social media analytics (Brito, 2021). This tool can be very useful to obtain data that is not accessed through the company's information, such as published posts, mentions, topics covered, links established, profile picture changes, followed groups, etc. In some industries, studies have shown that this data is responsible for 50% of churn in companies (Isson & Harriott, 2016).

2.9.1. Employee Churn Prediction

In the dynamic landscape of contemporary business, the pursuit of a resilient and committed workforce is paramount. The ultimate objective is to cultivate trust, commitment, and engagement among employees, both new and existing, enabling them to attain their goals and contribute significantly to the success of the organisation. Alarming statistics from the Bureau of National Affairs reveal that U.S. businesses suffer an annual loss of approximately $11 billion due to employee turnover, a cost magnified by recruiting expenses that run around 1.5 times the annual salary of the departing employee. Furthermore, the ability to engage and retain valuable employees significantly impacts an organisation's bottom line, making employee churn a critical concern (Brito, 2024).

Employee churn occurs when an employee leaves voluntarily or involuntarily from a company (Saradhi & Palshikar, 2010; Yigit & Shourabizadeh, 2017). Commonly, companies measure the voluntary churn rate because they can try to act on its causes and consequences. Unlike the concept of turnover, churn implies that the loss for the company does not have an immediate replacement. Finally, churn, unlike turnover, deals more with the financial consequences of an employee's departure (Pirrolas, Correia & Nascimento, 2022). "Churn" and "turnover" are concepts that are used interchangeably but are, in fact, different. "Attrition" is commonly used as a synonym.

The concept of churn is commonly used in the area of marketing and customer relationship management (Hassouna et al., 2015; Saradhi & Palshikar, 2010). "Customer churn" is the metric/rate that studies customers leaving a product or service. It is not as commonly used in the HRM realm, but recently the number of scientific and industry applications has increased as HRA has started to become an important trend in HR.

2.9.1.1. Turnover intentions

The costs of an employee's departure are various and extend beyond training costs to include the costs of finding another employee of the same value, the knowledge lost to a competitor, and the general loss of value. Most research on predictive models of employee churn and turnover intention is based on survey data or real company data (Ekawati, 2019). When it comes to real company data, it is possible to analyse longitudinal data or even real-time data, which enhances the reliability of the predictive models. For example, if satisfaction impacts turnover intention in each response of an employee, the model can capture changes daily. Conversely, when a researcher questions an employee using survey data, they only capture one perspective at a fixed time, and human behaviour can fluctuate. This is a cross-sectional approach. The advantage of this technique is that it is easier to deploy, and if the methodology and performance metrics of the model used are reliable, it has predictive ability.

Alternatively, the construct "turnover intention" is used instead of the employee's departure when it happens. The variable "turnover intention" represents the employee's propensity to leave their organisation (Ali et al., 2022; Rombaut & Guerry, 2018), not the act itself. The decision to leave the company follows a process of reflection and awareness called "turnover intention," which precedes the act of leaving (Hussain et al., 2020). Turnover intention is found to be the best antecedent to actual turnover (Griffeth, Hom & Gaertner, 2000; Joseph et al., 2007). It is described as a "withdrawal cognition process" (Jano, Satardien & Mahembe, 2019, p. 2). It includes the following elements: first, the employee considers leaving the organisation. The next step is to proactively pursue employment in another company. The final step is the ultimate intention to depart or resign (Mobley et al., 1979). Organisations frequently find it difficult to discover this objective unless the person discloses it to other employees (Jano, Satardien & Mahembe, 2019).

2.9.1.2. Turnover in Airlines

When it comes to the aviation sector, the topic of turnover is complex and nuanced. It is generally high (Efthymiou et al., 2021; IATA, 2018; Kiernan, 2018), although it varies depending on various factors such as the type of airline, profession, and aviation sub-sector. The three aviation professionals that suffer the most from shortages and experience higher turnover rates are ground staff, customer service, and cabin crew, with turnover rates of 20%, 18%, and 18%, respectively (IATA, 2018). Overall, turnover and absenteeism have significant impacts on airline operations (Chen, 2006), and recent numbers indicate that turnover is increasing significantly in the commercial air transport and aerospace & defence sectors (IATA, 2018; AIA, 2022).

The shortage of professionals is a key challenge in these sectors. An undeniable fact is that before the pandemic, it was predicted that 110,000 new pilots would need to be recruited and trained by the year 2028, with an expected annual loss of 3% of pilots over the following 10 years (CAE, 2018). CAE updated its estimate in June 2023, projecting a shortage of 252,000 new commercial pilots needed by 2032. In other words, if the commercial airline sector was thought to be at risk due to the pandemic, this assumption was incorrect. Demand for pilots doubled, with manufacturers' estimates even higher. Boeing predicted a demand for 649,000 new commercial airline pilots over the next 20 years (2023 to 2042). Airbus forecasted the need for 585,000 new pilots from 2022 to 2041. These estimates mirror forecasts for new aircraft deliveries: Boeing forecasted 42,595 deliveries between 2023 and 2042, while Airbus forecasted the delivery of 40,850 new aircraft (CAE, 2023). These numbers also reflect the anticipated increase in air traffic flows, which are expected to return to 2019 levels in 2024 and continue to grow (Airports Council International (ACI), 2023). This growth trend has been maintained for decades, despite setbacks like oil price crises, 9/11, or other pandemics (Brito, 2020).

In their latest HR report, the International Air Transport Association (IATA, 2018) concluded that the principal challenges faced by the HR function in aviation are recruitment, followed by employee retention, and thirdly, training and development. This study analysed a survey of 100 leading HR aviation professionals. 77% of respondents stated that employee retention in commercial aviation is an increasingly difficult challenge. Ground workers, customer service, and cabin crew experience 20%, 18%, and 18% turnover rates, respectively. The study also pointed out that traffic growth will demand more professionals, and that the area of training and development faces urgent needs. Providing training and development is a principal concern for prospective employees, especially the millennial generation. Safety and customer service skills are the main training needs for HR aviation professionals, even after the pandemic (IATA, 2021). Although technology is transforming the aviation business, the human role remains key to the customer experience in air transport, with IT skills ranked only 6th in training needs. The three main areas to attract talent in commercial air transport are a better salary and benefits package (70%), career progression opportunities (49%), and development and training opportunities (33%). The training and development budget already accounts for more than 50% of the overall HR budget in North America, Asia-Pacific, and the Middle East.

The great need for hiring professionals such as pilots and aeronautical maintenance technicians is especially noted in the Asia/Pacific Region (CAE, 2023). There is also the phenomenon of "talent theft" from eastern countries to western countries, where the latter are unable to match the conditions offered by companies with larger budgets and more robust fleet expansion needs. Conversely, legacy airlines offer better salaries, benefits, schedules, professional perks, and the prestige of operating in flag carriers with intercontinental routes, making their reality different from low-cost carriers (LCC).

The cost of turnover and absenteeism of flight crew is high and a critical problem in commercial airlines (Chen, 2006). For pilots and aeronautical maintenance technicians, the impact is significant not only on operations and revenue but also due to the cost of hiring, training, and complying with strict commercial airline regulations on training and safety (e.g., aircraft type certifications). A senior pilot and an entry-level first officer will have different motivations: the senior pilot prefers job stability and geographic location, while the entry-level pilot is primarily motivated by financial factors and has fewer family responsibilities (Efthymiou et al., 2021).

Turnover among pilots is also high due to the number of pilots reaching the maximum age to practice the profession (CAE, 2023). However, this is not voluntary turnover. It is also important to note that turnover is not uniformly high across the industry, as there are several areas within aviation. Following the International Civil Aviation Organization (ICAO) classification, these areas include "commercial air transport," "general aviation," "airport," "air navigation," and "maintenance and overhaul" (ICAO, 2019). This study focuses on "commercial air transport," commonly referred to as "airlines" or "commercial airlines." Within air passenger transport, there are various types of workers with different functions, making it challenging to compare satisfaction, turnover, and other variables.

Efthymiou et al. (2021) studied the factors of retention among pilots at the low-cost carrier Ryanair, which has high turnover rates due to its business model based on low wages and cost containment. This study assessed the factors influencing pilot retention in an LCC. It concluded that the main retention factors for Ryanair pilots were lifestyle, economic factors, and attractive rosters. The "Lifestyle" factor includes sub-factors such as a predictable roster, vacation time, family-friendly policies, the possibility to be based at home, and travel benefits. The economic factor includes "Competitive Salary," "Allowances," "Healthcare/Health Insurance," "Loss of License Insurance," and "Job

Security." The most valued sub-factors for respondents were being based at home, a predictable roster, and vacation time. In economic factors, the most chosen sub-factors were job security, salary, and healthcare/health insurance.

Pilots have traditionally been seen as having strong bargaining power for negotiating job conditions. Therefore, there is no evidence of generalised dissatisfaction and turnover intentions among pilots in legacy airlines. However, in a heavily unionised sector, there may be pressure and stress from operational and safety complexities, as well as the challenges and potential conflicts resulting from customer interactions, especially with cabin crew (Cheng et al., 2018b; Karatepe & Eslamlou, 2017; Karatepe & Kim, 2020; Vatankhah & Darvishi, 2018). While dissatisfaction may exist, union representation often channels these concerns, preventing them from manifesting as turnover intentions (Freeman & Medoff, 1984). However, turnover intentions can still exist with consequences such as "boreout" (Karatepe & Kim, 2020) or "quiet quitting," which have been less addressed in the literature.

Lambeth, Lei, & Cheung (2022) studied pilot remuneration policies at Virgin Australia and concluded that during COVID-19, this highly unionised class with significant bargaining power saw their salary conditions and benefits reduced. The authors viewed this as a potential case study for future airline management to gain more negotiating space. However, the circumstances contradicted this conclusion, as pilots and other commercial airline and hospitality professionals saw their conditions deteriorate due to the pandemic's temporary external shock and reduced demand. In Portugal, as soon as pandemic restrictions were lifted, demand for air transport increased, and so did the need for pilots and professionals. Consequently, salary and benefits cuts applied during the pandemic were reversed, leading to improved labour relations (Forbes, 2023).

Karatepe & Kim (2020) investigated the correlation between boreout and customer-oriented service among cabin crew members in South Korea. Boreout is defined as a negative psychological state of low arousal, represented by indicators such as a crisis of meaning at work, job boredom, and a crisis of growth (Stock, 2015, cited by Karatepe & Kim, 2020). They found that boreout undermines good customer service and has a negative correlation with customer-oriented service (loyalty, service orientation, participation).

Jano, Satardien & Mahembe (2019) studied the impact of perceived organisational support and organisational commitment on turnover intentions among commercial airline professionals. They found that lower perceived organisational support led to higher turnover intentions, resulting in lower organisational commitment.

In short, there aren't many studies on retention and turnover intentions among commercial airline professionals, and none with the characteristics of the present study.

2.9.1.3. Job Satisfaction

The literature on the topic of job satisfaction is extensive. However, despite its development, there is no unanimous definition. Nevertheless, certain elements are consistently present in the most widely disseminated conceptions in the literature (Wyrwa & Kaźmierczyk, 2020). The dimensions of job satisfaction most addressed in the literature are emotional and cognitive, and the degree of subjectivity that arises from individual perceptions and feelings regarding job satisfaction.

In addition to these differences in the evaluation of job satisfaction, situational factors also play a role. The most popular definition of job satisfaction is "an attitude that determines the degree to which employees find their work favourable or unfavourable" (Wyrwa & Kaźmierczyk, 2020, p. 152). However, this definition poses problems regarding the subjectivity of individual cognitions and emotions and the interaction between both. This conditioning brings an even greater level of variability to the characterisation of job satisfaction.

According to the conclusions of a recent systematic review of the literature on job satisfaction by Wyrwa & Kaźmierczyk (2020), there is not a single type of job satisfaction, but several aspects of job satisfaction; likewise, there is a degree of job satisfaction rather than a single perspective on the various aspects of work. Regarding the factors contributing to job satisfaction, there is a consensus in the literature that they are divided into two main groups: individual factors and group factors, that is, intrinsic and extrinsic, respectively. There are reasons for satisfaction/dissatisfaction that depend on the perceptions, attitudes, emotions, and cognitions of the individual, and factors generated by the external environment, namely the organisation in which the worker operates and the broader business and social environment. The interaction between these factors is also complex and can generate mixed influences on job satisfaction that are difficult to disentangle (Wyrwa & Kaźmierczyk, 2020).

Pujol-Cols & Dabos (2018), in a recent literature review on the same construct, draw the same conclusion. There are essentially two types of factors that motivate job satisfaction/dissatisfaction: 1) dispositional factors: personality qualities, for example, consistently influence job satisfaction; 2) situational factors: the nature of the work and the surroundings are important. The study emphasises the significance of considering both situational and dispositional aspects simultaneously to comprehend job satisfaction fully.

Job satisfaction is a concept that has been studied for many years and with thousands of contributions. The concept is not definitive as job satisfaction varies from person to person and involves several dimensions of analysis. In any case, job satisfaction can be associated with a set of feelings, cognitions, beliefs, and attitudes that people have in relation to their work. It is a set of positive or negative feelings (Armstrong, 2006; Huang et al. 2016; Spector, 1997; Vroom, 1964); it is also characterised as a set of emotional rewards that the person receives for this work (Statt, 2004); it is a combination of psychological, physiological, and environmental circumstances that lead a person to conclude that they are satisfied/dissatisfied at work (Hoppock, 1935; Williams & Hazer, 1986). According to this perspective, job satisfaction presents both a set of external factors that provoke an internal feeling of satisfaction and internal factors that determine this satisfaction. It's often associated with motivation, but it's not the same as motivation. In addition to an attitude, it can be a sense of success, whether quantitative or qualitative (Mullins, 2005) or a set of expectations that are met or not (Davis & Nestrom, 1985). From this, it follows that employee satisfaction will lead to a set of behaviours, positive or negative, resulting from satisfaction or dissatisfaction. Employee satisfaction is usually associated with improved performance and improved organisational efficiency and effectiveness (Aziri, 2011).

There are several ways to measure job satisfaction. The most used are two. A single global assessment of satisfaction and the assessment of various dimensions of job satisfaction (Robbins & Judge, 2009). In the first case, participants are asked: "All things considered, how satisfied are you with your work?" Participants must answer with a number on a scale between 1 and 5, "highly satisfied" to "highly dissatisfied". The other strand evaluates various dimensions of job satisfaction, such as the nature of the job, supervision, current remuneration, opportunities for promotion, and relationships with colleagues. The result will be an overall job satisfaction rating. There is evidence that the first approach is not incomplete because it effectively expresses a general feeling, which is rarely biased, in relation to the affection that the worker has for the function performed (Wanous, Reichers & Hudy, 1997). However, the second approach may provide a more in-depth analysis of the complex phenomenon of job satisfaction in its multiple characteristics and points of view.

More than the nature of the job, supervision, current compensation, promotion opportunities, and relationships with colleagues, the factor most correlated with job satisfaction is interest in the job itself. If the worker enjoys their work, it makes them more motivated and satisfied. Jobs that provide training, novelty, independence, and control satisfy most workers (Robbins & Judge, 2009).

When it comes to pay, it seems almost intuitive that it's the most cited reason for job satisfaction, but the evidence does not support this. Compensation is an important factor in lower income brackets, but once the employee starts receiving more money, compensation is no longer the primary motivation for job satisfaction. There is even no variation in satisfaction in compensation for an American earning $40,000 and $70,000. Money motivates people, but motivation is not the same as happiness. There is also often more satisfaction from good benefits than high salaries (Robbins & Judge, 2009).

Job satisfaction is also not only related to working conditions, but also to personality type. People who are less positive, believe less in themselves and their self-worth, and are less ambitious, are more likely to have less job satisfaction (Judge & Hurst, 2007). There is also evidence that there is more job satisfaction in Western countries, as there are more positive feelings and effort to improve working conditions and happiness (Gelfand, Erez & Aycan, 2007).

Since satisfaction is a feeling and an attitude, affective movements and ways of being led to behaviours. The "exit-voice-loyalty-neglect" framework (Farrell, 1983) explains how there are varied behavioural pathways to job satisfaction or dissatisfaction. The "exit" situation corresponds to the one that is active and destructive. The person reacts to dissatisfaction in an extreme way, which means starting to look for a position or leaving the company. The "voice" response is one that is active and constructive. The person is dissatisfied, but also interested in contributing to the improvement of their position and the organisation, as they still appreciate it or may still have some hope for the situation to change. In the "loyalty" reaction, the worker is passive and constructive. They are dissatisfied but do nothing because they think the situation can still change, defend the organisation to outsiders and believe in its good intentions. Finally, neglect is the passive and destructive response. The person is dissatisfied but does not leave the company. They miss work, show a lack of interest and motivation, arrive late and break schedules, and slack off their professional obligations.

It is not frequent to find relationships between several variables and job satisfaction partitioned by dimensions in academic literature, like “relationship between pay satisfaction and performance”, for example. However, there are several relationships between job satisfaction dimensions and other variables. Narrowing the study of relationships between job satisfaction and other variables to more specific dimensions of job satisfaction could be a good avenue of research.

2.9.1.4. Job satisfaction, Turnover Intentions and Performance

Positive correlations have been found in the literature between job satisfaction and performance, organisational citizenship behaviour, and customer satisfaction, as well as negative correlations between job satisfaction and absenteeism, turnover, and workplace deviance (Robbins & Judge, 2009).

Pay satisfaction significantly impacts turnover intentions (Singh & Loncar, 2010; Vandenberghe & Tremblay, 2008). However, there is no academic literature in the hospitality sector about the relationship between pay satisfaction and turnover intentions (Meira et al., 2024). Effective leadership styles, particularly transformational, entrepreneurial, and coaching leadership, are associated with higher satisfaction and lower turnover intentions (Gan & Voon, 2021; Wee, Bang & Park, 2020; Wells & Peachey, 2011; Yang, Pu, & Guan, 2019). Career-related factors significantly impact job satisfaction (Gu et al., 2010; Huang et al., 2017; Mosadeghrad, Ferlie & Rosenberg, 2008). Work/family satisfaction significantly affects turnover intentions, mediated through various factors such as job satisfaction, work-to-family conflict, and the specific context of the employment (e.g., family businesses, healthcare) (Chen et al., 2015; Lim et al., 2021; Mihelic & Tekavcic, 2014; Shu et al., 2018). The literature illustrates a clear link between safety satisfaction and turnover intentions across various industries, with a particular focus on the transport sector in general (Huang et al., 2016; Smith, 2018; Siu, Cheung & Lui, 2015; Zhang et al., 2023).

There is consistent evidence showing a link between job satisfaction and turnover intentions in the commercial airline sector (Chen, 2006; Jou, Kuo, & Tang, 2013; Suifan, Diab & Abdallah, 2017). Finally, job dissatisfaction is one of the strongest predictors of turnover intentions in an organisation (Mowday, Porter & Steers, 1982; Mulki, Jaramillo & Lokander, 2006). Literature demonstrates a nuanced relationship between turnover intentions and job performance, with an overall negative relationship between turnover intentions and job performance (Bishop, 1990; Hancock et al., 2013; Trevor et al., 1997; Wynen & Kleizen, 2019).

Job satisfaction is a critical determinant of employee performance in the commercial airline industry. Improving job satisfaction through positive work environments, recognition, and support can lead to enhanced employee performance and organisational success (Isnanto, 2021; Petty et al., 1984; Mansour et al., 2021; Hoole & Vermeulen, 2003; Firdaus et al., 2022; Lin-jing, 2010; Ng et al., 2009; Bakhsh, 2020). However, it has also been found that job satisfaction can have a negative impact on performance in commercial airlines (Supriyanto, 2018).

Historically, the academic literature on the relationship between job satisfaction and performance is not unanimous and clear (Iaffaldano & Muchinsky, 1985; Judge et al., 2001; Petty, McGee, & Cavender, 1984; Whitman, Van Rooy, & Viswesvaran, 2010). It is highly dependent on the various dimensions of job satisfaction and different types of job satisfaction and job performance relationships (Edwards et al., 2008).

2.9.1.5. Employee Churn Predictive Models

Several machine learning algorithms can be used to predict employee churn. Numerous models have already been created, and various approaches have been tested. The most common methodology in the academic studies consulted involves first identifying the "features" or factors that most influence employee churn. These can be found in theoretical data or corpus. From this point, several algorithms and approaches, ranging from machine learning to linear regression, are tested to determine which factors most influence employee churn and their relative contribution. Secondly, the aim is to determine which methodological approaches yield more significant results, whether traditional predictive methods or more complex machine learning-based approaches.

2.9.1.6 Factors Influencing Employee Churn

Many factors influence employee churn, and academic literature has studied several. Below is a rundown of the factors that most influence churn/attrition. From the literature review, the most used approaches are presented below (Table 2.1). This study conducted a literature review with the following criteria: searches were performed in the most reliable academic repositories, SCOPUS and WEB of SCIENCE, for the most recent scientific papers in Business/Management on employee churn predictive models, written in English, with no time frame for publication, using the search term "EMPLOYEE

CHURN" in the title. All publications that were not scientific papers, such as conference communications, book chapters, posters, etc., were excluded. After debugging the search, 13 papers were returned, and 9 were validated and are presented in the table (Table 2.1).

Table 2.1: literature review on employee churn predictive models (2011-2022)

Authors	Factors influencing employee churn	Method
Saradhi & Palshikar (2011)	Age, designation, gender, department, qualification, experience in years, employee location, experience in parent organization, experience in client organization, billed or not billed, on-site/off-site, designation in client organization	ML (Machine Learning). SVMs success over other techniques; use of ELTV
Yiğit & Shourabizadeh (2017)	Education, Education Field, Environment Satisfaction, Gender, Job Involvement, Job Level, Job Role, Job Satisfaction, Marital Status, Over-Time, Performance Rating, Relationship Satisfaction, Stock Option Level, Years Since Last Promotion, Years with Current Manager.	ML. SVM is the best method.
Dolatabadi & Keynia (2017)	Age, Marital status, Level of Education, Work experience (total), Area of expertise, Average number of services given per year, Average time assigned to each service, Sex, Relating certificate to employee service, Duplicate service or not, Miss Call service or not, Number of duplicate service, Resolved service on the first day or not, Service Class, Request Channel, Scope of service, Service time, Service Type, Referring to the software	ML. SVMs success over other techniques.

	development team or not , Year, Resolved service on the first calling or not, several features of customers and employees should be examined.	
Sisodia Vishwakarma & Pujahari (2017)	employee's salary, current position, promotion, (? ineligible)	ML. Random Forest better performanc e
Yahia, Hlel & Colomo-Palacios (2021)	Age, Marital status, Tenure, Grade, Rewards, Job involvement, Training, Business Travel, Job satisfaction, Job performance, Environment satisfaction	ML: deep and ensemble learning; multiple linear regression.
Srivastava & Eachempati (2021)	employee satisfaction, appraisal_rating, employee_CTC_level, number of projects/tasks assigned per quarter, time spent per project per quarter, safety measure, promotion	ML vs Deep Learning techniques + multiple linear regression. Deep neural networks better predictor
Ekawati (2019)	Literature Review. SVM in general, provides a reliable result to predict employee churn accurately.	
Jain, Tomar, & Jana (2021)	satisfaction level, last evaluation, number project average monthly hour time spent,	ML: CatBoost algorithm

	work accident, left, promotion last 5year, department, salary	outperforms other ML algorithms
Pirrolas, Correia & Nascimento (2022)	work environment, salary, recognition, leadership, work schedule	Multiple linear regression model; exploratory/ confirmatory factor analysis

"Turnover status" as a dependent variable appears a few times in these studies instead of "turnover intentions." The table summarises the most relevant recent studies on predictive models of employee churn carried out between 2011 and 2023. The table highlights two types of information: (1) which factors were found to most impact employee churn; and (2) the most effective statistical techniques considered for better predicting the phenomenon.

There are few studies in the literature that consider employee churn prediction and analysis (Yiğit & Shourabizadeh, 2017) and few with the dependent variable "turnover intentions," which predicts the phenomenon of churn better (Griffeth, Hom & Gaertner, 2000; Joseph et al., 2007), especially in terms of the actions that can still be taken if data is known beforehand. Some measures and policies can be implemented to prevent the churn of the employee.

The most recurrent factors associated with turnover intentions across these studies seem to be salary (Sisodia, Vishwakarma & Pujahari, 2017; Yahia, Hlel & Colomo-Palacios, 2021; Jain, Tomar & Jana, 2021; Pirrolas, Correia & Nascimento, 2022), job satisfaction (Yiğit & Shourabizadeh, 2017; Yahia, Hlel & Colomo-Palacios, 2021; Jain, Tomar & Jana, 2021; Srivastava & Eachempati, 2021), and promotion opportunities (Sisodia, Vishwakarma & Pujahari, 2017; Srivastava & Eachempati, 2021; and Jain, Tomar & Jana, 2021). Other factors such as age, marital status, job performance, leadership quality, and work environment also appear significant but are mentioned less frequently or are more study specific. These factors might be interconnected, influencing churn in combination rather than alone.

It is concluded that the factors influencing turnover intentions most used in the models are essentially extrinsic job satisfaction variables, and the following dimensions were retrieved and created for the model to be tested: “Pay satisfaction” (PS), “safety satisfaction” (SS), “work/family satisfaction” (WFS), “career satisfaction” (CS), “leadership satisfaction” (LS), and finally, Job Performance (JB) (Figure 2.11). The goal is to test how each one contributes separately to the churn phenomenon. According to the research carried out in the literature, this is not a usual approach; it is more common to address the factors that influence job satisfaction. Satisfaction has many dimensions and is the most determining factor influencing turnover intentions (Mowday, Porter & Steers, 1982; Mulki, Jaramilo & Lokander, 2006).

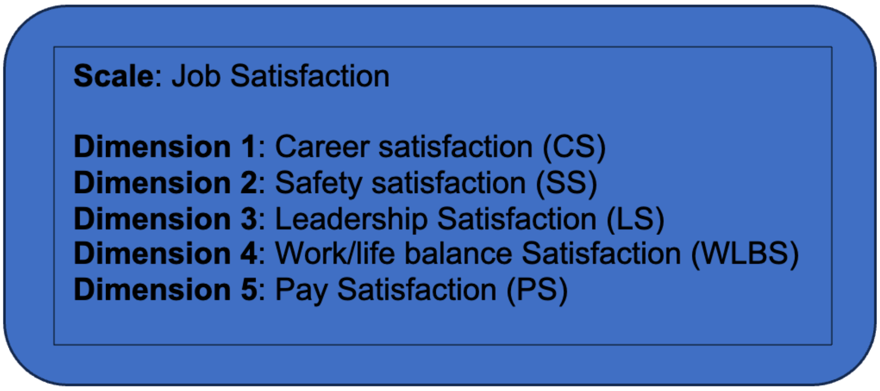

Figure 2.11: Dimensions of Job Satisfaction (author)

Srivastava & Eachempati (2021) pointed out two limitations to most churn predictive models in the literature. Most of them claim to know which factors motivate and predict churn but do not calculate the relative contribution of each of these factors to the model. Multiple linear regression models are proposed to make them more robust and beyond the simple linear prediction of churn. This is one of the research gaps intended to be filled by this PhD study.

Ekawati (2019), in a recent literature review of the predictive models of employee churn, presents several techniques that are most used, and the Machine Learning Support Vector Machine approach is outlined as the most reliable to predict the phenomenon (Table 2.1).

Four of the ten papers analysed in the most recent literature review by Srivastava & Eachempati (2021) on predictive models of churn are regression models. In only two models, qualitative methodologies are used, and in the remaining publications (4), machine learning models are used. The author classifies good models as those that compare various techniques, commonly machine learning and regression.

In the literature review done by this PhD study on the most relevant scientific publications on employee churn predictive models, almost all of them have the same methodological structure: an empirical study proposing a model to predict employee churn. There are essentially two ways to realise and test these models. The first, and the one that has been most used recently, is related to machine learning models in which large amounts of data are worked on (Yahia, Hlel & Colomo-Palacios, 2021) (Figure 2.12). It is customary to work based on real data, using a specific data lake, either from a company or from a public data repository such as Kaggle or IBM. Once there is access to that data repository, the pre-processing phase follows. This is where the data is cleaned and categorised. The next step is to split the data into training data and test data to test machine learning models such as Artificial Neural Networks, Decision Trees, Support Vector Machine, or Naive Bayes. After testing the effectiveness of the models in predicting employee churn, the interpretation phase follows, in which the goal is to explain to HR managers the reason for employee churn. Various performance metrics are tested to evaluate the predictive capability of the models. The result, with practical and strategic implications for decision-making, are recommendations of solutions for employee retention.

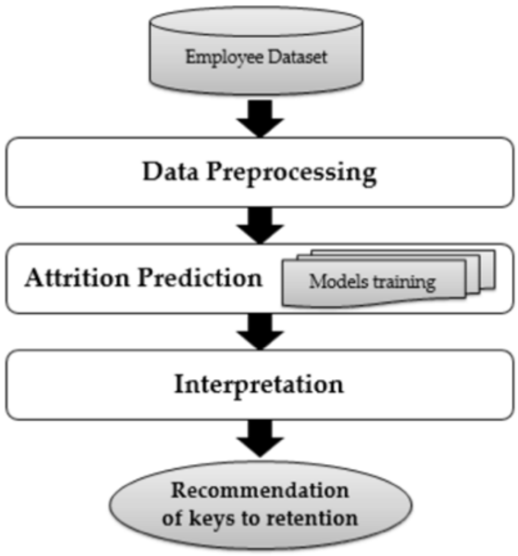

Figure 2.12: Architecture of a proposed approach to predict employee attrition/ churn with machine learning models (Yahia, Hlel & Colomo-Palacios, 2021)

The second most used methodological approach and the most traditional is exploratory factor analysis (Figure 2.13) (Pirrolas, Correia & Nascimento, 2022; Srivastava & Eachempati, 2021; Yahia, Hlel & Colomo-Palacios, 2021).

The starting point is to use an exploratory methodology to test which factors influence employee churn. The literature review is a more frequently used approach, in which factors identified as motivating employee churn are collected from several recent and relevant sources. From this research, some more relevant factors will remain. These will then be tested with data to assess their significance. Multiple linear regression models are used, and statistical tests are performed to verify the solidity and significance of the contribution of these factors (independent variables) to the dependent variable: turnover status or turnover intentions (both are used). After these tests, the most relevant factors that best explain the employee churn model will emerge. In practice, what are the factors that contribute most to employee churn? The goal is also to issue recommendations for HR management to improve employee retention and reduce employee churn.

In the most recent literature review of employee churn models, the most used approaches are machine learning, and in three papers, several techniques are used in conjunction with machine learning and more traditional methodologies. What is rarer is the use of mixed quantitative and qualitative methodologies. Only one study (Srivastava & Eachempati, 2021) found the combined use of quantitative machine learning and factor analysis techniques, along with the use of interviews.

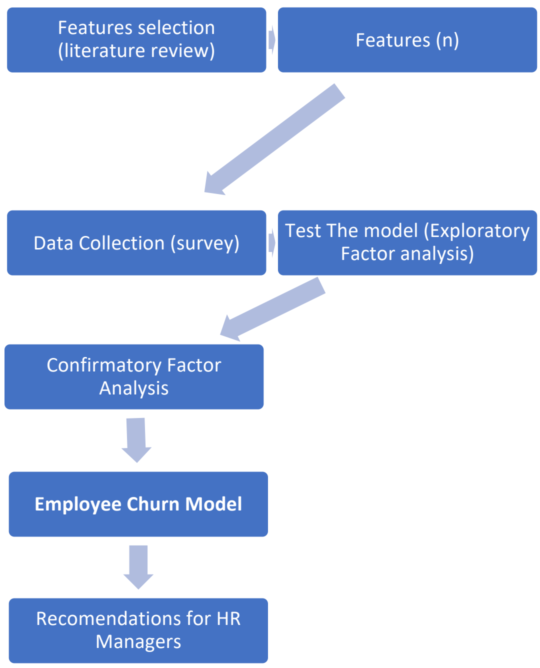

Figure 2.13: Employee Churn model methodology with Exploratory

Factor Analysis (EFA) (scheme from the author)

2.10. Research contributions of the PhD

In the quantitative study of this PhD research, a multi-linear regression model will be used, incorporating feature selection and factor analysis. Following Margherita (2022), a recent literature review on HR Analytics, recommended the need for more case studies in future research. Consequently, a case study on the commercial airline sector is proposed. Additionally, there are few studies employing a mixed-method methodology.

This study offers several unique contributions to the field of HR Analytics:

1. Provide additional evidence of the effectiveness of HR Analytics for business decision-making.
2. Few predictive employee churn models combine quantitative and qualitative methodologies. In a sectoral approach, each industry has specific problems and nuances that cannot be captured by public repositories of general data or by applying general factors to any area. A truly strategic HRA analysis requires good stakeholder knowledge (see CRISP-DM approach chapter). The contributions of HR experts and executives from the commercial airline sector, along with AI experts, are invaluable for the robustness of the model. Furthermore, the proponent's connection and experience in the commercial airline sector is useful, as any HRA analysis must start with the business problems (Rasmussen & Ulrich, 2015).
3. To date, no validated employee churn scale exists for Portugal's commercial airline sector.
4. No predictive model of employee churn has been developed for the commercial airline sector in Portugal.
5. Srivastava & Eachempati (2021, p. 5) concluded in their recent literature review on employee churn predictive models that the majority of methodological approaches are machine learning for prediction. "However, the feature importance that emerges is not validated by a robust statistical model like multiple linear regression." This study aims to address this gap.

6. Additionally, as stated by Srivastava & Eachempati (2021, p. 5), this study not only seeks to identify the factors influencing employee churn using a survey dataset but also aims to "compute or consider the relative importance of the factors influencing employee attrition/churn rate."
7. Current discussions on HRA mainly address two concerns: the lack of empirical evidence of the effectiveness of HRA and the need for more studies, particularly case studies (Margherita, 2022), and qualitative and mixed-method studies (Espegren & Hugosson, 2023).

CHAPTER III

Methodology

3.1. General Method

3.1.1. Introduction

The methodology used in this PhD study will be an HR Analytics case study based on a mixed-methods approach, both qualitative and quantitative. This methodology is used in few studies of this kind (Ergle, Ludviga & Kalvina, 2017; Hazarika et al., 2019; Srivastava & Eachempati, 2021). Recent literature reviews highlight the limitation of previous studies for not addressing qualitative methods in HRA academic studies: "It also goes hand in hand because studying HRA praxis in its context requires the application of qualitative methodology, such as observations and interviews" (Espegren & Hugosson, 2023, p. 16).

In the first phase, a literature review on HR Analytics was performed. Secondly, a qualitative methodology will be employed, conducting semi-structured interviews with HR professionals, executives in commercial airlines in Portugal, and general AI experts. These relevant professionals and academics will discuss the dimensions and priorities of people management in the commercial airlines sector to create value for people management and the business. Useful information about the companies involved in the case study, HR policies, and practices will also be analysed. Content analysis will be conducted on the semi-structured interviews to analyse, classify, and code relevant information (Lai & To, 2015). After the collection, analysis, and coding of qualitative empirical data, conclusions will be presented.

After obtaining information about HR management priorities and other useful data, a quantitative approach will be carried out in the third phase of this project, based on data collected from the interviews. These data will be related to the dimensions of analysis considered important by the experts. The employee churn phenomenon was chosen as an indicator to test in the airline industry. These data will be analysed, and through exploratory/confirmatory factor analysis, a new scale will be created and validated to predict employee churn in commercial airlines in Portugal. Multiple linear regression and other bivariate descriptive statistics will be used to test the model and understand the relationship between variables. A sample of 369 responses from airline professionals will be analysed through a questionnaire. The aim is also to generate a predictive model on employee churn and job satisfaction. Finally, the sample analysis results will be presented, with theoretical and practical implications explained (See Figure 3.1).

This study is exploratory, so no hypotheses are formulated beforehand. The empirical qualitative research and literature review will identify the variables to be analysed and the correlations to be established and verified in the quantitative part. In the last part of this PhD project, final conclusions, recommendations for practice and academia, limitations, and future directions will be drawn.

3.1.2. Why a Case Study? Why Mixed-Methods?

A case study is chosen to understand a phenomenon and generalize results (Eriksson & Kovalainen, 2016). An intensive approach will be conducted, using just one case. The number of cases to be studied will depend on the number of theories to be examined (Lokke & Sorensen, 2014). It can be concluded that a single case study is sufficient as all theories are evaluated under the same unique conditions (Ragab & Arisha, 2018).

The first step is to question, what is the subject of the study? In reviewing the literature on HR Analytics, there is a lot of questioning about the feasibility of these techniques and, despite the buzz around the topic, why is this area still fraught with conceptual questions and so underdeveloped and under-implemented in companies? (see literature review, chapter II). As previously outlined, the literature answers this last question by explaining the lack of AI/statistical skills in HR departments, high costs, privacy/security concerns, etc., but also directs future research towards providing more evidence of the effectiveness of HRA. The first question arises to tackle the conceptual questions of the literature: What are HR Analytics? The second one addresses the lack of evidence of the effectiveness of HRA: How is HR Analytics applied in organisations? Because the application is so questioned and so few case studies exist in the area, a case study seems to be the right choice of methodology.

This research asks "how" and "what" questions (HRA works) and thus, "The essence of a case study, the central tendency among all types of case study, is that it tries to illuminate a decision or set of decisions: why they were taken, how they were implemented and why that result" (Schramm, 1971, cited by Yin, 2018, p. 14). Cases include "individuals", "organisations", "processes", and "programmes" (Yin, 2018). "The more that your questions seek to explain some contemporary circumstance ("how" or "why" some social phenomenon works), the more that case study research will be relevant. Case studies are also relevant the more your questions require an extensive and in-depth description of some social phenomenon" (Yin, 2018, p. 4). Case studies rely on multiple sources of evidence (Yin, 2014). The approach is deductive as the case study is utilised for theory testing (Yin, 2011). There are previous literature assumptions about HRA, and the case will work to confirm or deny this evidence. This study's tested hypotheses make it possible to compare the case study's actual results with those predicted by the suggested theory (Darke et al., 1998).

The case selection phase is essential as the representativeness of the population is sought, and a non-probabilistic purposeful sampling is recommended (Seawright & Gerring, 2008). Regarding the methods for case selection, a "typical case" was chosen. These are cases that are representative of the population and the use is confirmatory (Ragab & Arisha, 2018). The commercial airline sector was chosen because it can serve as a reality to test HRA strategies. Additionally, it was found that this sector has few studies and HR problems that could benefit from HRA techniques.

Finally, a case study can be part of a mixed-method (MM) approach (Yin, 2018), and this PhD study follows that option. "What and how" or "what and why" are common questions for mixed methods research. Unknown parts of a phenomenon are generally the focus of mixed methods research questions, which combine "what", "why", and "how" questions and usually ask for the collection and analysis of both narrative and numerical data to provide insightful responses. Both qualitative and quantitative information, sub-questions, and outcomes are needed for MM questions (Tashakkori, Johnson & Teddlie, 2021).

The literature suggests that HR Analytics should start from the problems of the business, but there is little empirical evidence of this fact in HRM in commercial airlines, and in Portugal specifically. An exploratory first phase of the study (literature, interviews) can inform further steps into the quantitative study to answer the research questions. However, some existing theory about HR Analytics in general, and in the commercial airlines area in particular, will be used to test and potentially generate new knowledge from the data analysis. The objective when using this type of research methodology is to test or generate new theory about the phenomenon of HR Analytics from the empirical analysis of the Portuguese commercial airlines case study (Eisenhardt, 1991; Hillebrand, Kok & Biemans, 2001).

The research methods used, both qualitative and quantitative, will be triangulated with the theory already generated on the subject. As stated, other types of data will be used as complementary and for triangulation purposes.

The writing of case studies is done in a specific way. As the research approach is participatory and qualitative, with influences from grounded theory and the ethnographic approach, the case study will also have to be written in accordance with these research approaches. The narrative format (Dyer & Wilkins, 1991), and storytelling will be considered in the writing, to make it accessible to academics and other audiences, such as business practitioners (Eriksson & Kovalainen, 2016).

According to Creswell and Plano Clark (2018), mixed methods research allows for complementarity by leveraging the strengths of both qualitative and quantitative approaches to provide a comprehensive understanding of the research problem. This method also facilitates triangulation, which enhances the credibility of the findings by cross-validating data from different sources (Creswell & Plano Clark, 2018). Additionally, mixed methods enable the development of quantitative instruments based on qualitative insights and expand the scope of research by addressing different aspects of a phenomenon (Creswell & Plano Clark, 2018).

3.1.3. Research Questions and Conceptual Model of the PhD

The following rationale was used to conduct this PhD thesis. First, there is a need to base an HRA analysis on business problems. The research problems to be studied in the PhD project are three essential questions (Leedy & Ormrod, 2019):

1. What are HR Analytics?
2. What are the HRM problems in airlines?
3. How is HR Analytics implemented in airlines?

The HR variables and factors influencing HR phenomena will be identified by empirical qualitative research. So, this is an exploratory study as will be explained ahead. The conceptual model is outlined below in Figure 3.1.

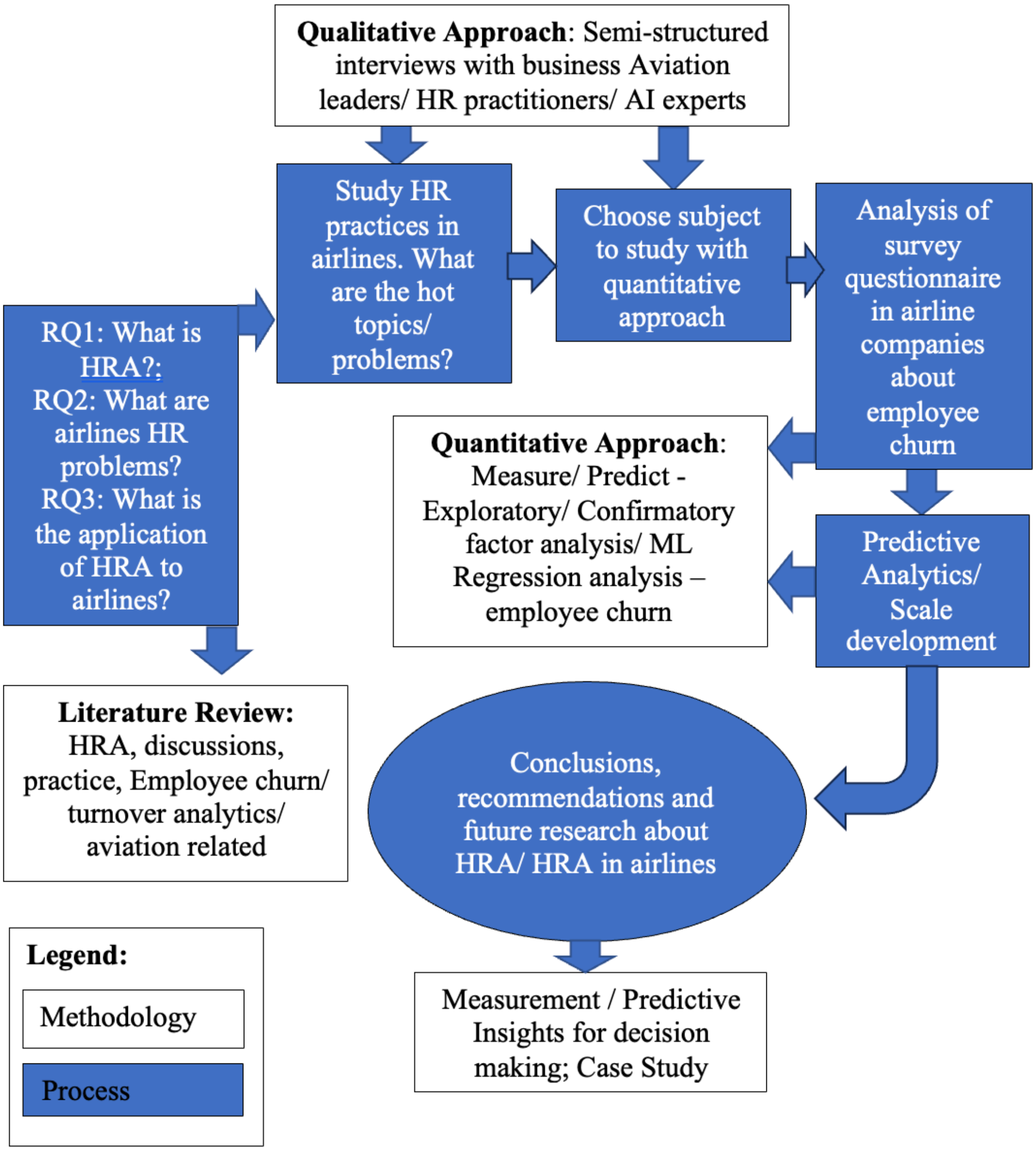

Figure 3.1: conceptual model of the PhD

3.2. Methodology – Qualitative Study

3.2.1. Introduction

A qualitative methodology was chosen for the first part of this study because, rather than testing known theories, the aim is to discover new theories through experiential observation of the data (Flick, 2005). There are few qualitative approaches to HR Analytics, which capture HRA praxis rather than conceptual knowledge (Espegren & Hugosson, 2023). There are no current perspectives on the challenges of human resources management in commercial airlines in Portugal, much less on the impact of data analytics on decision-making in people management in this specific sector, not only in Portugal, as seen in the previous literature review (see Chapter II). The choice of this exploratory approach allows for new insights, which can serve as a basis for more detailed analysis, as in the quantitative second part of this PhD study. Specifically, verbal data collection through semi-structured interviews was chosen (Bryman, 2012), and these were subsequently subjected to content analysis.

The research design followed the model of Miles & Huberman (1994), which structures data analysis in a qualitative approach with the following components: data collection, data condensation, data display, and conclusions (drawing/verifying) (Figure 3.2).

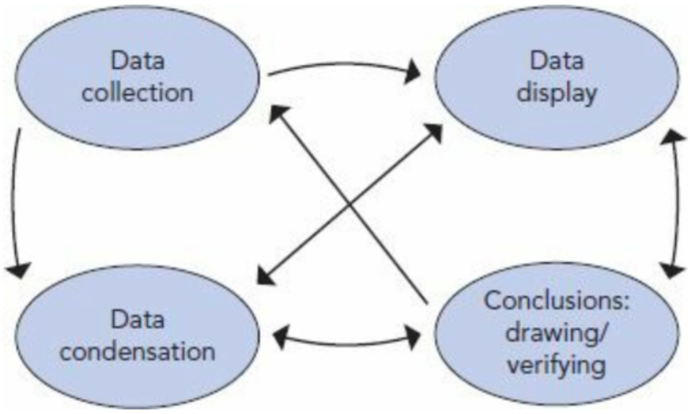

Figure 3.2: Components of Data Analysis: interactive model (Miles & Huberman, 1994)

In this PhD study, the qualitative research process began with data collection using semi-structured interviews. This was followed by data display, involving the listening and transcription of the interviews. After organizing the raw material from the interviews, content analysis was conducted. Here, conclusions are drawn from the data using methodologies such as interpretation, summarization, frequency counting, and clustering. This leads to data condensation, ultimately resulting in more definitive conclusions about the dataset. Regarding the crucial process of condensing information, “Data condensation is a form of analysis that sharpens, sorts, focuses, discards, and organizes data in such a way that ‘final’ conclusions can be drawn and verified” (Miles, Huberman & Saldaña, 2014, p.31).

In this specific PhD study, participants’ responses are interpreted, then summarized to their essentials, focusing on answering each question. They are clustered into major themes, paraphrased, using coding and interpretation. For each question, the responses of each participant are summarized, and finally, all responses are consolidated and grouped into thematic conclusions. For example, if the interview question is “What are the HR challenges in the commercial airline sector?”, the interpretation will create categories in which participants’ responses are placed.

Within the type of semi-structured interview, expert interviews were chosen. In this type of interview, the interviewee is valued more as an expert in the field than as an individual. They are included not as unique cases but as representatives of a particular group (Flick, 2005). Since the information provided by the interviewee is not as extensive as in other types of interviews, a more directive interview guide is constructed to avoid losing focus on the main topic and diverting the conversation to irrelevant subjects. It is essential and necessary for the interviewer to demonstrate knowledge in the area for the interview’s success (Flick, 2005).

3.2.1. Research Questions/Objectives

The qualitative approach of the study aims to serve as the first empirical data analysis tool for verifying the usefulness of HR analytics in the commercial airline sector. This qualitative approach is intended to be exploratory and will use semi-structured interviews, with the following research questions:

3.2.1. Research Questions/Objectives

RQ1: What are HR Analytics?
RQ2: What is its use in the airline sector?

In the literature review, the objective was to portray the principal knowledge present in academia and in practice. Now, the objective is to test theory in practice. The deductive approach aims to test theoretical assumptions in a real environment, such as aviation, and determine if the theory is confirmed.

Following the research questions, two general objectives (GO) guided the semi-structured interviews. These general objectives have resulted in six specific objectives (SO):

GO1: Understand the challenges in human resources management in the commercial airline sector

SO1: Understand the role, policies, and practices of HR in the commercial airline sector.

SO2: Identify the biggest HR challenges in the commercial airline sector.

SO3: Enumerate the business needs of the commercial airline sector.

GO2: Understand the application of HR Analytics in human resources decision-making in the commercial airline sector

SO1: Understand the perception of HR Analytics in the commercial airline sector.

SO2: Identify the possible applications of HR Analytics to HRM in the commercial airline sector.

SO3: List the existing dimensions and indicators of HR analytics.

3.2.2. Business Problems

Following the suggestion of Rasmussen & Ulrich (2015) and the CRISP-DM approach (Quinn, 2020), the most appropriate focus for HR Analytics is related to addressing business problems. Therefore, the research will start by seeking to understand the major challenges in human resources management in commercial airlines and the business challenges of commercial airlines. Subsequently, it will seek to verify how HR Analytics can help solve these problems by creating metrics, using techniques, and establishing strategies.

Another inspiration for focusing data analysis on actual business problems stems from the balanced scorecard approach applied to HR. The company's strategy is the starting point from which objectives are formulated, and then metrics are used to evaluate their execution, not the other way around: "The scorecard has to tell the story of a company's strategy. The biggest mistake organizations make is that they think that the scorecard is just about measurement" (Gabčanová, 2012). However, Analytics is a strategy that goes beyond the Balance Scorecard. HR Analytics uses Data Science techniques not only from a descriptive perspective (metrics) but also from a prescriptive, predictive, and autonomous perspective (Davenport, 2013; Roy et al., 2022).

Starting from another classic premise by business guru Peter Drucker that "What is not measured is not managed", HR Analytics can help solve the main HR management problems in commercial airlines in Portugal, an area of research not previously explored. Therefore, the PhD study will first seek to understand the role of human resources in the commercial airline sector. Then, the research will identify its challenges and, finally, determine how Big Data Analytics/HR Analytics can help measure these challenges and, through measurement and action based on these data, assist in decision-making. To provide empirical evidence for this premise, a qualitative study based on semi-structured interviews will be conducted with experts to create a decision-making model with recommendations for management. The main output of this approach will be recommendations for decision-making in human resources management in the commercial airline sector, particularly airlines.

The summary of the qualitative methodology developing the semi-structured interviews is expressed in Figure 3.3, represented below.

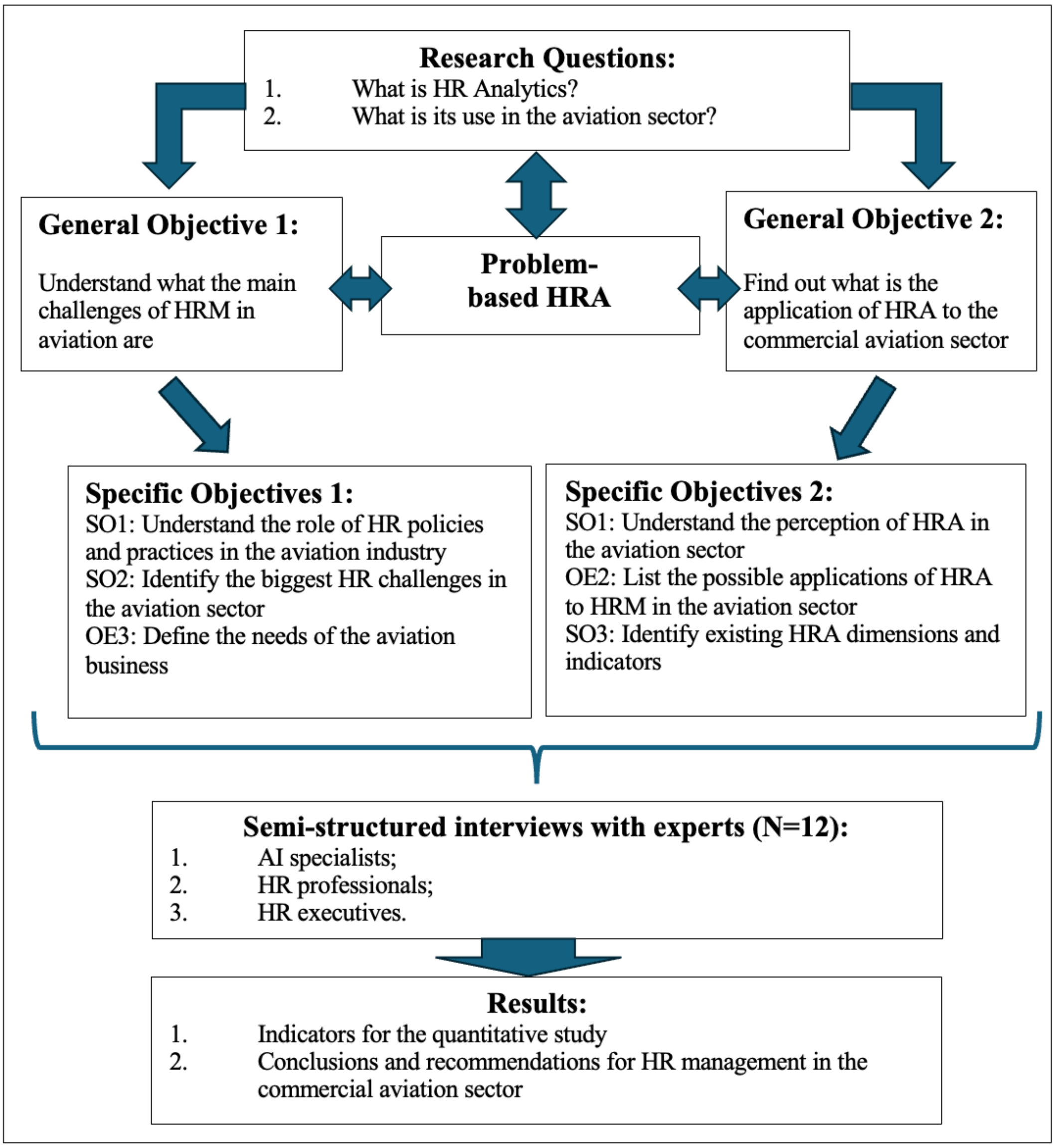

Figure 3.3: Summary of the qualitative methodology of the PhD study

3.2.2. Characterization of Study Participants

The participants in the study were chosen for their expertise in the area and ability to provide reliable testimony about the subjects. Twelve experts were interviewed, selected through intentional non-probabilistic sampling. Three types of professionals were chosen:

1. AI Experts (n=5): These individuals could provide insights into AI and the usefulness of Business and HR Analytics (HRA), including tools, methodologies, and applications. All these experts hold PhDs in Computer Science or similar fields and work as university professors. Three of them also have professional roles in private companies, either as full-time employees (2) or part-time consultants (1).
2. HR Professionals (n=2): These individuals have experience in the commercial airline sector, specifically mid-level managers involved in HR activities and functions. One is responsible for the HR analytics area of a large airline company in Portugal, and the other is a university professor, training director, and airline sector consultant. The latter also held positions in sales in two airlines.
3. HR Executives/Leaders in the Airline Sector (n=5):
   - One interviewee is a retired airline pilot with over 30 years of experience, who was an MCC (Multi-crew coordination), simulator trainer and training director at Portugal's flag carrier. He is now a consultant in human factors in airlines.
   - Another interviewee is a former HR director at the national flag carrier and now a business owner in HR consultancy.
   - The third interviewee is an airline pilot with over 30 years of experience in the airline sector and now the President of a relevant aviation association.
   - The remaining two interviewees include a director of an airline sector association and a business owner in HR management specializing in various sectors, including airlines (see Appendix A for the full characterization of the participants).

3.2.1. Demographic Characterization of Interviewees

The demographic characterization of the interviewees consists of males, aged between 32 and 65 years old, with experience in the field ranging from 7 to 41 years. The interviews were conducted between January and March 2023, via videoconference and in-person in some cases. They were recorded after obtaining written consent from the participants in the form of informed consent (see Appendix B) and final authorization from the ethics committee of ISCTE-IUL (see Appendix C). The main criterion for selecting the interviewees was their experience in human resources and AI, as well as the relevance and diversity of roles performed (tenure, function, seniority, type of company).

The interview guides (See Appendix D) were designed based on research questions (see conceptual model of the qualitative study, chapter 3.2.3.). The inspiration to use in this PhD study a mixed methods approach came from two sources: notably two case studies on HR Analytics in the commercial airlines sector: Ergle, Ludviga, and Kalvina (2017) and Hazarika et al. (2019) and the research gaps of the literature already outlined.

Three different interview guides were created depending on the type of expert: AI specialist, HR professional, or HR executive. The interview guide consists of 14, 12, and 8 questions for executives, managers, and AI experts, respectively (See Appendix D). The total number of questions of all the interview guides is 34, all of which were analysed individually and divided into the respective clusters of experts. Not all 34 questions are different; there are some same questions for all types of expert advisors and others specific to each type of expert. The interview guide for AI experts naturally did not include questions related to the commercial airline business. The process of transforming the questionnaire questions into categories observed the methodology of interpretation and categorization. A common question across all guides referenced the literature, specifically Isson & Harriott's (2016) seven pillars of HRA (see Chapter 2.3.3). Experts were asked about the existing HRA indicators for each dimension. During the interviews, it became apparent that AI experts were more acquainted with business analytics since few had worked specifically with HRA. However, this did not render the questionnaire inappropriate, as AI and Machine Learning techniques apply similarly in data science across various fields, including HR.

3.2.2. Data Collection Methods

In the chosen interview type, the semi-structured interview with experts, the reference questions are sufficiently open, allowing the interviewee to elaborate on the topic. There is no strict structure in that if the interviewee deviates from the topic the interviewer can use this opportunity to obtain more relevant content, follow the chosen conversation path, and ask new questions. However, there should be a guiding thread that leads the interview, which consists of the pre-conceived questions based on the research questions. The interview guide was developed based on the conceptual model where the research questions originate, which generate the general research objectives (GO1 and GO2), which in turn produce the specific objectives (SO1, SO2, SO3 for each GO) (see Chapter 3.2.2.).

The interview guides were validated by the supervisor regarding their content and coherence with the research goals and questions. After a pre-test with the first interviewee, the following adjustment was deemed necessary for the initial guides: initially, HR analytics was assumed to be an obvious concept for the respondents, but it was understood that this might not be the case for all. Therefore, the questionnaire was adjusted to include a priori definition of HRA.

3.2.3. Data Analysis Techniques

Once the interviews were recorded, they were transcribed, and the data was analysed using content analysis, employing semantic segmentation and thematic analysis (Braun & Clarke, 2006). The approach to creating categories was essentially inductive (open approach) (Fereday & Muir-Cochrane, 2006; Ghiglione & Matalon, 2005). This data treatment guides the interpretation and production of knowledge. Coding, categorization, and hypothesis formulation stem from the data itself rather than preconceived notions. Categories and subcategories are created from the data, generating new knowledge. Subsequently, the frequencies of these meanings are counted. Categories are created according to what is answered, then subcategories created, grouped, and counted in absolute and relative frequencies. Tables based on these categories and their frequencies are then generated. From these results, a ranking of themes most discussed by participants will be created by hierarchical classification. The methodology followed to create the subcategories (answers) started with the research questions. From these questions, a questionnaire was created. This questionnaire originated 10 categories of questions, which in turn originated 56 subcategories of answers. This process, from the research questions to the final content analysis of the answers, is represented in Figure 3.4.

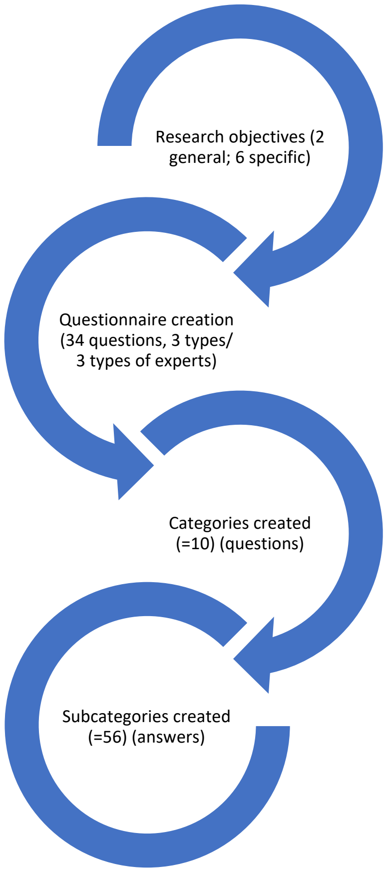

Figure 3.4. Content analysis's categories and subcategories creation process

The analysis phase of the interview corpus involves operations of coding, enumeration, and interpretation based on pre-established criteria (Bardin, 2011), consisting of four parts (Figure 3.5). These parts include identifying registration units consistent with research objectives, divided into categories (n=10); identifying subcategories (n=56); enumeration; and finally, consolidating the information (Figure 3.5).

The 10 categories correspond to the selected relevant questions subdivided among the three clusters of interviewees: AI experts, HR leaders, and HR managers in the airline sector. Subcategories of responses were identified within each category through an open inductive coding process, meaning they were generated spontaneously from the data as no pre-existing subcategory reference existed. The frequencies of these subcategories were then counted and identified as enumeration units (EU) (Bardin, 2011), resulting in 67 EUs (10 categories + 57 subcategories). Finally, all data was consolidated, interpreted, and inferred. The goal is to present a ranking of themes discussed by respondents and to quote the most significant and representative statements given by the majority.

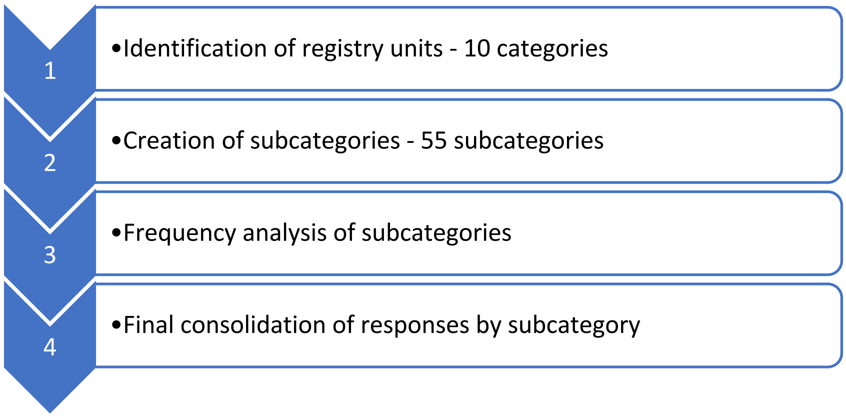

Figure 3.5: Data exploration phase of the interviews

Regarding the data presentation, it was finally consolidated into a table and then interpreted in text form. Microsoft Word and Excel were used for consolidating responses.

3.2.1. Execution phases

This study started with a review of the literature, which began with the characterization of HRA, what it is, and the state of the art of scientific and practical research in companies. The various dimensions of the topic, such as definitions and concepts, uses, best practices, technology, and challenges such as privacy and security, were addressed. The following study was carried out in this area specifically in the airline sector. It was justified to choose this sector to implement the HRA strategy. If data analysis is based on business problems (CRISP-DM), there is no better way to illustrate its usefulness than using a case study of a particular sector and country, with specific challenges and characteristics. The subject of retention was chosen, and therefore was also characterized in the literature review and presented as a key dimension in the semi-structured interviews ahead analysed. Finally, in the literature review, it sought to map which techniques and methodologies are most used in AI in this area. Not as a substitute for the chapter "methodology," but as a review of the literature precisely on methodologies. Data analysis is not only a strategic approach but also a methodology.

After this first phase and the premise that HRA should start from business problems, the researcher chose the qualitative approach as the first methodological phase of testing the main hypotheses of the study. As it was concluded that there was very little study on the application of HRA to the Portuguese commercial airline sector, the qualitative exploratory research, specifically the semi-structured interview, was chosen to find answers to the research questions: what is HRA? What is its usefulness in the commercial airline sector? What indicators are useful to measure?

The semi-structured interview part began by drawing up a screenplay of interviews, based on research questions and validated by the PhD supervisor. After this phase, professionals who would fit into the profile of interviewed experts were identified and listed. After this phase, the individual invitation of each specialist was made, to preserve the anonymity of the participation. After the acceptance of the invitations, the interview was scheduled, either in person or via videoconference (Zoom). The interviews were all recorded, with the prior acceptance of the respondents. It was subsequently distributed the informed consent document in which the respondents give their acceptance for participation in the study and the total privacy of all involved is ensured. A request for permission to conduct these interviews was also submitted to the ethics committee of ISCTE-IUL and the respective authorization was obtained.

After conducting the interviews and their transcription, the processing phase of the data was proceeded using qualitative content analysis. This methodology started by creating 2 (two) category tables corresponding to the two general objectives (GO) and their specific objectives (SO) (Table 3.1 and 3.2). The one corresponding to general objective 1 (GO1) (Table 3.1) represents five categories of questionnaire questions for 3 SOs. 5 (five) categories were created based on the same rationale on the SO (N=3) corresponding to GO2 (Table 3.2). After creating the categories, sub-categories were generated, based on the content analysis of the replies of the interviews. The results and discussion of the semi-structured interviews will be presented in chapter 4.1.

Table 3.1: Categories (questions) of General Objective 1 (GO1) and three Specific Objectives (SO).

General Objective 1 (GO1): Understanding the challenges in human resource management in the commercial airline sector	
Specific Objective (SO)	**Categories**
1	A. Role, policies and practices of HR in the commercial airline sector

2	B. Major current HR challenges in the commercial airline sector
	C. Differentiation HR generalist/ HR airlines
	D. Alignment business strategy/ HR strategy
3	E. Airlines, business needs

Table 3.2: Categories (questions) of General Objective 2 (GO2) and three Specific Objectives (SO).

GO2: understand the application of HR Analytics in human resources decision-making in the commercial airline sector	
(SO)	**Categories**
1	A. What is HRA?
2	B. Examples of predictive models
	C. AI/ HRA methods and techniques
	D. HRA Software
3	E. HRA/ Commercial airlines indicators

3.3. Methodology – Quantitative Study

3.3.1. Objectives

The quantitative study is constituted of two parts. The first part of this study is the creation and presentation of an instrument currently under validation of a new job satisfaction scale to predict employee churn in the commercial aviation sector in Portugal. An EFA (Exploratory factor analysis) and CFA (Confirmatory factor analysis) will be carried out to test the measurement capacity of this instrument.

The second one aimed to test the effect of job satisfaction on turnover intentions and performance, as well as whether turnover intentions affect the relationship between job satisfaction and performance. In this part a predictive model of employee churn will be tested, with the variables already mentioned, the five dimensions of job satisfaction from the literature review plus job performance and the sociodemographic variables.

Results will be presented. In the end, conclusions will be made along with theoretical implications and practical recommendations. As already pointed out the goal of this quantitative study is to test HRA predictive techniques and figure out the utility of these tools for decision making in HR. Also, it is aimed to understand what the theoretical implications of the empirical verifications of the models are testing.

3.3.2. Research model and hypotheses

The literature review carried out leads to formulate the following hypotheses, summarized in the research model (Figure 3.6):

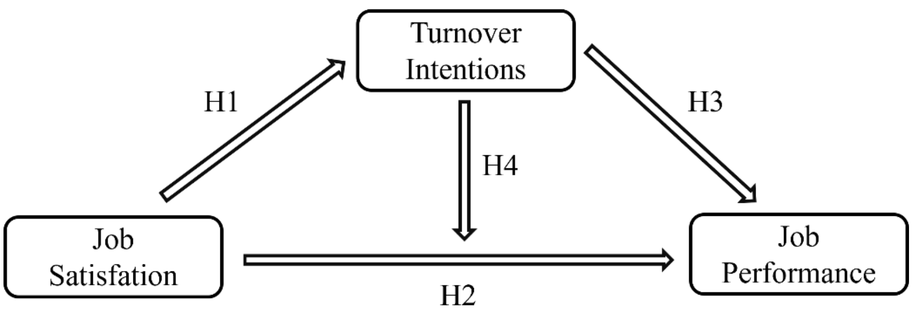

Figure 3.6: quantitative research conceptual model

Hypothesis 1: Job satisfaction has a significant negative effect on turnover intentions.

Hypothesis 2: Job satisfaction has a positive and significant effect on performance.

Hypothesis 3: Turnover intentions have a significant negative effect on performance.

Hypothesis 4: Turnover intentions have a moderating effect on the relationship between job satisfaction and performance.

3.3.3. Data collection procedure

A total of 369 subjects voluntarily participated in this study, all of whom worked for commercial air transport companies. Although 418 responses to the questionnaire were posted online on the Google Forms platform, 49 responses were not considered valid because the subjects needed to meet the conditions for working in the commercial air transport sector. The questionnaire link was distributed to members of the Portuguese Airline Pilots' Association (APPLA) and through LinkedIn to various airline professionals. Data collection took place between September 2023 and January 2024. The sample was non-probabilistic, intentional and snowball (Trochim, 2000). The first part of the questionnaire informed participants of the purpose of the study and guaranteed the confidentiality of their answers. As for informed consent, after the initial instructions, the participants answered a question about whether they wanted to take part in the study voluntarily. If they said no, they were sent to the final page (thank you). The questionnaire consisted of 7 sociodemographic questions and 15 items that make up an instrument designed to measure employee churn prediction.

3.3.4. Participants

This study's sample consisted of 369 participants, 139 (37.7%) female and 230 (62.3%) males. In terms of age, 59 (16%) were aged between 20 and 29, 99 (26.8%) were aged between 30 and 39, 143 (38.8%) were aged between 40 and 49, 59 (16%) were aged between 50 and 59 and 9 (2.4) were aged between 60 and 69. As for their profession, 78 (21.1%) belong to the Technical Crew (TC), 66 (17.9%) belong to the Cabin Personnel (CP), 67 (18.2%) belong to the Maintenance, Repair and Overhaul (MRO), 112 (30.4%) to the Ground Personnel (GP) and 46 (12.5%) perform other functions. In terms of academic qualifications, 88 (23.8%) had up to the 12th grade, 46 (12.5%) had a bachelor's degree, and 235 (63.7%) had a degree or higher. Among the participants, 95 (25.7%) had been with the organization for three years or less, 100 (27.1%) between 4 and 9 years, 95 (25.7%) between 10 and 19 years and 79 (21.4%) 20 years or more. About working hours, 93 (25.2%) work between 40 and 80 hours a month, 160 (43.4%) between 81 and 160 hours, 106 (28.7%) between 161 and 240 hours and 10 (2.7%) more than 240 hours. When asked if they had been promoted in the last five years, 202 (54.7%) said no, 157 (42.5%) said yes, and 10 (2.7%) said not applicable.

When seniority is cross-referenced with profession, the highest percentage for TC is between 5 and 9 years, for CP between 20 and 29 years, for MRO, GP, and others between 10 and 15 years (Table 3.3).

Table 3.3: Seniority of the participants by profession

	Profession					
Seniority	**TC**	**CP**	**MRO**	**GP**	**Others**	**Total**
Less than a year	3	10	5	1	4	23
	3.8%	15.2%	7.5%	0.9%	8.7%	6.2%
1 year	4	6	6	11	7	34
	5.1%	9.1%	9.0%	9.8%	15.2%	9.2%
2 years	4	7	5	7	4	27
	5.1%	10.6%	7.5%	6.3%	8.7%	7.3%
3 years	4	4	2	0	1	11
	5.1%	6.1%	3.0%	0.0%	2.2%	3.0%
4 years	6	2	1	5	1	15
	7.7%	3.0%	1.5%	4.5%	2.2%	4.1%
5 to 9 years	28	12	11	27	7	85
	35.9%	18.2%	16.4%	24.1%	15.2%	23.0%
10 to 19 years	15	10	21	41	8	95
	19.2%	15.2%	31.3%	36.6%	17.4%	25.7%
20 to 29 years	9	13	11	16	8	57
	11.5%	19.7%	16.4%	14.3%	17.4%	15.4%
30 to 39 years	5	2	5	4	6	22
	6.4%	3.0%	7.5%	3.6%	13.0%	6.0%
Total	78	66	67	112	46	369
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

When cross-reference the profession with the number of hours worked per month is performed, the study concludes that the highest percentage of TC and CP work between

81 and 160 hours per month. In contrast, the highest percentage of MROs, GPs and others work between 161 and 240 hours a month (Table 3.4).

Table 3.4: Profession of the participants crossed with hours worked per month

N. hr. worked/ month	Profession					Total
	TC	**CP**	**MRO**	**GP**	**Others**	
40 to 80 hours	31 39.7%	17 25.8%	8 11.9%	24 21.4%	13 28.3%	93 25.2%
81 to 160 hours	45 57.7%	41 62.1%	21 31.3%	39 34.8%	14 30.4%	160 43.4%
161 to 240 hours	1 1.3%	8 12.1%	35 52.2%	46 41.1%	16 34.8%	106 28.7%
Over 240 hours	1 1.3%	0 0.0%	3 4.5%	3 2.7%	3 6.5%	10 2.7%
Total	78 100.0%	66 100.0%	67 100.0%	112 100.0%	46 100.0%	369 100.0%

3.3.5. Data analysis procedure

The first step was to import the data into SPSS Statistics 29 software (IBM Corp., Armonk, NY., USA). The sample was then randomly divided into two parts, one with 106 participants and the other with 263 participants. Exploratory factor analysis aims to discover and analyse the structure of a set of interrelated variables to construct a measurement scale for (intrinsic) factors that somehow (more or less explicitly) control the original variables (Marôco, 2021). The KMO value was calculated, which should be greater than 0.70 (Sharma, 1996). Bartlett's sphericity test must be significant to indicate that the data comes from a multivariate normal population (Pestana & Gageiro, 2003).

The total variance explained was also calculated, which should be greater than 50%. As for the factor weights of each item, all items with factor weights greater than 0.50 were considered. Internal consistency was tested for each of the dimensions that make up the instrument by calculating Cronbach's alpha, which assesses the ratio between the variance of each item and the entire dimension. Its values vary between 0 and 1, with no negative values (Hill & Hill, 2002) and, in organizational studies, it should be higher than 0.70 (Bryman & Cramer, 2003).

With the other part, two confirmatory factor analyses were carried out, one factor and six factors. The confirmatory factor analyses were carried out using AMOS Graphics software for Windows (IBM Corp., Armonk, NY, USA). The procedure followed a "model generation" logic (Jöreskog & Sörbom, 1993). Following the established recommendations (Hu & Bentler, 1999), six fit indices were combined: Chi-square ratio/degrees of freedom (χ^2/gl); Tucker-Lewis Index (TLI); Goodness-of-fit Index (GFI); Comparative et al. (CFI); Root Mean Square Error of Approximation (RMSEA); Root Mean Square Residual (RMSR). The chi-square/degrees of freedom ratio (χ^2/gl) are considered an acceptable value if it is below 5. For the CFI, GFI, and TLI, values above 0.90 indicate a good fit and above 0.80 indicate an acceptable fit. As for RMSEA, values below 0.08 indicate a good fit (McCallum et al., 1996). The lower the RMSR, the better the fit (Hu & Bentler, 1999). The construct reliability for each scale's dimensions was then tested, whose value should be higher than 0.70. Convergent validity was tested by calculating the average variance extracted (AVE), which should be greater than 0.50 (Fornell & Larcker, 1981). As for discriminant validity, it was tested by comparing the root value of the AVE value with the correlation values between the factors. The square root of the AVE value must be greater than the correlation between the factors whose discriminant validity is being analysed.

Finally, with all the participants, the sensitivity of the items and their respective dimensions was tested. The items must have responses at all the response points, the median must not be close to one of the extremes, and the absolute values of asymmetry and kurtosis must be below 2 and 7, respectively (Finney & DiStefano, 2013).

3.3.6. Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is a technique used in data analysis to uncover and examine the structure of a set of interrelated variables. Its goal is to develop a measurement scale for intrinsic factors that, either explicitly or implicitly, influence the original variables. When two variables are correlated and the correlation is genuine, this relationship stems from a shared, common characteristic that is not directly observable (a common latent factor). EFA uses the observed correlations among the original variables to estimate the common factor(s) and the structural relationships linking these latent factors to the variables (Marôco, 2021).

This multivariate exploratory technique seeks to identify latent factors for a variety of applications. EFA's primary aim is to assign a score to constructs or factors that are not directly observable, generating a score that reflects highly correlated responses. This new score provides a concise representation of the information within the different variables, effectively summarizing the data from numerous variables into a smaller number of latent factors. These factors reveal structural relationships between variables that might otherwise be overlooked in the extensive set of original variables (Marôco, 2021).

For factor extraction, it is essential that the variables follow a multivariate normal distribution, as this process is highly sensitive to deviations from this assumption. The most commonly used method for assessing this is the "Kaiser-Meyer-Olkin measure of sampling adequacy." The KMO measures the homogeneity of variables by comparing simple correlations with the partial correlations observed among the variables.

The values of KMO can be characterized in the following manner (Table 3.5) (Sharma, 1996):

Table 3.5: KMO Scores for Exploratory Factor Analysis (Moreira (2013), adaptation and translation from the author)

KMO Value	Recommendation on EFA
]0.9; 1.0]	Marvelous
]0.8; 0.9]	Meritorious
]0.7; 0.8]	Medium
]0.6; 0.7]	Mediocre
]0.5; 0.6[	Bad but acceptable
≤ 0.5	Unacceptable

Regarding the number of factors to retain, only the minimum number of factors that allow us to adequately explain the phenomenon under study should be kept in mind. There are rules that should be used together to help the researcher decide on the most appropriate number of factors, such as the Kaiser criterion, or the "eigenvalue greater than 1" rule, which states that factors explaining more information (variance) than the standardized information of an original variable (value of 1) should be retained. The Scree plot criterion involves graphically representing the factors (on the x-axis) and their respective eigenvalues (on the y-axis) to understand the relative importance of each factor in explaining the total variance of the original variables. Factors should be retained until the point where there is an inflection in the curve relating the number of factors to their respective eigenvalues. The criterion of the variance extracted by each factor and the total extracted variance suggests retaining factors that extract at least 5% of the total variance or extracting a minimum number of factors that explain at least 50% of the total variance of the original variables.

However, the factor solution found in the EFA model is not always easily interpretable due to factor loadings being such that assigning empirical meaning to the extracted factors is difficult. Therefore, the Varimax Rotation Method is used. This method aims to achieve a factor structure where each original variable is strongly associated with only one factor and weakly associated with others (Marôco, 2021).

3.3.7. Confirmatory Factor Analysis

The strength of fit of a theoretical measurement model to the observed correlational structure of manifest variables (items) is evaluated using Confirmatory Factor Analysis (CFA) (Marôco, 2021). The main objective of CFA is to use the relationship between a small number of underlying variables to explain the covariance or correlation between several observable variables. This kind of analysis has a predefined model, a fixed number of latent variables, some latent variables' direct effects on observed variables set to zero or a constant, correlation between measurement errors, the ability to estimate or set the covariance of variables to any value, and the requirement for parameter identification, which calls for a comprehensive and identified initial model. Since CFA tests this hypothetical structure by postulating correlations between measured variables and preset components, it is best suited for situations in which a researcher has some prior knowledge of the latent variables under investigation (Lemke, 2005).

Two requirements must be met by all CFA measurement models: each factor must have a scale, and the number of free parameters must be less than or equal to the number of observations. Where v is the number of observed variables, the number of observations is equal to the number of observed variances and covariances [$v(v+1)/2$] (Kline, 1998).

Therefore, the entire number of variances and covariances of the components and measurement errors, along with the direct impacts on the indicator, add up to the number of parameters in CFA measurement models. Since latent variables cannot be measured directly, effect estimates including them must be computed using a measurement scale. Latent variables can be assigned a scale in two ways: either by loading an indicator by a factor of 1.00, which gives the latent variable the same metric as the indicator, or by setting the variance of a factor to a constant that standardises the latent variable (Wang & Head, 2007).

According to Marôco (2010), the broad CFA model is essentially the structural equation model's measurement model. The suitability of the calculated parameters and the overall suitability of the model are assessed while evaluating a structural equation model.

The correct sign and size of the estimated parameters, their estimates' admissible range, the correlations' absolute value being less than 1, the positive variances, covariance matrices, and/or correlations, the absence of excessively large or small standard errors, and the statistical significance of the parameter estimates are all necessary to confirm the adequacy of the estimates (Byrne, 2001).

To determine how well the model fits the sample data, the chi-square (χ^2) value, degrees of freedom, and probability value are analysed in the first stage. Assuming the model fits the population perfectly, the central chi-square distribution determines how sensitive the likelihood ratio test is to sample size. The difference between the data covariance matrix and the analysed model is assessed by the χ^2. The p-value needs to be less than or equal to the intended significance threshold (α) to reject the null hypothesis, which states that the given model replicates the population variances-covariances structure (Salgueiro, 2008). The chi-square ratio (χ^2/df) has multiple interpretations: less than five values are adopted by the more liberal ones (Garcia & Sánchez, 1992); The most acceptable interpretations take indices between two and three as indications of model adequacy to the observed data (Kline, 1994); the most cautious ones take model adequacy coefficients less than two (Ulman, 1996).

In order to overcome the shortcomings of the chi-square test, scientists created indices of goodness-of-fit to assess the model. The table below (Table 3.6) contains a list of the most popular ones.

Table 3.6: Adjustment Indexes for Factorial Models (Reference Values) (Moreira (2013), adaptation and translation from the author)

Adjustment Indices	Criteria	Adequacy level	Measurement
χ^2/gl Chi-squared ratio/ Degrees of Freedom	≤5.00	Excellent	According to Smith and McMillan (2001), it assesses the size of the difference between the sample and the matrix of the adequacy covariances.
TLI *Tucker-Lewis Index*	>.90 >.95	Satisfactory Excellent	It contrasts the tested model with the restricted null model, where all observable variables are independent (Bonnet and Bendler ,1980).
GFI *Goodness-of-fit Index*	>.90 >.95	Satisfactory Excellent	It contrasts a model's capacity to generate the variance/covariance matrix with the likelihood that no model could (Smith & McMillan, 2001).
CFI *Comparative Fit Index*	>.90 >.95	Satisfactory Excellent	Alternative to NFI, being more accurate on small size samples (Smith & McMillan, 2001).
RMSEA *Root Mean Square Error of Approximation*	<.08 <.05	Satisfactory Excellent	Estimates the amount of approximation of errors, by degrees of freedom, considering the sample size (Kline, 1998)
SRMR~ *Root Mean Square Residual*	≤ .08	Good	It estimates the square root of the error matrix divided by the degrees of freedom assuming that the fitted model is the correct one (Jöreskog & Sörbom, 1996, p. 30)

3.3.8. Reliability

The Cronbach Alpha coefficient is a useful tool for analysing the reliability of a scale and its dimensions. This coefficient assesses the ratio between the variance of each item and the total scale, representing the internal consistency of the scale. They do not assume negative values, and their values range from 0 to 1. (Hill & Hill, 2002). According to Bryman and Cramer (2003), an acceptable Cronbach Alpha in organizational research must be at least .70.

3.3.9. Sensibility

The ability of an item to discriminate against topics is referred to as item sensitivity. The median, asymmetry, flattening, maximum, and minimum of each item were examined for this reason. Items need to have answers in all points, the median cannot be next to any extreme, and the absolute values of flatness and asymmetry cannot be greater than 2 and 7, respectively (Finney & DiStefano, 2013).

A scale's sensitivity is defined as its ability to distinguish between subjects based on the factor that is being assessed. The average of the total items on each scale utilized in this study was determined for this purpose.

Kolmogorov-Smirnov (K-S) was the normality of distribution indicator employed in this investigation. If the significance level K-S exceeds.05., the normalcy hypothesis is adopted. The curve should be validated using the asymmetry and flattening criteria if the normalcy is not verified. If the coefficients given are near to zero, that is, fall into the range]-.50; +.50[, then the curve has a normal distribution. When the values exceed 1, it is considered that the data distribution is not of the typical kind (Marôco, 2021). According to Kline (1998), asymmetry and adherence are not problematic in evaluations of linear models that assume a normal distribution of residues if their absolute values are smaller than 3 and 7, respectively.

3.3.10. Stepwise Approach

This approach has the benefit of introducing new variables to replace a variable whose significance has decreased in the model; it is primarily suitable when there is a significant correlation between the independent variables (Marôco, 2021). When neither of the variables in the model is eliminated from the model nor can any of the independent variables that are still outside the model be included in the model, the process is over.

3.3.11. Instrument

This instrument was created based on a literature review (Table 3.7). It consists of 15 items that assess career satisfaction, safety satisfaction, leadership satisfaction, work/life balance satisfaction and career satisfaction (Table 3.7). The items are rated on a 5-point Likert scale (from 1 "Strongly Disagree" to 5 "Strongly Agree").

Table 3.7. Job satisfaction scale items (literature review)

Dimension	Item	Author (s)
Career Satisfaction	My career progression meets my expectations. My organization is concerned with developing employees' skills to progress in their careers. Career progression is complicated in my organization.	Sisodia et al. (2017). Yiğit & Shourabizadeh (2017). Yahia et al. (2021). Srivastava & Eachempati (2021). Jain et al. (2021).
Safety Satisfaction	I feel safe in my work environment. My organization cares about employee safety. My organisation often has accidents due to a lack of safety.	Jain et al. (2021). Srivastava & Eachempati (2021);
Leadership Satisfaction	My manager gives me every support in carrying out my duties. My manager cares about the well-being of his employees. My manager gives me zero support.	Yiğit & Shourabizadeh (2017). Pirrolas et al. (2022).
Work/life balance Satisfaction	My organization is concerned with reconciling employees' work and personal lives. My organization promotes initiatives that make reconciling work and personal life more manageable. My organization is not concerned with reconciling employees' work and personal lives.	Pirrolas et al. (2022);

Pay Satisfaction	My Salary is in line with my performance appraisal. I am satisfied with my Salary. My Salary does not reflect my professional performance, as it is too low.	Yiğit & Shourabizadeh (2017). Sisodia et al. (2017). Yahia et al. (2021). Srivastava & Eachempati (2021). Jain et al. (2021). Pirrolas et al. (2022);

CHAPTER IV

Results and Discussion

4.1. Qualitative Study

4.1.1. Roles, policies and practices of HR in the airlines sector

Regarding the results of the semi-structured interviews, GO1 (see table 3.1), "Understanding the challenges of human resources management in the commercial airline sector", 5 (five) categories have been created for the 3 SO (specific objectives), based on the questions in the interview script. For GO1/ SO1, 5 (five) sub-categories of responses have been created, as shown in bellow in table 4.1. At the end of this discussion chapter, the final summary table is presented in Tables 4.12 and 4.13. In addition to these general results, a column specially dedicated to the most significant quotes of the interviewees in direct speech of the answers given in each category is included (See summary Tables 4.12 and 4.13).

Table 4.1: Sub-categories of General Objective 1 (GO1) and Specific Goal 1 (SO1), Category A.

SO	Categories	Conclusions of the interviews (subcategories)
1	**A. Roles, policies and practices of HR in airlines**	1. Training - qualifications, certifications, reskilling and upskilling (71%)
		2. Careful recruitment and selection (57%)
		3. Strategic alignment with business (43%)
		4. Individualized care of people (43%)
		5. Implement the company agreements and labour legislation of the country (43%)

Regarding SO1, there are various roles, policies and practices of HR in the commercial airline sector. This category was created from the questions asked to experts (see Appendix D) namely the merger of the questions, "1) What do you think is the main role of human resources management in an commercial airline company", asked to executives and HR professionals, the question "4) What are the main human resources policies and practices of an airline", and "5) What are day-to-day tasks of a human resources manager?" both put to HR professionals. From the analysis of the answers, in this case the executives and HR professionals, it could be found that 71% of the respondents (5 out of 7) consider that the area of training is the main role of the HR department in a commercial airline company. In this area of "training" the results of qualifications and certifications, which are so important in the commercial airline regulatory framework, were included in the analysis of the responses. Finally, the respondents considered that it is not only important to grant these qualifications and preparation to employees, but it is essential that there is the updating of these skills with reskilling and upskilling, according to the needs and the constantly changing market situation. "*The sector has very specific requirements in qualifications and compliance", "Maintain/manage professional qualifications required for the function"*[1].

Secondly, with 57% of responses (4 out of 7) the main role and focus that HR departments should have in their practices should be in recruitment and selection. Not only has it been mentioned that this area is critical to success as this should be critical and not be done in any way: *"Recruitment and selection are critical", "The attraction and recruitment in this activity is more critical," "It is not enough to have recruiting, which already exists, but that it should be cautious"*.

Thirdly, fourth and fifth place in ex-aqueo, 43% (3 out of 7) of respondents identified that the main role and where should be focused the effort of HR policies should be in the strategic alignment between HR strategy and business strategy; in the care for people and, finally, the implementation of the company agreements and labour legislation in the country. Regarding strategic alignment, it was decided to create this subcategory considering the answers given and their consistency. 3 of the 7 respondents stressed that the alignment between the HR strategy and the business strategy is one of the main roles of personnel management in the commercial airline sector:

"Human resources can't just serve to process wages and fire someone from time to time, they should play a central role in outlining organizational strategy", "One of the key roles of human resources departments is to align with business strategy," "HR must speak the language of business", "HR should sit more in the board of directors as essential strategic voice." "There is a divorce between HR and the operational area. The first thing it should happen is to assess needs, there is no dialogue of both sides"

[1] The citations are from the respondents and the translation from Portuguese to English is from the author.

The approach given to legislation and labour relations is consistent with the nature of the commercial airline business, which is strongly syndicated, as has already been addressed. On this particular the respondents stated: *"one of the main roles of HR is to implement the company agreements and labour legislation of the country"* and *"negotiate better agreements with workers representative entities in order to obtain social peace"*.

4.1.2. Major current HR challenges in the commercial airline sector

From SO2, 3 categories of answers have been created (Table 4.2). Category B was created based on the merger of the answers to the questions (see Appendix D): 5) and 2), "What are the biggest human resources challenges in the commercial airline sector?" placed to executives and HR professionals, respectively. Based on the answers, 5 sub-categories have been created, presented the results in the same Table 4.2, below.

Table 4.2: Sub-categories of general objective 1 (GO1), specific objective 2 (SO2), category B.

SO	Categories	Interview Conclusions (subcategories)
2	**B. Major current HR challenges in the commercial airline sector**	1. Lack of soft skills (57%)
		2. Low retention (57%)
		3. Lack of strategic alignment with business (57%)
		4. Recruitment: lack of staff; poor recruitment (43%)
		5. Low HR Power (43%)

With 57% of the responses from the interviewees (4 out of 7) stating that the lack of soft skills is a major current challenge in HR management in the commercial airline sector. It can be said that this finding is in line with those made for the previous SO (see table 4.1), that is, both the main vocation and the main challenges of the HR departments in the commercial airline sector according to these experts revolve around the need for acquisition/reinforcement of skills, whether technical (hard) or non-technical (soft): *"Technical skills are not enough. Non-technical skills are critical"; "Adaptability is a key skill in today's commercial airline industry."*

Also, with 57% of the responses, HR professionals and leaders considered another major challenge in the sector to be the low retention of employees. *"Unfortunately, this* *happens, people not only leave the company but the country. The word is 'escape'. "In recent times, 15 mechanics have left. And it's not about money. In other companies, they have other career prospects, other salaries, and benefits."*

This conclusion aligns with the literature review conducted for this study (see chapter 2.9.1.2.). Also tied for first place in responses, the lack of strategic alignment of HR with the business strategy is considered by interviewees as a pressing challenge. This is also a present as the role of HR in SO1 (see table 4.1). In fourth and fifth place among the challenges, with 43% of the responses from interviewees (3 out of 7) are recruitment and the limited power of HR in the commercial airline sector: *"There is a lack of communication between strategic and operational aspects"; "There is a lack of understanding of the overall business strategy."*

In the area of recruitment (4), respondents mentioned the lack of people to hire and especially the lack of quality in these recruitments as pressing challenges in the sector. Finally, the challenge with 43% of the responses is linked to 3, which is the perceived lack of power of HR in commercial airline companies (3 out of 7 interviewees): *"HR has progressively lost power in commercial airline companies" "HR should assert themselves more on the boards of directors."*

The findings on SO1 and SO2 and category A and B, HR practices and challenges, respectively, are in line with the IATA findings (IATA, 2018). The 100 HR professionals interviewed for this study considered recruitment, retention of employee and training and development as the biggest HR challenges in aviation (see chapter 2.9.1.2.).

4.1.3. Differentiation between Generalist HR and Commercial airlines HR

Category C of SO2 was created based on question 2) of the interview guide: "Is there something that differentiates the human resources management of a commercial airline company from others?" asked only to HR leaders. From the content analysis of the interviews, 6 (six) subcategories of responses were created and presented in Table 4.3, below.

Table 4.3: Subcategories of General Objective 1 (GO1) and Specific Objective 2 (SO2), category C.

SO	Categories	Interview Conclusions (subcategories)

2	**C. Differentiation between Generalist HR and Airlines HR**	1.Compliance/ qualifications/ certifications/ specific regulations in addition to labour laws (80%)
		2. Critical soft skills (60%)
		3.Critical recruitment (40%)
		4. High HR costs (20 to 30%) (40%)
		5. More critical error management (40%)
		6. Unionization (strong politicization) (40%)

Most interviewees (4 out of 5) stated that what differentiates HR management in any sector compared to the commercial airline sector is the compliance component. The need for mandatory qualifications and regulatory requirements in terms of specific professional certifications, issued by the corresponding aeronautical authorities for each area and profession in the sector.

"Specific skills required (mastery of languages – communication technologies, languages, social networks, openness to difference, adaptability)" "Maintain/manage necessary professional qualifications for the role."

Secondly, with 60% of the responses, HR executives considered that what also differentiates the sector from others are the demands for non-technical skills crucial for operation: *"Create analytical processes that identify, recognize, and promote skills such as adaptability, resilience, self-motivation."* The term "critical" is often used not only in the skills component but also in the consequent recruitment area: *"Recruitment and selection in commercial airlines is critical because it deals with error management which can be fatal if not well managed."* This relates to flight safety as a critical area in commercial airlines and human intervention in the error issue, responsible for 70% of commercial airline accidents (Kharoufah et al. 2018). With 40% of the responses is then "3. Critical recruitment" as well as high HR costs (4) due to the cost of investment in specific qualifications; error management (5) (critical once again) of *"life or death"* and finally, once again the issue of unionization as an aspect not as present in other sectors. This strong *"politicization"* (in the sense of HR) is a challenge as something that differentiates the commercial airline sector from other sectors according to the interviewees: *"80% of HR's time is spent meeting with unions and worker committees."*

4.1.4. Alignment of Business Strategy with HR Strategy

Category D of SO2 was created based on question 4): "Is it easy to align the company's strategy with the human resources strategy?" asked only to HR leaders. This question was only posed to HR executives as it is a topic they may deal with more easily and which involves the delineation of a business or HR strategy and the consequent connection between both. Only one subcategory of response was created based on the interviews (Table 4.4).

Table 4.4: Subcategories of General Objective 1 (GO1) and Specific Objective 2 (SO2), category D.

SO	Categories	Interview conclusions (subcategories)
2	**D. Alignment of business strategy/HR strategy**	1. Doesn't exist (100%)

All interviewees (5 out of 5: 100%) unanimously stated that there is no alignment between HR strategy and the commercial airline business strategy as of the date of the interviews. The HR department *"is not considered in important decisions,"* it is not *"included in the board of directors,"* it is not included as a relevant part of the airline management, nor does it *"speak the language of operation"*. Once again, this subcategory (strategy alignment) is a recurrence of the responses already obtained on this topic as the "major challenge" (subcategory 3/category B/SO2 see table 4.2) and "main role" of HR in airlines (subcategory 3/category A/SO1, see Table 4.1).

4.1.5. Commercial airline Business Needs

For SO3 "What are the biggest business needs of commercial airlines" a question was created in the interview with HR leaders: "What are the biggest business needs in a commercial airline company? Based on the responses obtained in the interview, 6 subcategories were created and presented in the Table 4.5 below:

Table 4.5: Subcategories of General Objective 1 (GO1) and Specific Objective 3 (SO3), category E.

SO	Categories	Interview Conclusions (subcategories)
3		1. Customer service (punctuality, comfort, quality) (60%)
		2. Flight safety (40%)

E. Airlines business needs	3. Matching capacity to demand (40%) (fleet, resources)
	4. Cost differentiation (40%)
	5. Right people (40%)
	6. Financial resources (40%)

The most given response by the interviewees was "1. Customer service" as the greatest business need in commercial airlines (43% of the responses, that is 3 out of 5 interviewees). This subcategory was created and encompassed responses such as *"punctuality," "comfort,"* and *"quality."* As discussed by the participants in the interview, flight safety figures in second place below 50% of the responses and with equal weight for other types of responses: *"Without flight safety, there is nothing."* It's also possible to place the safety issue in the first subcategory as it is also a criterion of customer satisfaction naturally, but it was decided to extract this criterion and isolate it due to its importance and essential nature beyond general customer satisfaction as a mandatory and survival factor.

In subcategory 3, the need to match the available capacity in airplanes to the actual demand for air transport was included: *"Today the main problem is the need to match capacity to air transport demand."* In subcategory 4, the need for business cost differentiation was extracted, operational cost management that can create competitive advantages over other companies. These two categories fall under the need for operational efficiency. Only with 2 out of 5 responses did the interviewees mention people management as a business need (5). This result aligns with the responses to other questions, for example, the strategic alignment issue (Table 4.4). There is a subordination of HR in the commercial airline sector in favour of the core business area according to the interviewees.

It was also perceived by the researcher that there was a poor understanding of what HRA is. The general impression was that for the interviewees, "*operations (or sales) are what matters,"* even if they claim that HR should have more relevance in management and that careful recruitment is essential (5. Right people): *"There is a great need to hire the right person for the right place."*

Finally, the need for capital (6. Financial resources) is mentioned as an important business focus with 40% of the responses (2 out of 5): *"The commercial area is the most important as it allows the increase of the company's funds."*

In summary, according to the interviewees, the focus on the customer is the most pressing business need in commercial airlines.

4.1.6. What is HRA?

Regarding GO2 (general objective 2) (see table 4.6), “Understand what the application of HR Analytics in human resources decision making in the commercial airline sector is” there are 3 SO and 5 categories based on the questions asked to the interviewees. These categories already include AI experts. For SO1, a category (A) “HRA, what is it?” was created based on the question “8. Does the company you work for have a HR Analytics area? What do you think is the role of HR Analytics in a company?” asked to HR executives and managers; and “6. What is the usefulness of establishing human resources performance metrics in the commercial airline sector?” asked to HR leaders and managers. This is a conceptual category that seeks to unravel the views that the interviewees have about the main area of the study, HRA.

Five subcategories of responses were created (Table 4.6), and a high dispersion of response types was observed, that is, there was not a very significant or most adhered to definition. 43% of the interviewees (2 out of 7), almost half, responded: “1. Use of performance averages,” which is a definition somewhat below reality but indicative of the concept of HR Analytics being very associated with employee performance evaluation rather than HR policies. The reason interviewees oriented their responses this way may have been due to the way the question was posed and the term “performance metrics.” This may be a limitation of the questionnaire to improve in future studies. Other hypotheses are that the respondents are not directly involved in this area, the most probable one. This is partly the case as already outlined in the interviewees profile. Only one person provided a definition more in line with the most recent literature (subcategory 4): “Before it was the creation of metrics, now it is more predictive”.

Table 4.6: Subcategories of responses for SO1/ OG2 in category A: “What is HRA?”

SO	Categories	Interview conclusions (subcategories)
1	A. What is HRA?	1. Use of performance averages (43%);
		2. Strategic data analysis (29%);
		3.Does not know or deal with this area (29%);

	4.Before it was metric management, now it is more predictive (14%);
	5.Pattern identification (14%)

Nonetheless, all the definitions encompass some aspect of the HRA concept: *"Strategic data analysis"* (29%), *"pattern identification"* (14%). 29% of the interviewees responded that they do not know or deal with this type of area. In fact, only one of the interviewees is in an HR Analytics area in commercial airlines. Another stated having an academic publication on the area, and the rest demonstrated not being very connected to this field, with the majority being unanimous in defending its strategic importance in people management and commercial airlines business management. There were also responses expressing distrust in the effects of HRA, especially in the implications it has on people management and the problem of measuring subjective and sensitive indicators like human ones. Two interviewees (an executive and a manager), stated:

"There are processes of this type that are counterproductive. Either false expectations or bad environments are created".

"Portugal is made up of small and medium-sized companies, and it is very difficult to use this type of approach"

"It is necessary to train managers in the human part"

These statements are in conformity with the literature review made about this area, namely the perils/ risks and challenges HRA faces (Arora et al, 2022; Gal, Jensen & Stein, 2020; Giermindl et al., 2022; Minbaeva, 2021; Tursunbayeva et al., 2018).

4.1.7. Examples of predictive models

For SO2, which consists of understanding the applications of HRA in the commercial airline sector, 3 (three) categories were created: Models (B); Methods and techniques (C); and software (D). Category (B) "Examples of predictive models" was created based on the question "4. Can you present an example of how artificial intelligence could help in decision making based on Big Data in human resources management?" asked to AI experts. Five sub-categories of responses were created (Table 4.7, below).

Table 4.7: Subcategories of responses for OE2/ OG2 in category B: "Examples of predictive models"

SO	Categories	Interview conclusions (subcategories)
2	**B. Examples of predictive models**	1. Employee Churn (60%)
		2. Prediction of better recruitment (60%)
		3. Employee lifetime value (20%)
		4. Team coaching models (20%)
		5. Anticipation of employee stress; (20%)
		6. Prediction of training proposal actions; (20%)

With 3 responses out of 5 (60%), the most given response was "1. Employee Churn model." This is one of the, if not the most, popular predictive model in HR:

"Technology companies like this one often have people come here, stay for 2 years, gain knowledge, and then leave. This is a great investment made in people and then lost. This could be avoided with churn indicators and models that predict who will leave and proactively offer solutions to those people." (expert interviewed for this PhD).

In second place, with the same number of AI experts, respondents provided an example of a model that could predict the recruitment of the best HR profiles (2) (60%), two of them a recruitment model and another based on social networks:

"Given examples of CVs of people who have been approved or rejected in the past, trying to define which model determined which variables led to their approval or rejection, automating the selection process or at least indicating the approval level of a CV based on past experiences."

Finally, with only one response each, the interviewees discussed more examples of models such as "3. employee lifetime value":

"I worked in the past on a customer lifetime value model which calculated the value of a customer per operated flight, and this then had consequences in making some decisions. This indicator can also be used in people management."

Other examples that motivated the creation of more subcategories were “4. team coaching models,” “5. anticipation of employee stress due to supply chain disruptions,” and finally, the same specialist provided two examples of “6. prediction of training proposal actions to employees.”

4.1.8. AI methods and techniques

Still in SO2, the second application of HRA to the HR area in the commercial airline sector is the second category of questions: AI methods and techniques (C) based on the questions: “1. Regarding the use of artificial intelligence, what technologies/methodologies are used in establishing descriptive, predictive, and prescriptive models?” and “2. How could artificial intelligence be useful in the data analysis process and HR decision making in the commercial airline sector?” asked exclusively to AI experts.

Interestingly, in response to this question, participants unanimously circumvented it and considered that there is something more important than the techniques used. More than the techniques and software used, there are other critical success factors in the use of AI in decision making. These factors guided most of the responses. Within this category, three subcategories of responses and a list of the most used techniques and methodologies are presented in Table 4.8, below:

Table 4.8: Subcategories of responses for SO2/ GO2 in category C: “AI methods and techniques”

SO	Categories	Interview conclusions (subcategories)
2	**C. AI methods and techniques**	1. The availability, quality, and processing of data are critical success factors;
		2. The problem needs to be formulated first;
		3. CRISP-DM is a popular and useful data-mining approach and methodology;
		4. Methods and Techniques:
		[] Natural language processing (60%)
		[] Classification and regression algorithms (60%)
		[] Neural Networks (60%)
		[] Machine learning (60%)

	[] CRISP-DM (40%)
	[] Data Science (40%)
	[] Decision Trees (40%)
	[] Multi-agent system (intelligent agent)
	[] Sentiment Analysis
	[] Data Visualization
	[] Cross Functional work
	[] Deep Learning
	[] Exploratory Data Analysis
	[] Data mining
	[] Support vector machine
	[] Reinforcement learning
	[] Search Algorithms

Firstly, experts unanimously stated that the question about quality, processing, and access to data are more critical than the question about the use of which AI technique to utilize. Of course, as experts stated, the match between the correct algorithm for the specific problem is crucial, but with the wrong data, there is no algorithm that can help to extract true insights.

"Machine learning algorithms are all invented; what is done depends on the problem presented, asking ourselves what data we have that can help answer the problem's questions"

"The problem is not the algorithm but the data. What data will you use?"

"It is more important to discover the variables than to choose the approaches"

Access to data and ensuring they are of high quality depend on the researcher/manager and often do not happen because it is difficult:

"Convince yourself that the most important thing in your work is your dataset"

Secondly, it was mentioned that the conceptual methodology is also crucial, particularly the formulation of the research problem. Thirdly and lastly, the use of the CRISP-DM methodology was mentioned by a large part of the experts as a guide in the effective and pragmatic data-mining task with a strategic vision focused on business problems:

"CRISP-DM: contemplate various phases of data mining"

"CRISP-DM can be a good way to organize data-mining work"

"CRISP-DM is a possible methodology to guide the various steps of data processing"

"CRISP-DM is an iterative process, and we keep testing the model"

Finally, in the mentioned Table 4.8, the most frequently mentioned techniques (subcategory 4) by respondents are then listed. Respondents also said about the use of multiple techniques:

"Linear regression is a good starting point to enter other methodologies like decision trees or neural networks"

"With natural language processing (NLP), you process unstructured text to extract useful information or knowledge"

"Supervised classification algorithms: emulate the way a system works given examples of that system's operation"

"Unsupervised algorithms (clustering): look for, e.g., target profiles to determine which profiles were most successful within the company that does not require a fixed desired response but need to find sets and subsets and partition and then examine differences"

4.1.9. Software

In the chapter on HRA applications to HRM in the commercial airline sector, the third and final application (OE2) is Software (D) based on the question “3. What software can be used in data analysis?” asked exclusively to AI experts (Table 4.9). Once again, the participants unanimously stated that this question is secondary when there are other more important aspects, namely access and quality of data and added the data governance protocols factor.

“The problem is always access and data quality, not the software. They must be representative, for example. And the data must be correct. You have missing values and that makes it difficult for the algorithms to discover patterns.”

“Here, not only is the treatment important but also defining the methodologies, the data treatment protocol. From the point of view of access, etc. Building the entire component of master data management.”

There are many types of software, some more intuitive than others, but they serve to store, treat, and model data. The Table 4.9 below presents the subcategories based on the participants’ responses, resulting in a list of popular software used for data treatment and modelling.

Table 4.9: Subcategories of responses for SO2/ GO2 in category D: “Software”.

SO	Categories	Interview conclusions (subcategories)	
2	**D. Software**	1. Microsoft Azure	7. SPSS
		2. Amazon AI	8. IBM Watson
		3. Orange Machine Learning	9. Google Cloud Auto ML
		4. Python	10. SAP Success factors
		5. R	11. MATLAB
		6. Google Vertex AI	12. Google Colab

As with other subcategories, the general summary table presents some significant quotes from respondents (see Tables 4.12 and 4.13), like the following:

"There are tools that help the Data Scientist. Just upload the data to one of these cloud platforms – Google, Amazon, or Microsoft, for example - they will help you discover the important or unimportant features and have a pool of available algorithms."

4.1.10. HRA Indicators

A fundamental topic that was decided from the beginning to be part of the study were the relevant HRA indicators in the HR area in the commercial airline sector (Sousa et al. 2019). Therefore, the last specific objective (SO3) was to understand what the HRA indicators are in the commercial airline sector. What measures are used to gauge parameters and patterns, and which forms of measuring HR realities are most used in commercial airlines? This was the guiding question for creating the interview guide. The question that ended up being included in the corpus of questions was: "I will now present areas in which the Analytics literature demonstrates as relevant for performance measurement in Human Resource Management. Can you indicate some performance indicators by area?" asked to HR leaders, managers, and AI experts.

The literature on which this question is based includes the 7 pillars of effective HRA by Isson & Harriott (2016) (see Chapter 2.3.3.). The pillars are: 1) workforce planning; 2) recruitment; 3) selection/hiring; 4) integration, cultural fit, and engagement; 5) employee loss and retention; 6) performance evaluation and ELTV (Employee lifetime value), and finally; 7) employee well-being, health, and safety. Five subcategories were created based on the content analysis of the responses and presented in Table 4.10, below:

Table 4.10: Subcategories of responses for OE2/ OG3 in category E: "HRA Indicators".

SO	Categories	Interview Conclusions (subcategories)
3	**E. HRA indicators**	1. Operational performance and efficiency;
		2. Customer satisfaction and experience;
		3. Human resources management and recruitment;
		4. Employee skills and development;
		5. Employee health and well-being;

After the transcription was made and the answers were consolidated in the form of an enumeration of the mentioned HRA indicators by the participants, with the number of frequencies found, by interpretation and thematic analysis, clusters of HRA indicators were created. After creating the subcategories of indicators, some results were corrected, and the final complete list presented in Table 4.11.

First, respondents rarely provided effective indicators but rather themes on which indicators could focus, i.e., dimensions. Secondly, not only HRA indicators were mentioned but this is symptomatic and proves once again the importance of analytics leaving out of the HR department (Rasmussen & Ulrich, 2015). The dimensions were mentioned and are now systematized in Table 4.11.

Table 4.11: HRM Analytics in Commercial airlines Dimensions and Measures based on experts' interviews (organization and translation from Portuguese from the author)

HRM Analytics in airlines - Dimensions and Metrics	
Dimensions	**Indicators/ Dimensions**
1. Operational Performance and Efficiency	Number and quality of errors committed during flights
	Number of hours flown / number of workers
	Number of flights
	Annual route and flight plan
	Double checks
	Number of accidents
	Number of incidents
	Flight turnaround time
2. Customer Satisfaction and Experience	Customer satisfaction
	NPS by crew
	Demand for air transport
	Check-in service time per passenger
3. Human Resources Management and Recruitment	Employee satisfaction (5)
	Turnover (3)
	Match between task and required training (2)

	Training actions (2)
	Networking (2)
	Absenteeism
	Last-minute absenteeism
	Volume of training hours
	Bradford factor
	Overtime work
	Recruitment time for a given area
	Reasons for mismatch between task and training
	Selection process time
	Number of labour conflicts
	Training instructor score
	Balanced scorecard
	Job-person fit
	Recruitment success after 2 years
	Qualitative onboarding evaluation
	Employee retention rate after recruitment
	Employee performance level
	Pool of potential recruits
	Professional profiles
	First-year retention rate
	Exit interviews
	Retention rate in the first and fifth year
	Employee motivation
	Identification with leadership

	Tenure at the company
	Company tenure benchmarking
	Professional attrition/ churn benchmarking
	Periods of professional attrition/ churn
	Employee churn
	Employee lifetime value
	Employee experience
	Content analysis of employee interviews
	Organizational climate study
	Employee coaching
	Ages
	Qualification levels
	Socio-demographics (metrics)
4. Employee Competencies and Development	Soft skills - employee adaptability
	Employee market knowledge
	Knowledge of the competition
	Availability to change roles
	Ability of employees to learn other roles
	Business literacy among employees
	Use of skills applied in the first months of hiring
	Intuitive evaluation of forecasts
	Requested and verified skills
	Proactivity
	Merit
	Employees' holistic vision capacity

	Employees' understanding of the organization's mission
	Job rotation rate (number of roles performed in the company)
	Communication evaluation
	Leadership evaluation
	Workload evaluation
	Initiative capacity
	Employee fit to projects
	Cost/benefit intersection of the employee
	Retention causes
	Job performance measurement
	Performance management
5. Employee Health and Well-being	Mental health
	Lifestyle
	Rest periods outside of work
	Stress management
	Psychotropic substances
	Balanced diet
	Physical exercise
	Safety compliance
	Health-related absenteeism
	Sense of belonging
	Internal merchandise sales
	Disease prevalence
	Health regulations

	Medical control
	Number of interactions/ socializations with employees

Without any order of frequency, several "1. operational performance and efficiency" indicators are related to air operation (*number of flights, route plans, number of accidents, etc*.) were indicated by the respondents. The participants did not answer the question as these are not HR indicators. However, they are useful as they reveal relevant dimensions to create indicators. They also prove what is important to measure and the place that HR has for the participants and for the commercial airline industry. Secondly, participants considered it very important to measure indicators related to "2. customer satisfaction and experience,". Once again outside the scope of HR but not less interesting to acknowledge (*NPS – Net Promoter Score, customer satisfaction, service time, etc.*). In third place is the HR dimension: "3. Human resources management and recruitment" with indicators like *absenteeism, Bradford factor, motivation, job satisfaction, turnover*. The other two dimensions are again human resources related. They are: "4. Employee skills and development" and finally "5. Employee health and well-being.". In subcategory 4, indicators mentioned include the assessment of the presence of various technical but mainly non-technical skills in employees, and finally, in health and well-being, the indicators mentioned include, for example: *mental health, rest periods, stress management, physical exercise, etc.* (see complete summary Tables 4.12 and 4.13, bellow). The dimensions related to HR indicators are three out of five, which shows the importance of HR given by the participants.

Table 4.12: Summary table of the results of semi-structured interviews with experts (1)/ GO1 - Understand the role of HR in the commercial airline sector and its connection with the business

SO	Categories	Interview findings (subcategories)	Quotes from the interviews
1	A. Roles, policies and practices of HR in airlines	1. Training – qualifications, certifications, *reskilling* and *upskilling* (71%) 2. Careful recruitment and selection (57%) 3. Strategic alignment with the business (43%) 4. Individualized care for people (43%) 5. Enforce the company agreements and labour laws (43%)	• *"human resources professionals who know how to effectively understand what employees' problems are (...) and work closely with them. Now we see a lot of "head of people". This culture begins to enter. I think this is the way".* • *"the sector has very specific requirements in terms of qualifications and compliance".* • *"there is a chronic misalignment of HR with the business".*
2	B. Today's Biggest HR Challenges in Airlines HR	1. Lack of soft skills (57%) 2. Low retention (57%) 3. Lack of strategic alignment with the business (57%) 4. Recruitment: poor; lack of people; (43%) 5. Low HR power (43%)	• *"Unfortunately, this happens people don't just leave the company, but the country. The word is "escape".* • *"There is a habitual lack of knowledge among human resources departments regarding business strategy".* • *"Technical skills are not enough. The non-technical ones are critical".* • *"Adaptability is a key skill in today's commercial airlines".*
	C. Differentiation Generalist HR/ airlines' HR	1. Compliance / qualifications / certifications / specific regulations (80%) 2. Critic soft skills (60%) 3. Critical recruitment (safety) (40%) 4. High HR costs (20-30%) (40%) 5. Most critical error management (40%) 6. Unionization (strong politicization) (40%)	• *"In some professions such as commercial airlines, health has a special impact on people's lives - life or death"* • *"Specific skills required (mastery of languages – communication technologies, languages, social networks, openness to differences, adaptability)"* • *"Unionization. 80% of HR's time is meeting with unions and worker committees"* • *"Critical systems"*

	D. Strategic alignment business/ HR	1. Doesn't exist (100%)	• *"There is a common lack of knowledge among human resources departments regarding business strategy. The worst thing is that they don't know how to speak the business language"* • *"Human resources must participate more in the business strategy"* • *"There is a problem with transferring the strategic plan to the operational aspect"* • *"There is a lack of communication between the strategic and operational aspects"* • *"There is a misalignment between the commercial area and human resources in the commercial airline sector"* • *"In commercial airlines, human resources are usually a mere receiver of requests for people's needs raised by the operational area"* • *"Human resources cannot just be used to process salaries and fire someone from time to time. They must play a central role in outlining the organizational strategy."* • *"HR must impose itself more on boards of directors"*
3	E. Airline's Business needs	1. Customer service (punctuality, comfort, quality) (60%) 2. Flight safety (40%) 3. Adequacy of capacity to demand (40%) (fleet, means) 4. Differentiation by cost (40%) 5. Right people (40%) 6. Financial resources (29%)	• *"Without flight safety there is nothing".* • *"Today the main problem is the need to adapt capacity to the demand for air transport".* • *"The commercial area is the most important as it allows the company to increase funds".* • *"There is a great need to hire the right person for the right job."*

Table 4.13: Summary table of the results of semi-structured interviews with experts (2)/ GO2 - Application of HR Analytics to commercial airline's HR

SO	Categories	Interview findings (subcategories)	Quotes from the interviews
1	A. What is HRA?	1. Use of performance averages (43%). 2. Strategic data analysis (29%). 3. Does not know or deal with this area (29%). 4. Previously, metrics management, now a predictive dimension (14%). 5. Pattern identification (14%).	• *"Area that is responsible for providing maximum information to management. Firstly, it must guarantee the quality of information".* • *"I see the use of data analytics more as information analysis for decision making and process improvement, people analytics in a less prominent position as it deals with a variable that is difficult to measure (emotions) and using this approach can be counterproductive".* • *"There is no point in having analytics if it is not related to a real concern for people".* • *"It is one thing to analyze non-emotional processes, another to collect information from people".* • *"We produce indicators for ourselves and associated companies".* • *"Simply spectacular. Big Data and analytics are very important things for commercial airlines. Having indicators that are reflected on a daily basis is very important"*
2	B. Predictive models: examples	1. Employee Churn (60%). 2. Better recruitment forecast (60%). 3. Employee lifetime value; (20%) 4. Team coaching models (20%) 5. Anticipated stress in employees due to supply chain disruptions; (20%)	• *"Technology companies like this, people often come here, stay for 2 years, gain knowledge and then leave. This is a huge investment that is made in people and then lost. This could be avoided with churn indicators and models, in which it was predicted that people would abandon and proactively offered solutions to these people"*

	6. Proposal for training actions depending on the profile and skills of employees; (20%) 7. Forecast of necessary training actions depending on marketing campaigns carried out. (20%)	• *"We use predictive machine learning models, forecasting models, for example, for the sales area or even other diagnostics, through data lakes, to try to anticipate future scenarios"* • *"Given examples of CVs of people who have been approved or failed in the past, try to define which model determined it, which variables determined their approval or disapproval, thus automating the selection process, or at least giving an indication of the level of approval of a CV, based on past experiences"*
C. AI methods and techniques	1. Data availability, quality and processing are critical success factors. 2. You need to formulate the problem first. 3. CRISP-DM is a popular and useful data-mining approach and methodology. 4. Methods and techniques: [] Natural language processing (60%) [] Classification and regression algorithms (60%) [] Neural Networks (60%) [] Machine learning (60%) [] CRISP-DM (40%) [] Data Science (40%) [] Decision trees (40%) [] Multi-agent system (intelligent agent) [] Sentiment Analysis [] Data Visualization	• *"First of all, it is necessary to have a problem statement and not have the data and want to study everything. Formulating the problem comes first and then analysing the data according to this specific problem"*. • *"First of all, you need to have the data"*. • *"The algorithms in machine learning are all invented, what we do is, depending on the problem presented, we ask ourselves what data we have that can help answer the questions of the problem presented"*. • *"Artificial intelligence is used to identify patterns"*. • *"Linear regression is a good starting point to enter other methodologies such as decision trees or neural networks"*. • *"CRISP-DM is a framework that guides in a simple way the various steps that we must follow in data mining"*. • *"Another contribution of humans, in addition to machines in building models, is cross functional work. It is the ability for different business functions or different departments to collectively try to assess problems and create models and solutions for them through AI"*.

	[] Cross Functional work [] Deep Learning [] Exploratory Data Analysis [] Data mining [] Support vector machine [] Reinforcement learning [] Search algorithms	• *"It is more important to discover the variables than to choose the approaches".* • *"First, we must find a way to put the problem solved in one of these ways. Or classification, clustering, or searching or sequence of actions. This then leads us to the techniques that are used".* •*Data scientists take existing algorithms adjusted to the reality/problem in question and try to adjust them to the data presented and thus develop a machine learning model".*
D. Software	1. Microsoft Azure 2. Amazon AI 3. Orange Machine Learning 4. Python 5. R 6. Google Vertex AI 7. SPSS 8. IBM Watson 9. Google Cloud Auto ML 10. SAP Success factors 11. MATLAB 12. Google Colab	• *The problem is always data access and quality, not software. They have to be representative, for example. And the data has to be correct. You have missing values, and it is difficult for algorithms to discover patterns".* • *"It depends on who is using it and what they want to do"* • *"80% of a data scientist's work is around data".* • *"Orange Machine learning is a good user-friendly tool that helps us build machine learning models. Through tutorials. Minimally follows CRISP-DM".* •*" Depending on the data medium. Depending on whether they are structured or not".* •*" Python – when there is some complexity".* • *"There are tools that help the Data Scientist. Just upload the data to one of these cloud platforms – Google, Amazon or Microsoft – for example, they help you discover the important features or not, and they have a pool of algorithms available".*

3	E. HRA indicators	1. Operational performance and efficiency. 2. Customer experience. 3. Human resources management and recruitment. 4. Skills and development of employees. 5. Health and well-being of employees;	• *“You need to understand the reasons why people stay or leave a company”* • *“How long do people retain compared to other sectors”* • *“Create analytical processes that identify, recognize and promote skills such as adaptability, resilience, self-motivation”* • *“It is very difficult to measure a person’s nature. The person’s character, righteousness and choosing the right person is very important.”* • *“Candidate recruitment forecast based on organizational culture, skills and performance of a specific employee”*

4.1.11. Conclusions

The qualitative study aimed to explore the utility of HR Analytics (HRA) in addressing the challenges of human resources (HR) management in the commercial airline sector. Through semi-structured interviews with AI experts, HR professionals, and HR executives, several themes emerged, providing valuable insights into the current state and potential of HRA in this industry.

4.1.11.1. Role of HR in Commercial airlines

The findings reveal that HR in commercial airlines predominantly focuses on training, recruitment, strategic alignment, individualized care, and compliance with labour laws. Training, including qualifications, certifications, and continuous reskilling and upskilling, was identified as the primary role, reflecting the sector's high regulatory standards. Recruitment and selection were also critical, emphasizing the need for careful and strategic hiring processes. The alignment of HR strategy with business strategy, although recognized as important, is currently insufficient, highlighting a gap in strategic HR management.

4.1.11.2. Challenges in HR Management

Key challenges identified include the lack of soft skills, low retention rates, poor strategic alignment, recruitment difficulties, and limited HR influence within organizations. The lack of soft skills points to a broader need for non-technical competencies such as adaptability and resilience. Low retention rates and recruitment challenges underscore the competitive and dynamic nature of the commercial airlines labour market. The limited influence of HR suggests a need for greater integration and recognition of HR functions in strategic decision-making.

4.1.11.3. Differentiation of Commercial airline's HR

HR management in commercial airlines is distinguished by stringent compliance requirements, critical recruitment processes, high costs, and significant unionization. These factors necessitate a specialized approach to HR that is tailored to the unique demands of the commercial airline's sector. The importance of compliance and specific qualifications was particularly emphasized, reflecting the industry's regulatory environment.

4.1.11.4. Business Needs in Commercial airlines

Customer service, flight safety, capacity management, cost differentiation, and the need for the right personnel were highlighted as critical business needs. Customer service and flight safety were the most frequently mentioned, indicating their central role in business success. The alignment of capacity with demand and efficient cost management are operational imperatives, while the right personnel are crucial for maintaining service quality and operational safety.

4.1.11.5. Perception and Application of HRA

There is a varied understanding of HRA among respondents, with some associating it with performance averages and others recognizing its strategic potential for data analysis and predictive modelling. Commonly cited predictive models include employee churn, recruitment forecasting, and employee lifetime value, demonstrating the potential of HRA to address key HR challenges. However, there is also a recognition of the difficulties in measuring human factors and the need for quality data and proper data governance. Finally, the participants' perceptions match the literature in the perspective that HRA is not so known in the business and still is an area in its infancy. Also, there is doubts about the proper implementation not only because of the high costs but also derived from ethical concerns.

4.1.11.6. AI Methods and Techniques

The study identified several AI methods and techniques used in HRA, including natural language processing, classification and regression algorithms, neural networks, and machine learning. The CRISP-DM methodology was particularly noted for its structured approach to data mining. Despite the availability of sophisticated techniques, the quality and availability of data were consistently highlighted as critical success factors. The respondents again showed more knowledge about business analytics in general than HRA, confirming again the less visible role of this sub-area of Data/ Business Analytics.

4.1.11.7. HRA Indicators

The relevant HRA indicators identified span operational performance, customer satisfaction, HR management, employee skills, and health and well-being. These indicators reflect a comprehensive approach to measuring various dimensions of HR effectiveness and their impact on organizational performance. With this perspective of putting customer satisfaction first in people management indicators, it challenges human resources to leave their office and their processes, in a more traditional view and encourages them to meet the business problems that are at the forefront of the company. Only in this way will Human Resources be able to create value for people and ultimately for the business. This is another valuable insight from this study and serves as a recommendation for strategic human resource management. This recommendation is in line with the change that human resources have seen in recent years but there's doubts that the change will happen (Minbaeva, 2021). HRA only encourages even more this shift, the HR area is no longer subordinate to the business strategy but is itself a participant in the business strategy in which people are at the centre.

4.1.11.8. More Findings

This qualitative exploration underscores the potential of HRA to significantly enhance HR management in the commercial airline sector by providing data-driven insights and predictive capabilities. The findings highlight several key areas for improvement and strategic focus:

- **Strategic Alignment:**

There is a critical need for better alignment between HR and business strategies. HR must be integrated into strategic decision-making processes to ensure that HR policies and practices support and drive business goals.

- **Skill Development:**

Addressing the lack of soft skills through targeted training programs and development initiatives is essential. Investing in non-technical skills will enhance employee adaptability and resilience, which are crucial in the dynamic commercial airline industry.

- **Data Quality and Governance:**

The effectiveness of HRA relies heavily on the quality and availability of data. Establishing robust data governance protocols and ensuring access to high-quality data are fundamental to leveraging AI and HRA techniques effectively.

- **Predictive Modelling:**

Developing and implementing predictive models, such as those for employee churn and recruitment, can help anticipate and address HR challenges proactively. These models should be continuously refined and validated to ensure their relevance and accuracy.

- **Comprehensive Metrics:**

Establishing comprehensive HRA indicators that cover operational performance, customer satisfaction, HR management, and employee well-being will provide a holistic view of organizational health and performance. These metrics should be regularly monitored and used to inform strategic decisions.

Overall, this qualitative study provides a foundational understanding of the current state of HR in the commercial airline sector and the transformative potential of HRA. The qualitative study provides something that the quantitative study does not allow and that is the in-depth view of the HR area in aviation. By using an exploratory approach, by addressing the identified challenges and leveraging data-driven insights, HR in commercial airlines can play a more strategic and impactful role in organizational success. Future research should continue to explore the integration of qualitative studies in HRA. Additionally, HRA with business strategies and the complementary development of advanced predictive models, namely machine learning, tailored to the unique needs of airlines.

4.2. Quantitative Study

To assess the results of the quantitative study, the first step is to test the metric qualities of the instrument to be used, since it is a new instrument built for this PhD study.

4.2.1. Exploratory Factor Analysis

Exploratory factor analysis was initially conducted with 106 participants. A KMO value of 0.91 was obtained, which can be considered very good (Sharma, 1996). Bartlett's test of sphericity was significant at $p < 0.001$, which is an acceptable value for continuing the analysis, as well as an indicator that the data comes from a normal multivariate population (Pestana & Gageiro, 2003). It was found that the factor structure of this scale is based on five factors, as expected, which explain 79 % of the total variability of the scale. The remaining items have weights equal to or greater than 0.50, as shown in the Table 4.14 below.

Table 4.14. Factors and factor weights obtained in the exploratory factor analysis.

Item	Factor				
	1	2	3	4	5
My career progression meets my expectations.	0.34	0.35	0.14	0.34	0.51
My organization is concerned with developing employees' skills to progress in their careers.	0.42	0.33	0.28	0.24	0.53
Career progression is complicated in my organization.	0.17	0.13	0.16	0.12	0.87
I feel safe in my work environment.	0.49	0.13	0.27	0.58	0.23
My organization cares about employee safety.	0.49	0.15	0.39	0.56	0.20
My organisation often has accidents due to a lack of safety.	0.17	0.17	0.13	0.88	0.11
My manager gives me every support in carrying out my duties.	0.82	0.27	0.27	0.23	0.11
My manager cares about the well-being of his employees.	0.83	0.32	0.30	0.07	0.12
My manager gives me zero support.	0.78	0.18	0.18	0.19	0.26
My organization is concerned with reconciling employees' work and personal lives.	0.31	0.18	0.79	0.07	0.24

My organization promotes initiatives that make reconciling work and personal life more manageable.	0.21	0.23	0.79	0.10	0.31
My organization is not concerned with reconciling employees' work and personal lives.	0.21	0.14	0.72	0.23	0.06
My Salary is in line with my performance appraisal.	0.16	0.86	0.10	0.16	0.14
I am satisfied with my Salary.	0.22	0.87	0.17	0.17	0.16
My Salary does not reflect my professional performance, as it is too low.	0.24	0.81	0.25	0.04	0.08

4.2.1.1. Internal consistency

The internal consistency of each dimension of this instrument was tested by calculating Cronbach's alpha. Cronbach's alpha values vary between 0.77 and 0.91, which indicates that all the dimensions have good internal consistency, except career satisfaction, which has reasonable internal consistency (Table 4.15).

Table 4.15: Internal consistency of the dimensions

Dimension	Number of items	α
Career Satisfaction	3	0.77
Safety satisfaction	3	0.82
Leadership Satisfaction	3	0.91
Work/life balance Satisfaction	3	0.81
Pay Satisfaction	3	0.90

4.2.1.2.Confirmatory Factor Analysis

Two confirmatory factor analyses were conducted with 263 participants, one and five factors. The fit indices were inadequate in the one-factor confirmatory factor analysis ($\chi 2/gl = 9.66$; CFI = 0.66; GFI = 0.65; TLI = 0.60; RMSR = 0.15; RMSEA = 0.18). The five-factor confirmatory factor analysis obtained adequate fit indices ($\chi 2/gl = 1.27$; CFI = 0.99; GFI = 0.95; TLI = 0.99; RMSR = 0.05; RMSEA = 0.03). These results indicate that the five dimensions extracted in the exploratory factor analysis have been confirmed. All the items have factor weights greater than 0.50 (Table 4.16).

Table 4.16: Factor weights obtained in the confirmatory factor analysis

Dimension	Item	Factor weights
Career Satisfaction	My career progression meets my expectations.	0.79
	My organization is concerned with developing employees' skills to progress in their careers.	0.85
	Career progression is complicated in my organization.	0.51
Safety Satisfaction	I feel safe in my work environment.	0.74
	My organization cares about employee safety.	0.91
	My organisation often has accidents due to a lack of safety.	0.56
Leadership Satisfaction	My manager gives me every support in carrying out my duties.	0.90
	My manager cares about the well-being of his employees.	0.91
	My manager gives me zero support.	0.82
Work/life balance Satisfaction	My organization is concerned with reconciling employees' work and personal lives.	0.85
	My organization promotes initiatives that make reconciling work and personal life more manageable.	0.84
	My organization is not concerned with reconciling employees' work and personal lives.	0.67
Pay Satisfaction	My Salary is in line with my performance appraisal.	0.87
	I am satisfied with my Salary.	0.95
	My Salary does not reflect my professional performance, as it is too low.	0.76

4.2.1.3. Construct Reliability

The construct reliability value for each of the scale's dimensions was calculated and found that the values ranged from 0.76 to 0.91 (Table 4.17), which is higher than the minimum acceptable in organizational studies (0.70).

Table 4.17: Construct reliability of the dimensions

Dimension	Number of items	CR
Career Satisfaction	3	0.77
Safety Satisfaction	3	0.78
Leadership Satisfaction	3	0.91
WLB Satisfaction	3	0.83
Pay Satisfaction	3	0.90

4.2.1.4. Convergent validity

Regarding convergent validity, the AVE values ranged from 0.51 to 0.77 (Table 4.18), which indicates that there is good convergent validity since, according to Fornell and Larcker (1981), for there to be good convergent validity, the AVE values must be greater than 0.50.

Table 4.18: Convergent validity of the dimensions

Dimension	Number of items	AVE
Career Satisfaction	3	0.53
Safety Satisfaction	3	0.56
Leadership Satisfaction	3	0.77
Work/life balance Satisfaction	3	0.62
Pay Satisfaction	3	0.74

4.2.1.5. Discriminant Validity

For discriminant validity, the square root of the AVE value for each of the dimensions was calculated, and as can be seen in Table 4.19, all the values are higher than the correlation between the factors whose discriminant validity is being tested.

Table 4.19: Discriminant validity of the dimensions

Dimension	1	2	3	4	5
1. Career Satisfaction	**0.73**				
2. Safety Satisfaction	0.54**	**0.75**			
3. Lead/ Satisfaction	0.53**	0.63**	**0.88**		
4. WLB Satisfaction	0.50**	0.52**	0.55**	**0.79**	

5. Pay Satisfaction	0.59^{**}	0.41^{**}	0.51^{**}	0.46^{**}	**0.86**

Note. ** p < 0.01

The square root values of the AVE are shown in bold.

4.2.1.6. Sensitivity of items and dimensions

The median, minimum, maximum, skewness and kurtosis were calculated to test the items' sensitivity. As can be seen in Table 4.20, none of the items has a median that is close to one of the extremes, all the items have responses at all points, and their asymmetry and kurtosis values are below 2 and 7, respectively, which indicates that they do not grossly violate normality.

Table 4.20: Sensitivity of items

	Median	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Min.	Max.
SL1	3.00	-0.03	0.13	-1.18	0.25	1	5
SL2	3.00	0.09	0.13	-1.10	0.25	1	5
SL3R	3.00	0.14	0.13	-0.86	0.25	1	5
SL4	4.00	-0.77	0.13	-0.02	0.25	1	5
SL5	4.00	-0.78	0.13	-0.01	0.25	1	5
SL6R	5.00	-1.38	0.13	1.11	0.25	1	5
SL7	3.00	-0.34	0.13	-.71	0.25	1	5
SL8	3.00	-0.25	0.13	-0.87	0.25	1	5
SL9R	4.00	-0.63	0.13	-0.80	0.25	1	5
SL10	3.00	0.12	0.13	-0.96	0.25	1	5
SL11	2.00	0.36	0.13	-0.69	0.25	1	5
SL12R	3.00	0.08	0.13	-1.06	0.25	1	5
SL13	2.00	0.29	0.13	-1.01	0.25	1	5
SL14	3.00	0.21	0.13	-1.16	0.25	1	5
SL15R	3.00	0.03	0.13	-1.41	0.25	1	5

The normality of the dimensions that make up the instrument was then tested. None of the dimensions follow a normal distribution ($p < 0.05$) (Table 4.21). However, the results indicate that none of the dimensions grossly violate normality since their absolute values of asymmetry and kurtosis are below 2 and 7, respectively (Table 4.21).

Table 4.21: Sensitivity of the dimensions

Dimension	Kolmogorov-Smirnov			Skewness	Kurtosis
	Statistic	df	p		
Career Satisfaction	0.07	369	< 0.001	0.01	-0.64
Safety Satisfaction	0.16	369	< 0.001	-1.00	0.69
Leader/ Satisfaction	0.11	369	< 0.001	-0.45	-0.69
WLB Satisfaction	0.10	369	< 0.001	0.09	-0.59
Pay Satisfaction	0.11	369	< 0.001	0.17	-1.05

4.2.2. Descriptive statistics of the variables under study

Descriptive statistics were carried out on the variables under study to understand the position of the answers given by the participants in this study. To this end, a one-sample Student's t-test was carried out.

The results show that the participants in this study are not very satisfied with their careers, work/life balance and Pay since the average of these dimensions is significantly below the scale's central point (3) (Table 4.22). Concerning satisfaction with security and management, the average of these dimensions is significantly above the midpoint of the scale (3), indicating that they are satisfied with security and management. Finally, the various coefficients of variation (Cv) demonstrate that the Mean is a good estimator for this example, as the values are all bellow 50%.

Table 4.22: Descriptive statistics of the variables under study

Dimension	t	df	p	d	Mean	SD	Cv
Career Satisfaction	-3.22	368	< 0.001	0.17	2.82	1.05	37,2%
Safety Satisfaction	18.57	368	< 0.001	0.97	3.90	0.93	23,8%
Leadership Satisfaction	6.55	368	< 0.001	0.34	3.39	1.15	33,9%
W.L.B. Satisfaction	-6.75	368	< 0.001	0.35	2.64	1.03	39%
Pay Satisfaction	-3.96	368	< 0.001	0.21	2.75	1.21	44%

Finally, a table with all the items in this instrument in Portuguese and English is presented. It should be noted that among the items that make up this instrument, items 3, 6, 9, 12 and 15 should be inverted as they are formulated in the negative (See Appendix V).

4.2.2.1. Effect of sociodemographic variables on the variables under study

To test the effect of sociodemographic variables on the variables under study, several Student's t-tests for independent samples and One Way ANOVA were carried out.

Age only has a statistically significant effect on safety satisfaction ($F (4, 364) = 2.97$, $p = 0.019$) (Figure 4.1). Participants between 20 and 29 were the most satisfied with safety, followed by those between 60 and 69. Participants aged between 40 and 49 were the least satisfied with safety.

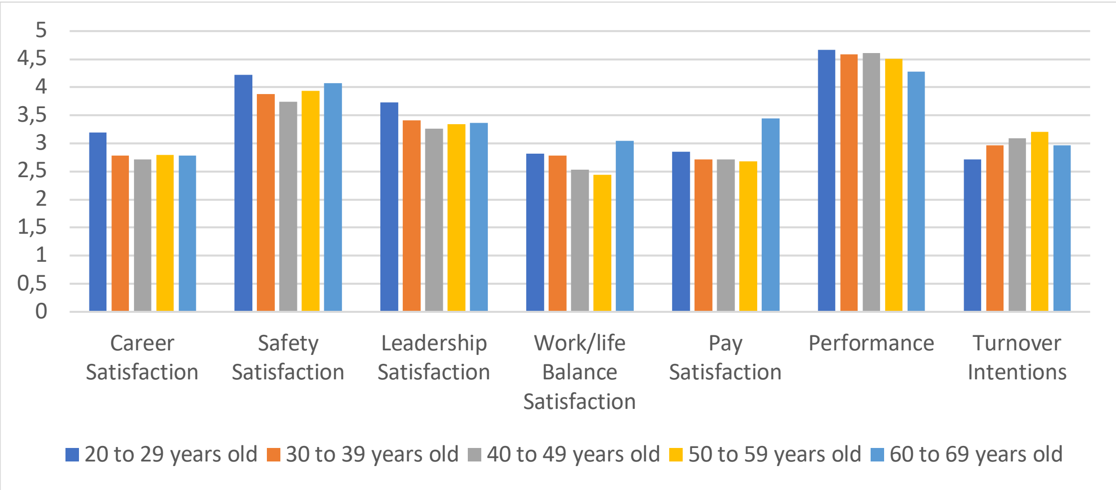

Figure 4.1: Answer scores on the variables per age

Gender has a significant effect on all the variables under study, except for performance (Table 4.23). Male participants have a significantly higher perception of satisfaction with career, safety, leadership, work/life balance, and pay than female participants. However, female participants have the greatest turnover intentions across the aviation organizations.

Table 4.23: Effect of Gender in Satisfaction variables

Variable	t	df	p	Female		Male	
				Mean	SD	Mean	SD
Career Satisfaction	-4.86***	367	< .001	2.49	1.02	3.02	1.02

Safety Satisfaction	-5.91***	367	< .001	3.54	1.08	4.11	.75
Leader/ Satisfaction	-3.98***	367	< .001	3.09	1.25	3.57	1.04
WLB. Satisfaction	-4.16***	367	< .001	2.36	1.05	2.81	.97
Pay satisfaction	-4.15***	367	< .001	2.42	1.22	2.95	1.17
Performance	-1.60	367	.111	4.54	.58	4.63	.47
Turnover intentions	3.64***	367	< .001	3.34	1.39	2.81	1.30

The results show that profession has a significant effect on career satisfaction ($F(4, 364) = 16.56$, $p < 0.001$), safety satisfaction ($F(4, 364) = 9.80$, $p < 0.001$), leadership satisfaction ($F(4, 364) = 6.34$, $p < 0.001$), work/life balance satisfaction ($F(4, 364) = 5.03$, $p < 0.001$), pay satisfaction ($F(4, 364) = 16.08$, $p < 0.001$), performance ($F(4, 364) = 4.56$, $p = 0.001$) and turnover intentions ($F(4, 364) = 9.67$, $p < 0.001$) (Figure 4.2). Regarding career satisfaction, the participants in TC roles were the most satisfied with their careers, differing significantly from all the others. Regarding safety satisfaction, participants in GP were the least satisfied with safety, differing significantly from all the others. Participants working in CP and on land are the least satisfied with leadership, differing significantly from those working in TC, MRO, and others. Those working in CP and onshore also feel least satisfied balancing work and personal life. Finally, about pay satisfaction, participants working in TC and MRO are the most satisfied with pay, differing significantly from all the others.

Participants working in CP have the highest perception of performance, differing significantly from ground staff and others. GP staff have the highest turnover intentions, differing significantly from all the others. Those with the lowest turnover intentions are those working in TC.

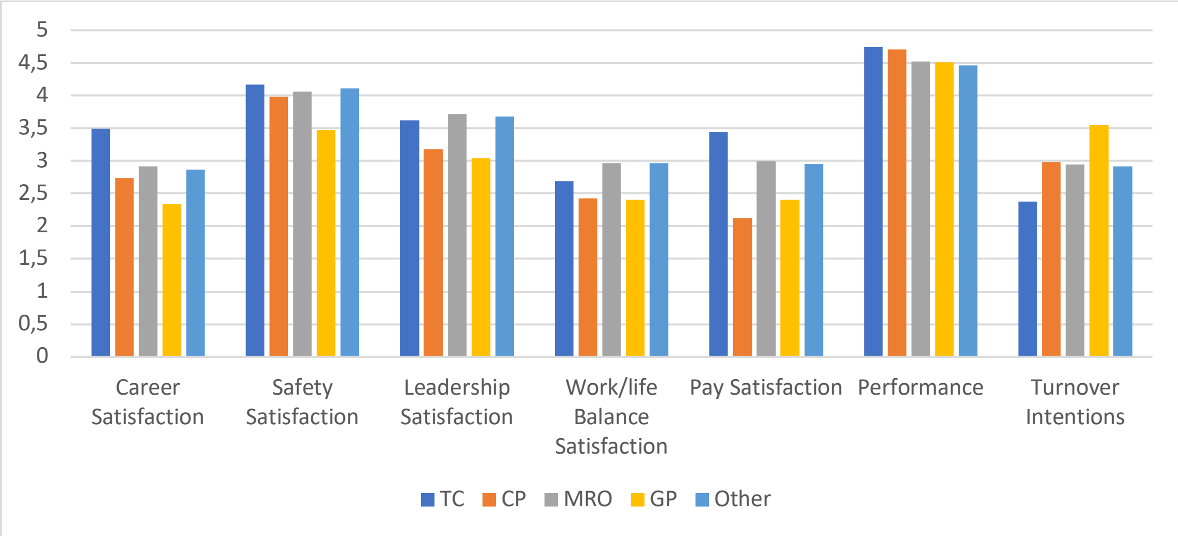

Figure 4.2: Answer scores on the variables per profession

Regarding the effect of seniority in the organization on performance and turnover intentions (Figure 4.3), there were only statistically significant differences in turnover intentions (F (4, 364) = 3.11, p = 0.002). As seniority in the organization increases, so do turnover intentions.

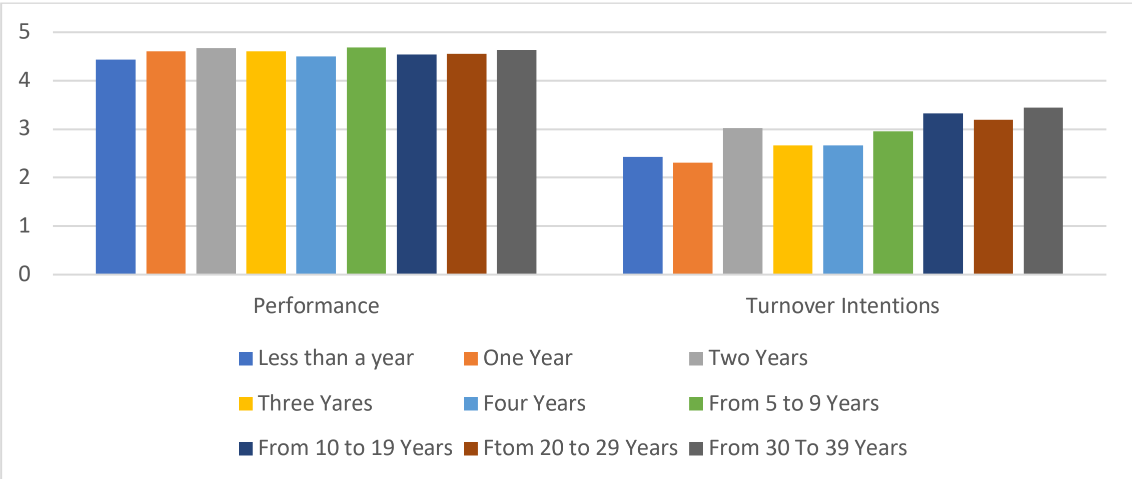

Figure 4.3: Answer scores on performance and turnover intentions per seniority

The results show that seniority in the organization has a significant effect on career satisfaction (F (4, 364) = 3.08, p = 0.002), leadership satisfaction (F (4, 364) = 2.52, p = 0.011) and work/life balance satisfaction (F (4, 364) = 3.15, p = 0.002) (Figure 4.4). In safety satisfaction (F (4, 364) = 1.81, p = 0.074) and pay satisfaction (F (4, 364) = 1.12, p = 0.347), the effect was not statistically significant. As can be seen in the figure 4.4, all types of satisfaction decrease as seniority in the organization increases.

Figure 4.4: Answer scores on the variables per seniority

Regarding the effect of the number of working hours on the variables under study (Figure 4.5), there are only statistically significant differences in safety satisfaction (F (3, 365) = 5.12, p = 0.002). Participants who work more than 240 hours a month feel significantly less satisfied with safety than all the other participants.

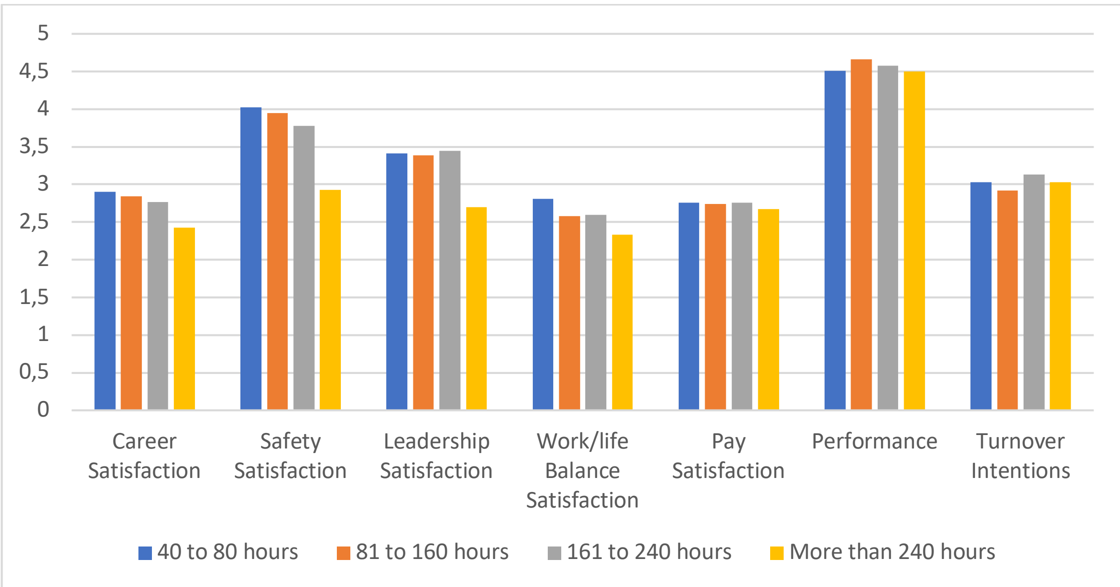

Figure 4.5: Answer scores on the variables per number of working hours

Regarding the effect of agreement with the last performance appraisal on the variables under study (Figure 4.6), there are statistically significant differences in satisfaction with career satisfaction ($F (4, 364) = 14.44, p < 0.001$), safety satisfaction ($F (4, 364) = 18.62, p < 0. 001$), leadership satisfaction ($F (4, 364) = 16.68, p < 0.001$), work/life balance satisfaction ($F (4, 364) = 7.81, p < 0.001$), pay satisfaction ($F (4, 364) = 10.77, p < 0.001$), perception of performance and turnover intentions ($F (4, 364) = 13.25, p < 0.001$). Participants who strongly agree with their performance appraisal feel significantly more strongly about their career, safety, leadership, work/life balance, and remuneration. They have a higher perception than all other participants but have lower turnover intentions.

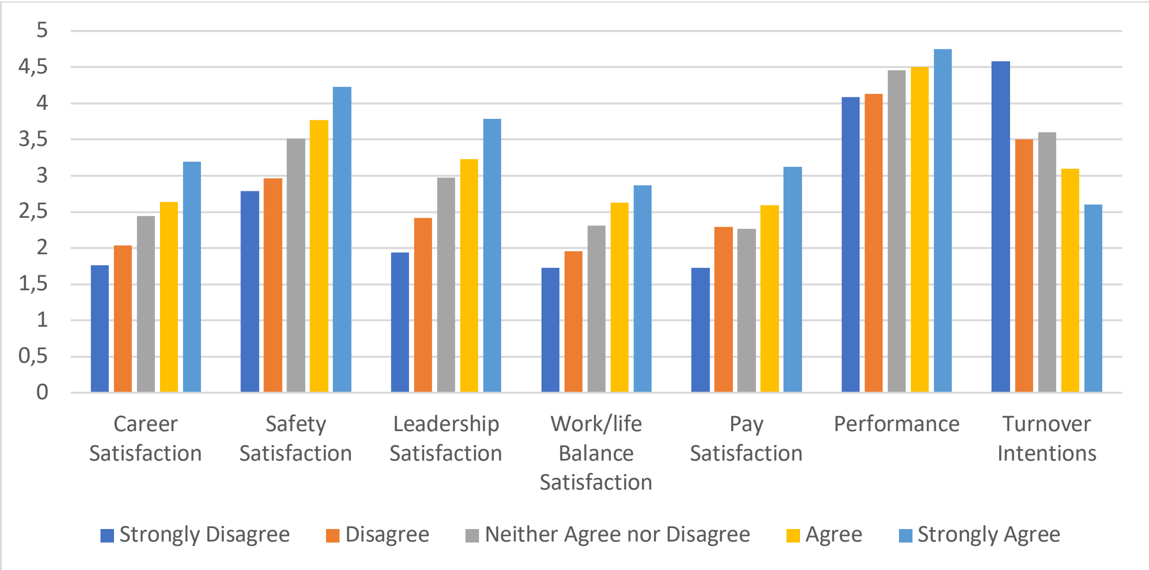

Figure 4.6: Answer scores on the variables per agreement on the last performance appraisal

The number of projects/tasks assigned per quarter (Figure 4.7) has a significant effect on career satisfaction ($F (2, 366) = 35.86, p < 0.001$), safety satisfaction ($F (2, 366) = 9.88, p < 0.001$), leadership satisfaction ($F (2, 366) = 14. 46, p < 0.001$), with work-life balance satisfaction ($F (2, 366) = 13.92, p < 0.001$), pay satisfaction ($F (2, 366) = 12.89, p < 0.001$) and turnover intentions ($F (2, 366) = 17.65, p < 0.001$). Participants who strongly agree that the number of projects/tasks assigned per quarter is too high are the least satisfied and have more turnover intentions than all the other participants.

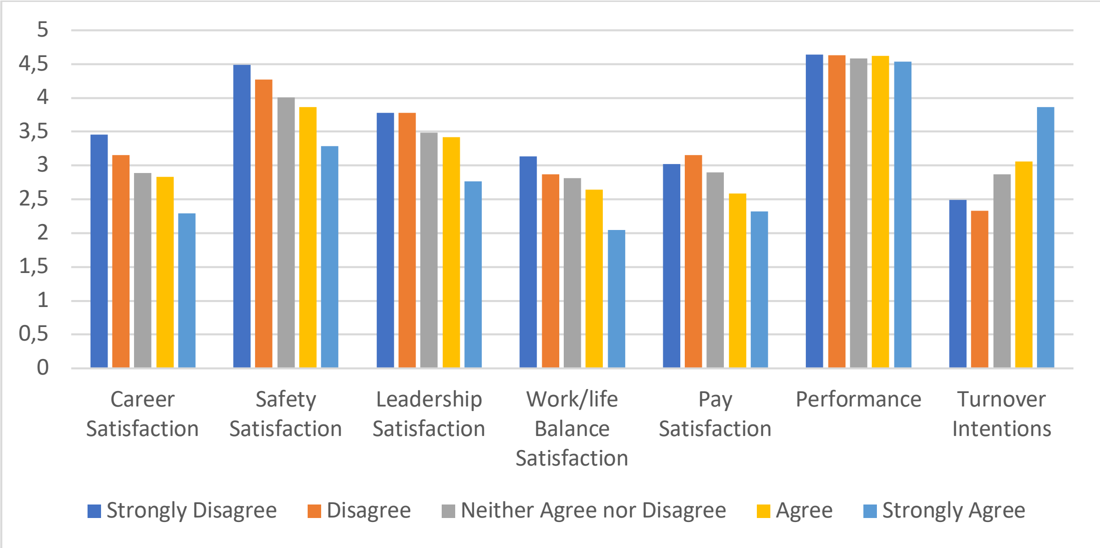

Figure 4.7: answer scores on the variables per number of projects/tasks assigned per quarter

The results show that career progression has a significant effect on career satisfaction (Figure 4.8) (F (2, 366) = 35.86, p < 0.001), safety satisfaction (F (2, 366) = 9.88, p < 0.001), leadership satisfaction (F (2, 366) = 14.46, p < 0.001), work/life balance satisfaction (F (2, 366) = 13.92, p < 0. 001), pay satisfaction (F (2, 366) = 12.89, p < 0.001) and turnover intentions (F (2, 366) = 17.65, p < 0.001). Participants who have not progressed are less satisfied with their careers, safety, leadership, work/life balance, and pay and have more turnover intentions than all the other participants (Figure 4.8).

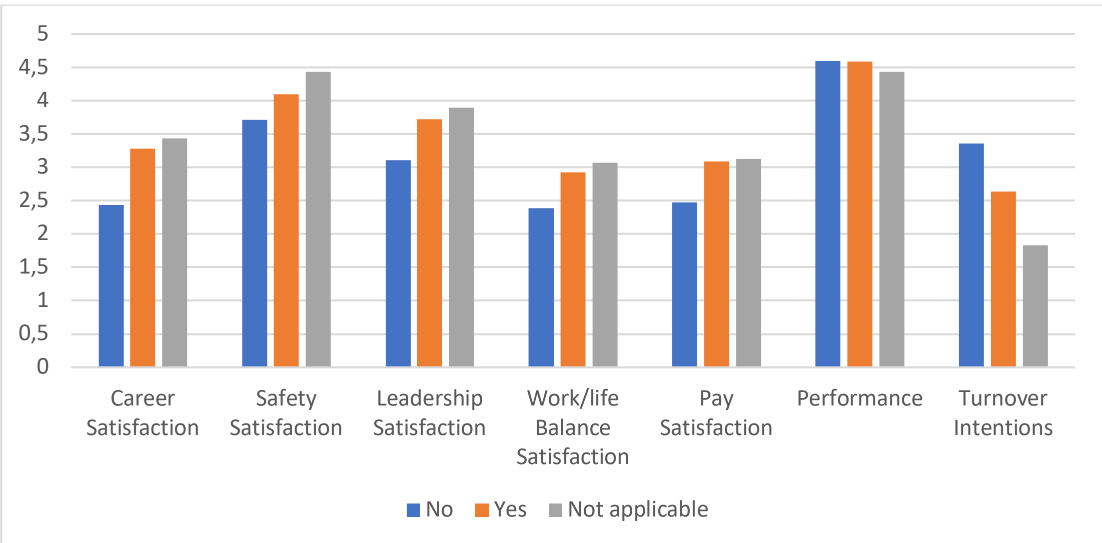

Figure 4.8: effect of career progression on the variables

4.2.3. Association between the variables under study

To study the association between the variables under study, Pearson's correlations were used (Table 4.24). The results show that performance is only significantly associated with satisfaction with safety Turnover intentions are negatively and significantly associated with career satisfaction, safety satisfaction, leadership satisfaction, work/life balance satisfaction and pay satisfaction. The most significant association is with career satisfaction.

Table 4.24: Correlation analysis between variables

Dimensions	CS	SS	LS	WLBS	PS	P	TI
Career Satisfaction	--						
Safety Satisfaction	.54***	--					
Leader/Satisfaction	.53***	.63***	--				
WLB Satisfaction	.50***	.52***	.55***	--			
Pay satisfaction	.59***	.41***	.51***	.46***	--		
Performance	.07	.18***	.07	.01	.02	--	
Turnover intentions	-.63***	-.49***	-.58***	-.50***	-.55***	-.09	--

4.2.4. Hypotheses

The hypotheses formulated in this study were tested with simple and multiple linear regressions using the stepwise method.

Hypothesis 1: Job satisfaction negatively and significantly affects turnover intentions.

Career satisfaction (β = -.34; p < .001), leadership satisfaction (β = -.25; p < .001), work/life balance satisfaction (β = -.12; p = -.012) and pay satisfaction (β = -.17; p < .001) have a significant and negative effect on turnover intentions. The model explains 50 per cent of the variability in turnover intentions. The model is statistically significant (F (4, 364) = 93.68, p < .001). This hypothesis was partially supported (Table 4.25).

Table 4.25: Results of the fourth step of multiple linear regression using the stepwise method (H1)

Independent Variable	Dependent Variable	F	p	R2a	β	p
Career Satisfaction	Turnover Intentions	93.68***	< .001	.50	-.34***	< .001
Leadership Satisfaction					-.25***	< .001
WLB. Satisfaction					-.12*	.012
Pay satisfaction					-.17***	< .001

Hypothesis 2: Job satisfaction has a positive and significant effect on performance.

The results show that safety satisfaction positively and significantly affects performance (β = .25; p < .001). On the other hand, work/life balance satisfaction has a negative and significant effect on performance (β = -.13; p = .035). The model explains 4 per cent of the variability in performance. The model is statistically significant (F (2, 366) = 8.59, p < .001). This hypothesis was partially supported (Table 4.26)

Table 4.26: Results of the fourth step of multiple linear regression using the stepwise method (H2)

Independent Variable	Dependent Variable	F	p	R2a	β	p
Safety Satisfaction	Performance	8.59***	< .001	.04	.25***	< .001
Work/life B. Satisfaction					-.13*	.035

Hypothesis 3: Turnover intentions have a negative and significant effect on performance.

Turnover intentions negatively and marginally significantly affect performance (β = -.09; p = .090). The model explains 1% of the variability in performance. The model is marginally significant (F (1, 367) = 2.88, p = .090). This hypothesis was partially supported (Table 4.27).

Table 4.27: Results of the fourth step of multiple linear regression using the stepwise method (H3)

Independent Variable	**Dependent Variable**	**F**	**p**	**R2a**	**β**	**p**
Turnover Intentions	Performance	2.88*	.090	.01	-.09*	.090

Hypothesis 4: Turnover intentions have a moderating effect on the relationship between job satisfaction and performance.

The results showed that turnover intentions have a marginally significant moderating effect on the relationship between pay satisfaction and performance (Table 4.28).

Table 4.28: results of the moderating effect of turnover intentions (H4)

Variables	**B**	**SE**	**t**	***p***	**95% CI**
	Career Satisfaction → Performance (R^2 = .10; p = .282)				
Constant	4.58***	.03	142.41***	< .001	[4.51, 4.64]
Career Satisfaction	.01	.03	.43	.669	[-.05, .08]
Turnover intentions	-.03	.03	-1.00	.316	[-.08, .02]
CS*TI	-.02	.02	-.90	.371	[-.06, .02]
	Safety Satisfaction → Performance (R^2 = .04; p = .005)				
Constant	4.58***	.03	152.04***	< .001	[4.52, 4.64]
Safety Satisfaction	.12	.04	3.13**	.002	[.04, .19]
Turnover Intentions	.01	.02	.19	.849	[-.04, .05]
SS*TI	-.02	.02	-.83	.407	[-.07, .03]
	Leadership Satisfaction → Performance (R^2 = .01; p = .189)				
Constant	4.57***	.03	144.95***	< .001	[4.51, 4.63]
Leadership Satisfaction	.02	.03	.71	.478	[-.04, .08]
Turnover Intentions	-.02	.02	-1.01	.314	[-.07, .02]
LS*TI	-.02	.02	-1.34	.182	[-.06, .01]

	Work/LB Satisfaction → Performance ($R^2 = .01$; $p = .233$)				
Constant	4.60***	.03	153.37***	< .001	[4.54, 4.66]
WLB Satisfaction	-.03	.03	-.94	.346	[-.04, .08]
Turnover Intentions	-.05	.02	-1.97*	.050	[-.09, .00]
WLBS*TI	.01	.02	.73	.469	[-.02, .05]
	Pay Satisfaction → Performance ($R^2 = .02$; $p = .092$)				
Constant	4.57***	.03	146.69***	< .001	[4.50, 4.63]
Pay Satisfaction	-.02	.03	-.90	.364	[-.07, .03]
Turnover Intentions	-.04	.02	-1.75*	.081	[-.08, .00]
PS*TI	-.03	.02	-1.73*	.083	[-.07, .00]

For participants with low turnover intentions, pay satisfaction becomes relevant to boosting their performance than for participants with high turnover intentions (Figure 4.9). This hypothesis was partially supported.

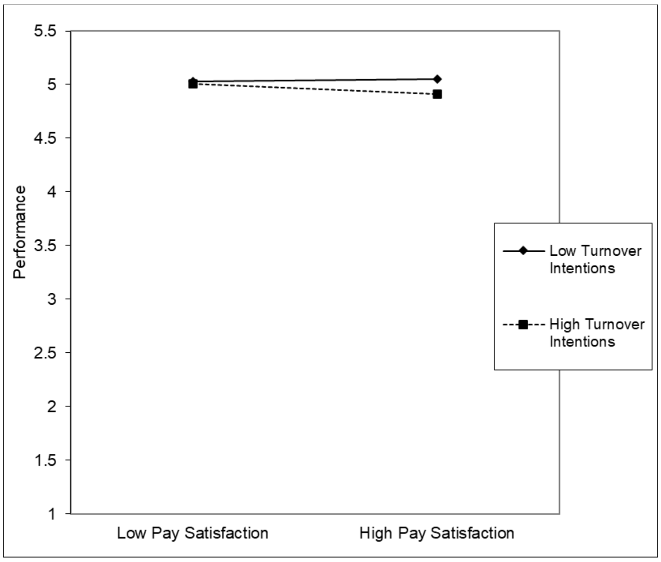

Figure 4.9: interaction plot with the illustration of the moderating effect of turnover intentions on the relationship between pay satisfaction and performance.

4.3. Conclusions

This quantitative study's main goal was to verify a job satisfaction measure that Portuguese commercial aviation experts might use to forecast employee churn. An instrument with 15 items was created with the intention of distributing them across five dimensions after a review of the literature. Examining the variables influencing turnover intentions and their effect on work performance among Portuguese professionals in commercial aviation was the quantitative study's second goal. This study adds to the scarce literature on employee churn in the commercial aviation industry by focusing on job satisfaction factors and how they affect performance and turnover intentions. This study is also novel since it provides a comprehensive view of the HR reality for commercial airlines in Portugal, supported by the mixed methods methodology.

A portion of the sample (N=106 participants) underwent an exploratory factor analysis, and the results met our expectations with a KMO of 0.91, suggesting the existence of 5 components. The following names were assigned to each of the five dimensions: pay satisfaction, work/life balance satisfaction, leadership satisfaction, career satisfaction, and safety satisfaction. With Cronbach's alpha values ranging from 0.77 (career satisfaction) to 0.91 (leadership satisfaction), all the measures exhibited strong internal consistency. Values above 0.70, the lowest permitted in organisational research, were observed (Bryman & Cramer, 2003).

Regarding the remaining individuals (N=263), a confirmatory factor analysis was performed, which verified the presence of the five components. Hu and Bentler (1999) reported that the fit indices found were adequate, and in fact, could be deemed extremely good. The values of the construct reliability ranged from 0.91 (leadership satisfaction) to 0.77 (career satisfaction). Regarding convergent validity, values higher than 0.50 indicated good convergent validity; the AVE values ranged from 0.53 (career satisfaction) to 0.77 (leadership satisfaction) (Fornell & Larcker, 1981). The fact that the square root of the AVE values for every dimension was greater than the correlation coefficients among the factors further supported discriminant validity.

None of the items' sensitivity flagrantly deviates from normality, indicating that they do not discriminate among subjects. The scale's measurements also don't blatantly deviate from normality.

The psychometric properties of this instrument show promise for use in future empirical research pertaining to personnel of airlines. This tool evaluates work/life balance satisfaction, leadership satisfaction, safety satisfaction, career satisfaction, and pay satisfaction in airlines. This evaluation can be quite important, particularly for businesses that experience a high rate of staff turnover as aviation. When workers are happy with their jobs, they will perform better and be less likely to want to leave the company (Moreira et al., 2022).

Only pay satisfaction, work/life balance satisfaction, career satisfaction, and leadership satisfaction have a negative and significant effect on turnover intentions, suggesting that the higher the satisfaction levels, the lower the turnover intentions. This means that, in terms of the churn predictive model, hypothesis 1 has been partially confirmed. The literature (Chen, 2006; Mowday, Porter & Steers, 1982; Jou, Kuo, & Tang, 2013; Mulki, Jaramilo & Lokander, 2006; Suifan, Diab & Abdallah, 2017) is consistent with these findings. It is unclear why turnover intentions are unaffected by the notion of safety satisfaction. There are two possible options suggested: 1) Insofar as there is evidence of a relationship between variables not directly in the aviation sector, but at least in the transport sector, this lack of a significant relationship between the variables supports the hypotheses of the literature (Huang et al. 2016; Smith, 2018; Siu, Cheung & Lui, 2015; Zhang et al., 2023); 2) However, as aeroplanes are the most technologically advanced means of transportation and are therefore subject to more stringent regulations and scrutiny—at least in the majority of them—the issue of aviation safety is one that is often taken for granted. As a result, its influence on turnover intentions may be minimal.

Hypothesis 2 was partially validated, as anticipated, since work/life balance satisfaction has a negative and significant impact on performance, while only satisfaction with safety has a positive and significant effect on performance. These findings suggest that higher levels of satisfaction with safety are associated with higher job performance, whereas higher levels of work/life balance satisfaction are associated with lower job performance. The findings align with existing research, as there has never been conclusive evidence in academic literature supporting a positive correlation between job satisfaction and performance (Iaffaldano and Muchinsky, 1985; Judge et al., 2001; Petty, McGee, and Cavender, 1984; Whitman, Van Rooy, and Viswesvaran, 2010). However, some findings have shown that job satisfaction and job performance are negatively correlated. For instance, in the case of air traffic controllers (Supriyanto, 2018). Specifically, our study's finding of a negative correlation between work/life balance satisfaction and performance defies common sense and adds to the body of knowledge regarding job satisfaction in the aviation industry. There is a significant research gap that this study fills because the association between these variables has not been extensively examined in this field.

Turnover intentions have a negative and marginally significant effect on performance, showing that the higher the turnover intentions, the poorer the performance, as predicted, and therefore partially confirms hypothesis 3. These findings support previous research (Bishop, 1990; Trevor et al., 1997; Wynen & Kleizen, 2019) and are consistent with a relationship observed in several industries, including transportation (Hancock et al., 2013).

Ultimately, there was some confirmation of hypothesis 4. There were conflicting findings about how turnover intentions affected the relationship between job satisfaction and performance. The association between pay satisfaction and performance was somewhat affected by turnover intentions, but not considerably so by them. This was not the case for the other satisfaction aspects. This implies that while turnover intentions do affect how pay satisfaction affects performance, they may not be a significant moderator in this situation.

The research gap identified by Srivastava & Eachempati (2021) was addressed with this study. They pointed out that while most studies identify the factors influencing employee churn, they do not identify the relative contributions of the variables. The questionnaire also includes an abundance of descriptive and sociodemographic information that highlights the heterogeneous workforce of Portugal's commercial aviation industry in addition to these metrics. Averages much above the midpoint (3) indicate that participants have a good opinion of their performance and are extremely satisfied with safety and leadership. Averages below the middle range indicate dissatisfaction with career, pay, and work-life balance (3). The typical participant's turnover intentions are neutral, cantered around the middle (3).

About the impact of sociodemographic factors, the results indicate that there is a considerable difference in participant safety satisfaction between the ages of 20-29 and 60-69, and between 40-49. In terms of how gender affects job satisfaction, male participants are more satisfied than female participants in every area, including career, safety, leadership, work-life balance, and pay satisfaction. Participants who are female are more likely to plan to leave the company. In the commercial aviation industry, the type of occupation has a substantial impact on all areas of job satisfaction. The most content with their professions and salary are those who work as technical crew members

(TCs. Pilots, for example). Participants who are ground personnel (GP) had the highest turnover intentions, as concluded by the sector reports (IATA, 2018).

The flight technical crew, or pilots, were found to be the most satisfied across a range of factors, with lower turnover intentions and a high opinion of their own performance. This conclusion is not in line with Efthymiou et al. (2021)'s conclusions for Ryanair pilots (high turnover).

Overall, except for safety and pay, satisfaction declines as seniority increases across the satisfaction criteria. Seniority increases turnover intentions.

In terms of how working hours affect job satisfaction, those who put in more than 240 hours a month of work report feeling less safe. Participants who strongly agree with their most recent performance appraisal are more content overall and are less likely to want to leave their jobs, according to research on the impact of performance appraisal perception on job satisfaction characteristics. The perception of the quantity of projects/tasks has a negative influence on satisfaction and raises turnover intentions when the effect of the variable "number of projects/tasks" (too high? y/n) on satisfaction aspects is examined.

Lastly, on how career advancements affect satisfaction. A stagnant career lowers overall satisfaction and raises turnover intentions.

The findings show that a variety of characteristics, including age, gender, occupation, seniority, working hours, performance reviews, workload, and career advancement, had an impact on participants' satisfaction. This demonstrates how intricate and interconnected these elements are in terms of job satisfaction and turnover intentions.

4.3.1. Practical implications

These findings highlight the significance of improving job satisfaction for HR managers and policymakers in the commercial aviation sector to lower turnover intentions and boost performance.

The first hypotheses that turnover rates depend on the type of profession and type of airline is corroborated by data. Ground staff members have far greater turnover intentions and are the most worn out and unsatisfied. This conclusion is valuable as it can drive decision making that impacts job satisfaction and ultimately airline operation. Ground staff are highly responsible for customer satisfaction. Customer satisfaction relevantly impacts airline financial results.

Regarding the finding that too many working hours impact safety satisfaction, this conclusion is also critical in practice for airline operations, as safety is a key component to safeguard above all strategic goals.

HR/business airline strategies ought to concentrate on:

- Direct human resources policies' attention on the role of ground staff in commercial airlines, with a focus on reviewing pay and benefit packages, reducing or restructuring long hours, attempting to mitigate recurring risks associated with direct customer contact and groundwork, improving career plans, ensuring compassionate, capable, and inspiring leadership, enhancing schedule flexibility, putting plans in place for balancing work and family obligations, and providing mental health support.

For every job in the commercial aviation industry:

- Enhancing possibilities for career development: Offering well-defined career trajectories and prospects for growth can augment job satisfaction and mitigate attrition/churn intentions.
- Ensuring health and safety at work: Upholding strict safety standards improves job performance and satisfaction while also guaranteeing regulatory compliance.
- Effective leadership: Programs for leadership development and training can raise leadership satisfaction and lower turnover intentions.
- Implementing flexible work arrangements and support programs: This can effectively address the negative impact of work-life balance satisfaction on performance.
- Achieving competitive pay packages: Routinely reviewing and adjusting pay structures to align with market standards or above can increase pay satisfaction and reduce the likelihood of employee turnover.

3.2.2. Limitations

There are a few study limitations to consider. The limited sample size and the method used to obtain the data are two of the study's shortcomings. It should be mentioned that it was somewhat challenging to collect respondents to the questionnaire, particularly among flight attendants. A further constraint is the self-administered nature of the questionnaire, which includes closed-ended questions that could have influenced the outcomes. To lessen the effect of common method variance, several methodological and statistical guidelines were adhered to (Podsakoff et al., 2003).

The fact that the sample consisted only of Portuguese commercial aviation industry workers may have limited the findings' applicability to other industries or geographical areas. It is also unable to conclusively demonstrate causal correlations due to the study's cross-sectional design. Large sample numbers or longitudinal designs may be used in future studies to better understand the dynamics of work satisfaction, turnover intentions, and performance over time.

Furthermore, there is room for development in the questionnaire. Specifically, the way the professions of airlines are divided up might be improved, and better designations for professions like "ground personnel" and "others," which include a wide range of tasks, should be specified. Even though several airlines have that vertical integration, it's dubious to include "Maintenance & Engineering" in the commercial aviation business. However, it enhances the research. There are other variables that affect turnover intentions, and there isn't much scholarly research on HRA analytics in the aviation industry.

3.2.3. Future Research

Additional investigation is required to examine additional putative moderating factors that could impact the correlation between job satisfaction and performance. For the sake of simplification, the variables "marital status" and "work environment," which have been linked in the literature to turnover intentions, were excluded from the churn predictive model. They could be added to a new model in upcoming research. Furthermore, investigating the effects of interventions meant to raise job satisfaction on turnover intentions and performance may offer insightful information for HR procedures. Additional research could be conducted in other sectors and geographical areas to improve the generalizability of the results.

Commercial aviation ("airlines") is merely one of the many activities that make up aviation. The relationship between job satisfaction, turnover intentions in the industry, and the performance of other aviation professionals—such as those in ground handling, maintenance & engineering, aircraft manufacturing, defence, airport personnel, ATC (air traffic controllers), pilot training activities, aviation professionals in firefighting, agriculture, rescue, and medical aircraft operations, flight catering, safety and security professionals, regulators, cleaning professionals, etc.—is still not well studied.

Relationships between many factors and the variable job satisfaction divided by dimensions, such as the “relationship between pay satisfaction and performance,” are uncommon in the literature. Nonetheless, there are a few connections between the various aspects of job satisfaction and other factors. It might be a worthwhile line of inquiry to focus on more aspects of job satisfaction when examining the links between job satisfaction and other variables.

The study concludes by highlighting the crucial impact that job satisfaction plays in affecting turnover intentions and job performance among Portuguese professionals in the commercial aviation industry. Organizations can lower the turnover intentions of employees and boost overall performance by concentrating on improving different aspects of job happiness. The results offer significant perspectives for human resources managers who aim to formulate efficacious retention tactics and foster a staff that is both content and efficient.

CHAPTER V

Conclusions, Recommendations, Limitations and Future Directions

5.1. Conclusions, theoretical implications and practical recommendations

This PhD thesis has delved deeply into the field of HR Analytics within the Portuguese airline sector, providing significant insights and contributing to the broader understanding of HR Analytics' impact and potential. The study has demonstrated that HR Analytics can substantially enhance decision-making processes in human resource management by offering data-driven insights into critical issues such as employee churn, job satisfaction, performance management, and strategic HR planning.

First, the literature review on the topic of HR Analytics is a detailed and developed state of the art and the most up-to-date main discussions that exist on the topic of HRA. The study started by characterizing what HRA is and understood that it is one of the hottest topics in the human resources sector, but still with potential for more contributions. The applications of HRA techniques in practice and the most recent scientific studies and the most relevant discussions on this topic were acknowledged. The discussions with the most contributions on HRA now are the effectiveness and concept of HRA and the dark side of HRA, namely privacy, security and bias. There are management and implementation strategies, the areas of HR in which HRA projects can be implemented and in which value can be created from data: Recruitment, performance evaluation, onboarding, employee experience, turnover, etc. The stages of HRA maturity and the technology were analysed, the skills needed to implement these strategies, and the most used AI, statistics, and management techniques. Then, the literature review delved into the less politically correct area of HRA's challenges and dark side. There was an effort to understand why HRA, being such a big trend, has not yet had the expected degree of implementation. There are several barriers that hold it back and the study highlighted which ones. However, the debate remains heated, and this thesis intended to contribute to its clarification. Finally, a literature review was carried out on the specific topic of employee churn, an HRA indicator that was used as a test for the effectiveness of HRA techniques.

The mixed-method approach employed in this research, combining qualitative interviews with quantitative data analysis, has been instrumental in uncovering the practical challenges and opportunities associated with implementing HR Analytics. Qualitative interviews provided rich, contextual insights into the attitudes and experiences of HR professionals, while quantitative analysis offered empirical evidence of the benefits and limitations of HR Analytics tools.

One of the key findings is the recognition of HR Analytics as a valuable tool that can bridge the gap between data and actionable insights. Despite the scepticism and resistance often encountered in academic and professional circles regarding the efficacy of HR Analytics, this study has provided concrete evidence that supports its value. The research highlights how HR Analytics can facilitate more informed and strategic decision-making, ultimately leading to better HR outcomes and enhanced organizational performance.

Moreover, the thesis has identified several critical success factors for the effective implementation of HR Analytics. These include the need for top management support, the importance of a data-driven culture within the organization, the necessity of appropriate technological infrastructure, and the requirement for skilled personnel capable of interpreting and utilizing HR Analytics outputs. Another barrier to the implementation of HRA that is not usually present in the literature and was found through this qualitative research is the lack of alignment between HR strategy and business strategy. The lack of this connection prevents HRA from being an active and crucial partner in the design of useful strategies that create value for the business. If an HRA strategy must be focused and use the language of the business, if it is divorced from this area, it will contribute little more than the usual administrative work and will remain in the "support function," from Michael Porter's perspective, and not in the "primary function" that create value for the business.

This PhD study filled several research gaps indicated by the literature, namely: (1) the need for more case studies (Margherita, 2022) and empirical research in the HRA literature (Espegren & Hugosson (2023); (2) the analysis not only of the factors that influence turnover, but also the relative contribution of these factors (Srivastava & Eachempati (2021)); (3) the in-depth study of the factors that influence employee churn, satisfaction and performance in the commercial aviation sector in Portugal, and the use of mixed methods as a methodology that is little used and more robust in terms of results (Espegren & Hugosson, 2023; Srivastava & Eachempati, 2021).

Regarding the conclusions of the qualitative and quantitative studies, the study discovered in the qualitative study that the area of human resources training/qualification building has a central role/ should have a top place in the work of human resources management in airlines, corroborating previous literature (IATA, 2018). Our interviewees not only stated that the main role of the HR department is to train, qualify, and certify aviation professionals, but also in the theme of challenges, they also place the "lack of skills", technical and non-technical, as an important problem. Compliance with qualifications and certifications is also invoked by respondents as the main differentiating factor between a generalist HR and an aviation HR. In second place is the topic of talent retention, which was addressed in our quantitative study. In addition to the constant mention of the lack of strategic alignment, another very focused topic is customer service as the biggest business need in aviation and the passenger experience should be the target of greater measurement by a data strategy.

Regarding the perception that the participants have about HRA, it is scarce, and the PhD study concludes that it is in line with the conclusion of the literature that this area is still taking its first steps and is subordinate to the operational area. Regarding indicators and HRA themes, another area often mentioned is the measurement of employee performance, usually associated with HRA. On the topic of technology adoption, many interesting conclusions came out of the qualitative study. More than the AI techniques and software to be used at HRA, the most important thing is the availability and quality of data, good data governance, and methodology. Without them, the best algorithms and technology can be a possession of an HRA team, but they are useless. Bringing together the various most important areas of HR in aviation plus the indication of employee churn as a useful indicator to measure and act on talent attraction/retention, the decision to explore this reality further in the quantitative empirical study was taken.

In the chapter of the quantitative study, it was concluded that using multiple linear regression techniques and exploratory analysis of relevant factors brings together good measurement and prediction of the phenomenon of employee churn, with reliability and can be used for decision-making. The study achieved the two objectives of the quantitative study. Firstly, to create an employee churn measurement instrument in Portugal focused on the aviation sector, the first to exist in Portugal and which is currently under validation. Good performance was achieved in the indicators from EFA and CFA. Secondly, a model that predicts professional employee churn in the aviation sector was created, in an innovative way that focuses on the main predictor of turnover intentions and that is job satisfaction. In an innovative way, five dimensions of job satisfaction were extracted from a "best of" of the literature, factors that impact turnover intentions and job performance.

As regards the hypotheses formulated, they have all been confirmed, in whole or in part. The one that obtained the model's best performance was number H1, "Job satisfaction negatively and significantly affects turnover intentions." All dimensions of satisfaction, except safety, were considered associated with turnover intentions, namely career satisfaction, leadership satisfaction, work/life balance satisfaction, and pay satisfaction. Many interesting associations were also found between satisfaction factors and sociodemographic factors, namely age, gender, profession, seniority, number of hours worked, performance appraisal, number of projects too high (y/n), and career progression.

Airline professionals are highly satisfied with safety and leadership and have a high perception of performance, with averages significantly above the midpoint (3). There is dissatisfaction with work-life balance, career, and pay, with averages below the midpoint (3). Participants' turnover intentions are neutral, with averages around the midpoint (3).

One of the most significant insights from this study is to conclude that airline ground professionals are much more dissatisfied, exhausted, and with more turnover intentions than any other airline professional, namely flight professionals, with high satisfaction rates and low turnover intentions. This consideration confirms the airline association IATA (2018)'s conclusions and is relevant for decision-making, as policies may be adopted to encourage this type of professional, so central to the air operation and to customer satisfaction. Even more so they are professions with a great shortage of personnel, not yet recovered from the COVID-19 pandemic.

One recommendation of the qualitative study is to increasingly use the customer experience as a rich source for creating HR indicators. Businesses usually either focus on measuring customer churn or employee churn results separately. Why not focus on the main business problem, the customer experience, and the attention on the human factors that influence this customer satisfaction, namely the impact of employee satisfaction on customers? NPS (Net Promoter Score) is a highly utilized metric to evaluate customer experience in airlines. A factor that surely impacts this metric will be employee satisfaction. Likewise, the performance evaluation system and the working conditions of employees can be improved. So, there is the focus on business problems and employees at the same time. More practical recommendations are important, as developed in the discussion chapters of this thesis, namely that human resources in the aviation sector should focus more attention on ground staff, in the areas of flexible schedules, mental health, remuneration, careers and family/work balance; that in general, more and better Human Resources policies can be implemented in the areas of careers, better family/work balance, and leadership training and preparation.

5.2. Limitations

While this research has made significant contributions, it is not without limitations. One of the primary limitations is the focus on the airline sector in Portugal. This sector-specific and geographically confined focus may limit the generalizability of the findings to other industries and regions. The unique characteristics and challenges of the airline industry, as well as the specific cultural and economic context of Portugal, Portugal, may not be fully representative of other contexts.

At the end of 2023, the largest Portuguese airline, the flag carrier TAP Air Portugal, reversed the remuneration cut to its employees in the COVID-19 event, and this factor contributed to the return of peace between unions and the company. However, it is not currently certain whether: 1) the ground staff is included in this return of peace to the company; 2) how are the other Portuguese airlines, also interviewed by this study; 3) what is the perspective of employees regarding other dimensions, namely job satisfaction. There can be an argument that this study has lost the relevance of some conclusions in Portugal because HR policies in key companies have changed positively during its course (the quantitative study was precisely started at the time of this airline announcement). Namely, remuneration and HR strategy were at the core of the restructuring plan of TAP Air Portugal, of course, because of an EU obligation following the COVID-19 catastrophe. However, this argument is not entirely true, as there are many more factors that impact turnover intentions and performance, as we have seen. It is not because an employee feels reasonably well paid that he cannot feel demotivated by leadership, schedules, stress, poor career plans, etc. These factors of discontent are also evidence collected in this study qualitatively, but not sufficiently explored, subject to future development. Therefore, more qualitative and quantitative studies are needed to confirm the continuity and type of perceptions and to ascertain the persistence of these phenomena, namely through a longitudinal study that can identify the perceptions by company.

Machine learning techniques could have been used in the topic of employee churn. As an AI expert stated in this study: regression algorithms are a good entry strategy technique in HRA, and it is not despicable, even inferior. It is recommended: 1) to use the right algorithm for the right problem; 2) use a combination of different techniques (ML, regression, classification) for the same problem and data set and then compare those that have better performance and predictive power. This is also a limitation of the study and is a recommendation for future studies applied to churn models or others.

Another limitation is the reliance on self-reported data from HR professionals within the airline industry. While the sample size of 369 respondents is substantial, self-reported data can be subject to biases, such as social desirability bias or recall bias, which may affect the accuracy and reliability of the findings. Additionally, the research was conducted during a specific period, and the dynamic nature of the airline industry means that some findings may not remain applicable over time.

The study also faced challenges related to the nascent stage of HR Analytics implementation in many companies. As HR Analytics is still an emerging field, many organizations may not yet have fully developed their HR Analytics capabilities, which could influence their perceptions and experiences. This nascent stage might have also limited the depth of insights that could be gathered from more mature implementations of HR Analytics.

1.2. Future Directions

Given the limitations and the findings of this study, several future research directions are recommended. Firstly, expanding the scope of research to include a wider range of industries and geographic regions would help to validate and generalize the findings. Comparative studies across different sectors and countries could provide a more comprehensive understanding of the diverse applications and impacts of HR Analytics.

Longitudinal studies would be particularly valuable in understanding the long-term effects and sustainability of HR Analytics implementations. Such studies could track the evolution of HR Analytics capabilities within organizations and their impact on HR outcomes and overall organizational performance over time. Longitudinal research could also shed light on how organizations adapt to and evolve their HR Analytics practices in response to changing business environments.

In addition to a longitudinal study, there are few studies that conceal internal data from the company, publicly available employee data, and labour market data for the churn/attrition model. Also, the model can add social media data to triangulate information and increase the robustness of the study (Brito, 2021; Isson & Harriott, 2016).

A future study of employee churn can add extrinsic factors and not only intrinsic factors that influence turnover intentions.

Another important area for future research is the integration of advanced technologies, such as artificial intelligence and machine learning, within HR Analytics. Exploring how these technologies can enhance predictive, prescriptive and autonomous analytics capabilities could offer new insights into optimizing HR processes and decision-making. Research could focus on specific applications, such as predictive modelling for employee turnover, AI-driven talent acquisition, automated performance management systems and the use of advanced LLMs in the creation and development of HR policies and practices.

Addressing ethical considerations and data privacy concerns is crucial for the wider acceptance and implementation of HR Analytics, a theme that is not sufficiently addressed specially by practice that has the tendency of only showing the positive side of HRA. Future research should investigate the ethical implications of HR Analytics, particularly in relation to employee privacy, data security, and potential biases in analytics algorithms. Developing frameworks and guidelines for ethical HR Analytics practices would be beneficial for organizations seeking to implement these tools responsibly.

Lastly, further research into the role of organizational culture in the adoption and effectiveness of HR Analytics is recommended. Understanding how different cultural contexts influence the acceptance and utilization of HR Analytics can help organizations tailor their strategies to foster a data-driven culture. Investigating the training and development needs of HR professionals to effectively leverage HR Analytics is also an important area for future exploration, especially in the airline sector.

To conclude, when will human resources take an important part in the boards of directors? When will human resources transition from being mere executors to becoming contributors to business strategy, focusing on recruiting the best professionals and paying close attention to their experience, which includes quality training, qualification, and a data-driven approach that produces value for both people and the business?

And for when the business strategy positions its main interest in people, and it guarantees the sustainability of its business model? When do people stop being more of an issue, to be THE question? For when business realizes that business and people are not a separate reality? In times of the "triple bottom line" of sustainability (business, people, environment), this triad must stop being theoretical and only for marketing campaigns to have real implementation. That is the real key of creating value that lasts in time.

While this PhD thesis has made significant strides in understanding the role and impact of HR Analytics in the Portuguese airline sector, there remains much to be explored. By addressing the identified limitations and pursuing the suggested future research directions, the field of HR Analytics can continue to evolve and provide valuable contributions to human resource management and organizational success.

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Appendices

Appendix A: profile of the experts interviewed for the qualitative study

Code	**Type of interview**	**Type of interviewee**	**Age**	**Gender**	**Years of experience/ field**
E1	Interview to expert	Expert in AI	41	M	15
E2	Interview to expert	Expert in AI	59	M	25
E3	Interview to expert	Expert in AI	32	M	7
E4	Interview to expert	Expert in AI	53	M	31
E5	Interview to expert	Expert in AI	52	M	25
E6	Interview to expert	HR/ Airline Professional	51	M	41
E7	Interview to expert	HR/ Airline Professional	58	M	30
E8	Interview to expert	HR/ Airline Executive	54	M	31
E9	Interview to expert	HR/ Airline Executive	65	M	41
E10	Interview to expert	HR/ Airline Executive	62	M	40
E11	Interview to expert	HR/ Airline Executive	47	M	20
E12	Interview to expert	HR/ Airline Executive	51	M	30

Appendix B: Informed consent (PT)

Termo de Consentimento Informado

Instituto Superior de Ciências do Trabalho e da Empresa (ISCTE)

iscte INSTITUTO UNIVERSITÁRIO DE LISBOA

Este documento vincula-se ao estudo intitulado de: "HR Analytics in the Commercial aviation sector in Portugal: a case study analysis", da autoria de António Pimenta de Brito, finalista do Doutoramento em Gestão. Neste âmbito, foram-me explicados os objetivos do trabalho e foi solicitada a minha colaboração para uma entrevista. Atendendo que a participação neste estudo tem carácter voluntário, posso desistir desta a qualquer momento e compreendo que não haverá lugar a qualquer remuneração ou custos pela minha participação, e que me será facultado esclarecimento sobre qualquer dúvida que me surgir. Assim, consinto de forma livre, esclarecida e informada, a gravação de áudio, na condição de se proceder à destruição da mesma logo após o seu tratamento. Por outro lado, o investigador compromete-se a guardar os dados recolhidos em condições seguras de armazenamento, não autorizando a partilha com terceiros e salvaguardado a privacidade dos entrevistados.

Nestes termos, aceito participar neste estudo.

Lisboa, 22 de Março de 2024

O investigador

____

O/A entrevistado(a)

____

Appendix B: Informed consent (EN)

Informed Consent Form (EN)

Instituto Superior de Ciências do Trabalho e da Empresa (ISCTE)

INSTITUTO UNIVERSITÁRIO DE LISBOA

This document is linked to the study entitled: "HR Analytics in the Commercial aviation sector in Portugal: a case study analysis", authored by António Pimenta de Brito, finalist of the PhD in Management. In this context, the objectives of the work were explained to me and my collaboration was requested for an interview. Given that participation in this study is voluntary, I can withdraw from it at any time, and I understand that there will be no remuneration or costs for my participation, and that I will be provided with clarification on any doubts that arise in my life. Thus, I freely consent, informed and informed, to the audio recording, on the condition that it is destroyed immediately after its treatment. On the other hand, the researcher undertakes to store the data collected in safe storage conditions, not authorizing sharing with third parties and safeguarding the privacy of the interviewees.

In these terms, I agree to participate in this study.

Lisbon, 22nd March 2024.

The researcher

____

The interviewee

Appendix C: ISCTE-IUL's Ethics Committee Opinion (PT)

iscte INSTITUTO UNIVERSITÁRIO DE LISBOA

CONSELHO DE ÉTICA

PARECER [Final] 79/2023

Projeto "*HR Analytics in the Aviation sector: a case study analysis*"

O projeto "*HR Analytics in the Aviation sector: a case study analysis*", submetido pelo investigador António Pimenta de Brito, foi apreciado pelo Conselho de Ética (CE) na reunião de 6 de junho de 2023, tendo dado origem ao parecer intercalar nº 79/2023.

O investigador veio, entretanto, disponibilizar esclarecimentos adicionais, em resposta às dúvidas suscitadas pelo CE.

O investigador garante que os dados que lhe são fornecidos se encontram anonimizados e que não existe possibilidade de reidentificação dos titulares dos dados.

No formulário de submissão à CE (secção "Problema de investigação e relevância do estudo"), é feita a seguinte referência: "Recorrendo a uma metodologia mista qualitativa e quantitativa, tanto com a entrevista e os modelos quantitativos ligados à inteligência artificial procurar-se-á criar este modelo preditivo e as consequentes recomendações de implementação para tomada de decisão na área de recursos humanos no setor de aviação.".

Não é feita, contudo, qualquer outra referência à entrevista no formulário de submissão ao CE.

Em suma, o investigador assegura que não são recolhidos dados pessoais no contexto do estudo, que todos os dados usados são anónimos e que não existe possibilidade de qualquer forma de reidentificação.

Caso o investigador tencione realizar as entrevistas referidas no formulário de submissão, deverá informar o CE dos termos em que serão realizadas essas entrevistas.

Caso contrário, se não forem realizadas quaisquer entrevistas, entende o Conselho de Ética emitir parecer favorável à realização da investigação.

Relator: Vítor Basto Fernandes

O Presidente do Conselho, Professor Sven Waldzus

Vítor Manuel Basto Fernandes

O Relator, Professor Vítor Basto Fernandes

1 | 2

ISCTE INSTITUTO UNIVERSITÁRIO DE LISBOA

iscte INSTITUTO UNIVERSITÁRIO DE LISBOA

CONSELHO DE ÉTICA

ADENDA AO PARECER Final 79/2023

Projeto "*HR Analytics in the Aviation sector: a case study analysis*"

O projeto "*HR Analytics in the Aviation sector: a case study analysis*", submetido pelo investigador António Pimenta de Brito, foi apreciado pelo Conselho de Ética (CE), tendo dado origem ao parecer final nº 79/2023.

O investigador veio, entretanto, disponibilizar esclarecimentos adicionais (em email que se junta em anexo), em resposta às dúvidas suscitadas pelo CE no referido parecer.

Na sequência dos esclarecimentos do investigador, entende o CE dever informar o seguinte:

- Tendo o estudo recorrido a dados "recolhidos através de gravador de voz" durante as entrevistas realizadas "remotamente usando a videoconferência" ou "de forma presencial", entende o CE, à luz do definido no Regulamento Geral de Proteção de Dados (RGPD), ter existido recolha de dados pessoais dos participantes no estudo;

- Dado a recolha de dados pessoais dos participantes, nomeadamente o registo de voz, já ter ocorrido e ser inviável, neste momento, obter o consentimento informado dos participantes para a recolha dos seus dados pessoais, o CE recomenda:

1) sejam destruídos os dados pessoais recolhidos, com a brevidade possível;

2) sejam informados os participantes sobre a recolha e posterior destruição dos seus dados pessoais.

Relator: Vítor Basto Fernandes (com Sven Waldzus)

Lisboa, 14 de dezembro de 2023.

O Presidente do Conselho, Professor Sven Waldzus

Vítor Manuel Basto Fernandes

O Relator: Professor Vítor Basto Fernandes

ANEXO

From: António Pimenta de Brito <antoniopimentadebrito@gmail.com>
Sent: Monday, December 4, 2023 5:14 PM
To: Conselho de Ética Iscte <conselho.etica@iscte-iul.pt>
Cc: Maria José Sousa <maria.jose.sousa@iscte-iul.pt>
Subject: Re: Parecer Final 79/2023

Exmos. Senhores,

Obrigado pelo email. Em resposta à vossa solicitação, venho esclarecer quanto às condições em que foram efetuadas as entrevistas.

As entrevistas efetuadas foram entrevistas semiestruturadas a 14 pessoas, as mesmas foram realizadas tanto remotamente usando a videoconferência como de forma presencial.

Os dados foram recolhidos através de gravador de voz e posteriormente estas gravações transcritas foram tratadas recorrendo a metodologias qualitativas de recolha e análise de dados.

Os nomes dos entrevistados não serão usados no estudo, mas apenas será mencionado a função profissional desempenhada e senioridade da pessoa. Espero ter esclarecido quando a esta questão.

Mais alguma questão, estou ao dispor.

Com os melhores cumprimentos,

António Pimenta de Brito, MBA
Assistant Professor in Management and Administration
ESCAD - IP Luso (Universidade Lusófona) | BRU-ISCTE (Instituto Universitário de Lisboa)
Lisbon, Portugal
p6326@ipluso.pt | acpbo@iscte-iul.pt
+ 351 91 466 50 90
LinkedIn

Appendix D: Interview Guide (PT) (HR Executives)

Entrevistas Semiestruturadas (executivos de RH)
No âmbito do Projeto de Doutoramento em Gestão – Especialização em Gestão de Recursos Humanos
ISCTE-IUL / BRU-IUL
António Pimenta de Brito

Enquadramento: pretendemos com esta entrevista compreender melhor a indústria da aviação e quais as suas necessidades principais, bem como o papel da gestão de recursos humanos na estratégia da empresa.
Duração: 60 minutos.

MUITO OBRIGADO PELA SUA COLABORAÇÃO. ESPERO TAMBÉM CONTRIBUIR COM CONHECIMENTO ADICIONAL PARA A SUA ATIVIDADE

1. O que lhe parece que seja o principal papel da gestão de recursos humanos numa empresa de aviação?
2. Existe algo que diferencia a gestão de recursos humanos de uma empresa de aviação, das outras?
3. Quais as maiores necessidades de negócio numa empresa de aviação?
4. É fácil o alinhamento da estratégia da empresa com a estratégia de recursos humanos?
5. Quais os maiores desafios dos recursos humanos no setor da aviação?
6. O que é para si uma estratégia de recursos humanos e qual a sua utilidade?
7. O que é para si o People Analytics?
8. A empresa em que trabalha tem uma área de *People Analytics*? O que lhe parece que é o papel do *People Analytics* numa empresa?
9. Qual a utilidade de estabelecer métricas de performance de recursos humanos no setor da aviação?
10. Quais os indicadores úteis que podem medir a performance dos recursos humanos no setor da aviação?
11. Agora apresentarei áreas em que a literatura sobre Analytics demonstra como sendo relevantes para medição de performance em Gestão de recursos humanos. Pode indicar alguns indicadores de performance por área?

11.1) Planeamento da força de trabalho:

11.2) Recrutamento:

11.3) Seleção/contratação;

11.4) Integração, adequação à cultura e envolvimento;

Appendix D: Interview Guide (PT) (HR Executives) (cont.)

11.5) Perda e retenção de funcionários;

11.6) Avaliação de desempenho e desenvolvimento e valor de tempo de vida do funcionário (“Employee life-time value” (ELTV))

11.7) Bem-estar, saúde e segurança dos funcionários

12. Por fim, é possível ordenar estas áreas por ordem de importância/ relevância para a criação de valor através das pessoas?
13. Mais algum indicador/ dimensão relevante analisar no HR analytics no setor da aviação que considere relevante?
14. Se tivesse que construir um sistema de People Analytics, quais seriam as principais áreas e critérios a considerar?

Appendix D: Interview Guide (EN) (HR Executives)

Semi-Structured Interviews (HR executives)

Within the scope of the PhD Project in Management – Specialization in Human Resources Management

ISCTE-IUL / BRU-IUL

António Pimenta de Brito

Background: With this interview we intend to better understand the aviation industry and its main needs, as well as the role of human resources management in the company's strategy.
Duration: 60 minutes.

THANK YOU VERY MUCH FOR YOUR COOPERATION. I ALSO HOPE TO CONTRIBUTE ADDITIONAL KNOWLEDGE TO YOUR ACTIVITY

1. What do you think is the main role of human resource management in an aviation company?
2. Is there anything that differentiates the human resources management of an aviation company from others?
3. What are the biggest business needs in an aviation company?
4. Is it easy to align the company's strategy with the human resources strategy?
5. What are the biggest challenges for human resources in the aviation sector?
6. What is a human resources strategy for you and what is its use?
7. What are People Analytics for you?
8. Does the company you work for have a *People Analytics* area? What do you think is the role of *People Analytics* in a company?
9. What is the use of establishing human resources performance metrics in the aviation sector?
10. What are the useful indicators that can measure the performance of human resources in the aviation sector?

11. I will now present areas in which the literature on Analytics demonstrates as being relevant to performance measurement in Human Resource Management. Can you indicate some performance indicators by area?

11.1) Workforce planning:

11.2) Recruitment:

11.3) Selection/hiring.

11.4) Integration, fit for culture and involvement.

11.5) Loss and retention of employees.

Appendix D: Interview Guide (EN) (HR Executives) (cont.)

11.6) Performance appraisal and development and employee life-time value (ELTV)

11.7) Employee welfare, health and safety

12. Finally, is it possible to order these areas in order of importance/relevance for the creation of value through people?
13. Any other relevant indicator/dimension to analyze in HR analytics in the aviation sector that you consider relevant?
14. If you had to build a People Analytics system, what would be the main areas and criteria to consider?

Appendix D: Interview Guide (PT) (HR Professionals)

Entrevista Semiestruturada (profissionais de RH)

No âmbito do Projeto de Doutoramento em Gestão – Especialização em Gestão de Recursos Humanos

ISCTE-IUL / BRU-IUL

António Pimenta de Brito

Enquadramento: pretendemos com estas entrevistas aferir quais as estratégias, políticas e práticas de RH de uma empresa de aviação, bem como as dimensões e indicadores principais para medir a performance dos RH no setor da aviação.
Duração: 90 minutos

MUITO OBRIGADO PELA SUA COLABORAÇÃO. ESPERO TAMBÉM CONTRIBUIR COM CONHECIMENTO ADICIONAL PARA A SUA ATIVIDADE

1. O que lhe parece que seja o principal papel da gestão de recursos humanos numa empresa de aviação?
2. Quais os maiores desafios dos recursos humanos no setor da aviação?
3. O que é para si uma estratégia de recursos humanos e qual a sua utilidade? Sabe qual é a da sua organização?
4. Quais as políticas e principais práticas de recursos humanos de uma empresa de aviação?
5. Quais as tarefas diárias de um gestor de recursos humanos?
6. A empresa em que trabalha tem uma área de People Analytics? O que lhe parece que é o papel do People Analytics numa empresa?
7. Qual a utilidade de estabelecer métricas de performance de recursos humanos no setor da aviação?
8. Quais os indicadores úteis que possam medir a performance dos recursos humanos no setor da aviação?
9. Agora, apresentarei áreas em que a literatura sobre Analytics apresenta como sendo relevantes para medição de performance em Gestão de recursos humanos. Pode indicar alguns indicadores por área?

9.1) Planeamento da força de trabalho;

9.2) Recrutamento;

9.3) Seleção/contratação;

9.4) Integração, adequação à cultura e envolvimento;

9.5) Perda e retenção de funcionários;

9.6) Avaliação de desempenho e desenvolvimento e valor de tempo de vida do funcionário (“Employee life-time value” (ELTV))

9.7) Bem-estar, saúde e segurança dos funcionários

Appendix D: Interview Guide (PT) (HR Professionals) (cont.)

10. Por fim, é possível ordenar estas áreas por ordem de importância/ relevância para a criação de valor através das pessoas?
11. Mais algum indicador/ dimensão relevante analisar no HR Analytics no setor da aviação?
12. Se tivesse de construir um sistema de People Analytics, quais seriam as principais áreas e critérios a considerar?

Appendix D: Interview Guide (EN) (HR Professionals)

Semi-Structured Interview (HR professionals)

Within the scope of the PhD Project in Management – Specialization in Human Resources Management

ISCTE-IUL / BRU-IUL

António Pimenta de Brito

Background: we intend with these interviews to assess the HR strategies, policies and practices of an aviation company, as well as the main dimensions and indicators to measure the performance of HR in the aviation sector.

Duration: 90 minutes

THANK YOU VERY MUCH FOR YOUR COOPERATION. I ALSO HOPE TO CONTRIBUTE ADDITIONAL KNOWLEDGE TO YOUR ACTIVITY

1. What do you think is the main role of human resource management in an aviation company?
2. What are the biggest challenges for human resources in the aviation sector?
3. What is a human resources strategy for you and what is its use? Do you know what your organization is?
4. What are the main human resources policies and practices of an aviation company?
5. What are the daily tasks of a human resources manager?
6. Does the company you work for have a People Analytics area? What do you think is the role of People Analytics in a company?
7. What is the use of establishing human resources performance metrics in the aviation sector?
8. What are the useful indicators that can measure the performance of human resources in the aviation sector?

9. Now, I will present areas in which the literature on Analytics presents as being relevant for performance measurement in Human Resource Management. Can you indicate some indicators by area?

9.1) Workforce planning.

9.2) Recruitment.

9.3) Selection/hiring.

9.4) Integration, fit for culture and involvement.

9.5) Loss and retention of employees.

9.6) Performance appraisal and development and employee life-time value (ELTV)

9.7) Employee welfare, health and safety

Appendix D: Interview Guide (EN) (HR Professionals) (cont.)

10. Finally, is it possible to order these areas in order of importance/relevance for the creation of value through people?
11. Any other relevant indicator/dimension to analyze in HR Analytics in the aviation sector?
12. If you had to build a People Analytics system, what would be the main areas and criteria to consider?

Appendix D: Interview Guide (PT) (AI Experts)

Entrevistas Semiestruturadas (especialistas IA)
No âmbito do Projeto de Doutoramento em Gestão – Especialização em Gestão de Recursos Humanos
ISCTE-IUL / BRU-IUL
António Pimenta de Brito

Enquadramento: pretendemos com estas entrevistas compreender melhor a indústria da aviação e quais as suas necessidades principais, o papel da gestão de recursos humanos na estratégia da empresa e, por fim, a inteligência artificial como metodologia de ciência de dados.
Duração: 60 minutos.

MUITO OBRIGADO PELA SUA COLABORAÇÃO. ESPERO TAMBÉM CONTRIBUIR COM CONHECIMENTO ADICIONAL PARA A SUA ATIVIDADE

1. No que toca ao uso da inteligência artificial, que tecnologias/ metodologias são usadas no estabelecimento de modelos descritivos, preditivos e prescritivos?
2. Como é que a Inteligência artificial poderia ser útil no processo de análise de dados e na tomada de decisão de RH no setor da aviação?
3. Que softwares se podem usar em análise de dados?
4. É possível apresentar um exemplo em como a inteligência artificial poderia ajudar na tomada de decisão com base em Big Data, na gestão de recursos humanos?
5. Agora apresentarei áreas em que a literatura sobre Analytics demonstra como sendo relevantes para medição de performance em Gestão de recursos humanos. Pode apresentar alguns indicadores por área? (de preferência, aplicados ao setor da aviação)

5.1) Planeamento da força de trabalho:

5.2) Recrutamento:

5.3) Seleção/contratação;

5.4) Integração, adequação à cultura e envolvimento;

5.5) Perda e retenção de funcionários;

5.6) Avaliação de desempenho e desenvolvimento e valor de tempo de vida do funcionário (“Employee life-time value” (ELTV))

Appendix D: Interview Guide (PT) (AI Experts) (cont.)

5.7) Bem-estar, saúde e segurança dos funcionários iniciativas

6. Por fim, é possível ordenar estas áreas por ordem de importância/ relevância para a criação de valor através das pessoas?
7. Mais algum indicador/ dimensão relevante analisar no HR analytics que considere relevante?
8. Se tivesse de construir um sistema de People Analytics, quais seriam as principais áreas e critérios a considerar?

Appendix D: Interview Guide (EN) (AI Experts)

Semi-Structured Interviews (AI experts)

Within the scope of the PhD Project in Management – Specialization in Human Resources Management

ISCTE-IUL / BRU-IUL

António Pimenta de Brito

Background: with these interviews we intend to better understand the aviation industry and its main needs, the role of human resources management in the company's strategy and, finally, artificial intelligence as a data science methodology.
Duration: 60 minutes.

THANK YOU VERY MUCH FOR YOUR COOPERATION. I ALSO HOPE TO CONTRIBUTE ADDITIONAL KNOWLEDGE TO YOUR ACTIVITY

1. Regarding the use of artificial intelligence, what technologies/methodologies are used in the establishment of descriptive, predictive and prescriptive models?
2. How could Artificial Intelligence be useful in the data analysis process and HR decision-making in the aviation sector?
3. What software can be used in data analysis?
4. Is it possible to present an example of how artificial intelligence could help in decision-making based on Big Data, in human resource management?
5. I will now present areas in which the literature on Analytics demonstrates as being relevant to performance measurement in Human Resource Management. Can you present some indicators by area? (preferably applied to the aviation sector)

5.1) Workforce planning:

5.2) Recruitment:

5.3) Selection/hiring.

5.4) Integration, adaptation to culture and involvement.

5.5) Loss and retention of employees.

5.6) Performance appraisal and development and employee life-time value (ELTV)

5.7) Employee welfare, health and safety
initiatives

Appendix D: Interview Guide (EN) (AI Experts) (cont.)

6. Finally, is it possible to order these areas in order of importance/relevance for the creation of value through people?
7. Any other relevant indicator/dimension to analyze in HR analytics that you consider relevant?
8. If you had to build a People Analytics system, what would be the main areas and criteria to consider?

Appendix E: Google forms questionnaire (PT)

BRU IUL
Business Research Unit
ISCTE-INSTITUTO UNIVERSITÁRIO DE LISBOA

Questionário – Abandono Profissional no Setor da Aviação Comercial
2023/2024

TERMO DE CONSENTIMENTO INFORMADO

Este estudo insere-se numa Tese de Doutoramento em Gestão, Especialização em Gestão de Recursos Humanos, realizada no ISCTE – IUL (BRU-IUL). O objetivo é estudar alguns fatores que influenciam o abandono profissional voluntário no setor da aviação comercial. **No entanto é direcionado a todas as pessoas que se encontram a trabalhar no setor, estejam em processo de saída, ou não, voluntária ou não.**

A sua participação é completamente voluntária e as suas respostas serão estritamente confidenciais. As respostas individuais nunca serão conhecidas, dado que a análise que faremos é do conjunto de todos os participantes.

Não existem respostas certas ou erradas, sendo que todas as respostas são válidas.

Para participar no presente estudo é necessário ter idade igual ou superior a 18 anos e dominar a língua portuguesa.

O preenchimento do questionário demora aproximadamente 5 minutos.

Agradecemos desde já a sua colaboração!

Para qualquer dúvida relativamente ao preenchimento do questionário ou outras informações adicionais, contacte:

Investigador principal: António Pimenta de Brito (acpbo@iscte-iul.pt)

Orientadores:

Professora Doutora Maria José Sousa, ISCTE – IUL

Professora Doutora Ana Moreira, ISPA – Instituto Universitário

1) Tendo tomado conhecimento sobre a informação acerca do estudo, declaro que tenho mais de 18 anos e que aceito participar nesta investigação:

Sim ☐ Não ☐

2) Trabalha atualmente numa empresa de transporte aéreo comercial?

Sim ☐ Não ☐

I. Dados Sociodemográficos

1) **Sexo**: ☐ Masculino ☐ Feminino

2) Idade:

- 20-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70 ou mais

3) Indique o grupo onde se enquadra a sua profissão:

☐ PNT (Pessoal Navegante Técnico)
☐ PNC (Pessoal Navegante de Cabine)
☐ Manutenção e Engenharia
☐ Pessoal de terra
☐ Outros . Qual?______________________

4) Qual o nível de escolaridade mais alto que completou?

☐ Licenciatura/ Mestrado/ Doutoramento
☐ Bacharelato (curso médio ou técnico superior)
☐ 10º a 12º ano de escolaridade (ou seja, de 10 a 12 anos de estudo)
☐ 4º a 9º ano de escolaridade (ou seja, de 4 a 9 anos de estudo)
☐ Menos de 4 anos de estudos ou sem escolaridade

5) Antiguidade (número de anos na empresa atual):

☐ 0 anos
☐ 1 anos
☐ 2 anos
☐ 3 anos
☐ 4 anos
☐ 5 – 9 anos
☐ 10 – 20 anos

- [ ] 20 – 29 anos
- [ ] 30 – 39 anos
- [ ] 40 – 49 anos
- [ ] 50 – mais anos

6) Número de horas médias trabalhadas por mês:

- [ ] 40 – 80 horas
- [ ] 80 – 160 horas
- [ ] 160 – 240 horas
- [ ] 240 ou mais horas

7) A última avaliação de desempenho foi satisfatória?

- [ ] Discordo totalmente
- [ ] Discordo
- [ ] Não concordo nem discordo
- [ ] Concordo
- [ ] Concordo totalmente

8) O número de projetos/tarefas atribuídos por trimestre demasiadamente alto?

- [ ] Discordo totalmente
- [ ] Discordo
- [ ] Não concordo nem discordo
- [ ] Concordo
- [ ] Concordo totalmente

9) Promoção: foi promovido nos últimos 5 anos?

Sim [ ] Não [ ]

II. Questionário sobre satisfação no trabalho

Pretende-se nesta secção, que indique, até que ponto concorda ou discorda com cada uma das seguintes afirmações, tendo em conta a escala de seguida apresentada:

1 – Discordo Totalmente
2 – Discordo
3 – Não concordo nem discordo
4 – Concordo
5 – Concordo Totalmente

1. A progressão da minha carreira vai ao encontro das minhas expectativas	1	2	3	4	5
2. A minha organização preocupa-se com o desenvolvimento de competências dos colaboradores, de modo a progredirem na carreira.	1	2	3	4	5
3. Na minha organização, é muito difícil a progressão de carreiras.	1	2	3	4	5
4. Sinto-me seguro no meu ambiente de trabalho	1	2	3	4	5
5. A minha organização preocupa-se com a segurança dos colaboradores.	1	2	3	4	5
6. Na minha organização é frequente haver acidentes por falta de segurança.	1	2	3	4	5
7. A minha chefia dá-me todo o apoio no desempenho das minhas funções.	1	2	3	4	5
8. A minha chefia preocupa-se com o bem-estar dos colaboradores.	1	2	3	4	5
9. O apoio dado pela minha chefia é nulo.	1	2	3	4	5
10. A minha organização preocupa-se com a conciliação entre o trabalho e a vida pessoal dos colaboradores.	1	2	3	4	5
11. Na minha organização promovem-se iniciativas que facilitem a conciliação entre o trabalho e a vida pessoal.	1	2	3	4	5
12. Na minha organização não há preocupação com a conciliação entre o trabalho e a vida pessoal dos colaboradores.	1	2	3	4	5
13. A minha remuneração está de acordo com a minha avaliação de desempenho.	1	2	3	4	5
14. Estou satisfeito com a minha remuneração.	1	2	3	4	5

15. A minha remuneração não reflete o meu desempenho profissional, pois é muito baixa.	1	2	3	4	5
16. Cumpro adequadamente as tarefas que me são destinadas.	1	2	3	4	5

III. Desempenho profissional

Nesta secção, pedimos-lhe indique até que ponto concorda ou discorda com cada uma das seguintes afirmações acerca do seu desempenho profissional, utilizando a mesma escala:

1. Realizo adequadamente as tarefas que me estão destinadas.	1	2	3	4	5
2. Independentemente das circunstâncias, tenho produzido um trabalho de elevada qualidade.	1	2	3	4	5
3. Atinjo os níveis de desempenho requeridos para a minha função.	1	2	3	4	5
4. Desempenho sempre as tarefas que me são atribuídas.	1	2	3	4	5

IV. Pretende-se nesta secção, que indique, até que ponto concorda ou discorda com cada uma das seguintes afirmações acerca das suas intenções de saída, tendo em conta a mesma escala:

1. Se pudesse, sairia desta empresa hoje.	1	2	3	4	5
2. Ultimamente, tenho sentido vontade de deixar este emprego.	1	2	3	4	5
3. Neste momento, gostaria de permanecer nesta organização o máximo de tempo possível.	1	2	3	4	5

Existem quaisquer outros fatores os quais sinta que são responsáveis pelo abandono profissional (de forma geral, não no seu caso particular)?

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Tem mais alguma observação, proposta de melhoria ao questionário, comentário a fazer?

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____

Muito Obrigado pela colaboração!

Acabou de contribuir para o avanço no conhecimento nesta área e para que melhores políticas de recursos humanos possam ser implementadas nas empresas!

Appendix E: Google forms questionnaire (EN)

BRU IUL
Business Research Unit
ISCTE-INSTITUTO UNIVERSITÁRIO DE LISBOA

Questionnaire – Professional Abandonment in the Commercial Aviation Sector
2023/2024

INFORMED CONSENT FORM

This study is part of a PhD Thesis in Management, Specialization in Human Resources Management, carried out at ISCTE – IUL (BRU-IUL). The objective is to study some factors that influence voluntary professional abandonment in the commercial aviation sector. **However, it is aimed at all people who are working in the sector, whether they are in the process of leaving, or not, voluntary or not.**

Your participation is completely voluntary and your responses will be strictly confidential. The individual answers will never be known, since the analysis we will make is of all the participants.

There are no right or wrong answers, and all answers are valid.

To participate in this study, it is necessary to be 18 years of age or older and master the Portuguese language.

Filling out the questionnaire takes approximately 5 minutes.

Thank you in advance for your cooperation!

For any questions regarding the completion of the questionnaire or other additional information, please contact:

Principal Investigator: António Pimenta de Brito (acpbo@iscte-iul.pt)

Supervisors:

Professor Maria José Sousa, ISCTE – IUL

Professor Ana Moreira, ISPA – University Institute

1) Having become aware of the information about the study, I declare that I am over 18 years old and that I agree to participate in this research:

   Yes ☐ No ☐

2) Do you currently work for a commercial air transport company?

   Yes ☐ No ☐

I. Sociodemographic Data

1) **Sex**: ☐ Male Female ☐

2) Age:

- 20-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70 or more

3) Indicate the group where your profession fits:

☐ PNT (Technical Navigation Personnel)
☐ PNC (Cabin Crew Personnel)
☐ Maintenance and Engineering
☐ Ground staff
☐ Other. Which?_____________________

4) What is the highest level of education you have completed?

☐ Bachelor's / Master's / PhD
☐ Bachelor's degree (high school or higher technical course)
☐ 10th to 12th year of schooling (i.e. 10 to 12 years of study)
☐ 4th to 9th year of schooling (i.e. 4 to 9 years of study)
☐ Less than 4 years of schooling or no schooling

5) Seniority (number of years in the current company):

☐ 0 years
☐ 1 years
☐ 2 years
☐ 3 years
☐ 4 years
☐ 5 – 9 years
☐ 10 – 20 years

☐ 20 – 29 years old
☐ 30 – 39 years old
☐ 40 – 49 years old
☐ 50 – more years

6) Number of average hours worked per month:

☐ 40 – 80 hours

☐ 80 – 160 hours

☐ 160 – 240 hours

☐ 240 or more hours

7) Was the last performance evaluation satisfactory?

☐ I totally disagree

☐ Disagree

☐ I neither agree nor disagree

☐ Agree

☐ I totally agree

8) Is the number of projects/tasks assigned per quarter too high?

☐ I totally disagree

☐ Disagree

☐ I neither agree nor disagree

☐ Agree

☐ I totally agree

9) Promotion: Have you been promoted in the last 5 years?

Yes ☐ No ☐

II. Job satisfaction questionnaire

The aim of this section is to indicate to what extent you agree or disagree with each of the following statements, considering the scale presented below:

1 – Strongly disagree
2 – Disagree
3 – I neither agree nor disagree
4 – I agree
5 – Totally agree

1. My career progression meets my expectations	1	2	3	4	5
2. My organization is concerned with the development of employees' skills, to progress in their careers.	1	2	3	4	5
3. In my organization, it is very difficult to progress careers.	1	2	3	4	5
4. I feel safe in my work environment	1	2	3	4	5
5. My organization cares about employee safety.	1	2	3	4	5
6. In my organization, there are often accidents due to lack of safety.	1	2	3	4	5
7. My boss gives me full support in the performance of my duties.	1	2	3	4	5
8. My boss cares about the well-being of employees.	1	2	3	4	5
9. The support given by my boss is nil.	1	2	3	4	5
10. My organization is concerned with reconciling work and personal life for employees.	1	2	3	4	5
11. In my organization, initiatives are promoted to facilitate the reconciliation of work and personal life.	1	2	3	4	5
12. In my organization there is no concern with reconciling work and personal life of employees.	1	2	3	4	5
13. My remuneration is in line with my performance evaluation.	1	2	3	4	5
14. I am satisfied with my remuneration.	1	2	3	4	5
15. My remuneration does not reflect my professional performance, as it is very low.	1	2	3	4	5
16. I adequately fulfill the tasks assigned to me.	1	2	3	4	5

III. Professional performance

In this section, we ask you to indicate the extent to which you agree or disagree with each of the following statements about your professional performance, using the same scale:

1. I adequately carry out the tasks assigned to me.	1	2	3	4	5
2. Regardless of the circumstances, I have produced high quality work.	1	2	3	4	5
3. I reach the performance levels required for my role.	1	2	3	4	5
4. I always perform the tasks assigned to me.	1	2	3	4	5

IV. This section is intended to indicate the extent to which you agree or disagree with each of the following statements about your exit intentions, taking into account the same scale:

1. If I could, I would leave this company today.	1	2	3	4	5
2. Lately, I've been feeling like leaving this job.	1	2	3	4	5
3. At this time, I would like to stay in this organization as long as possible.	1	2	3	4	5

Are there any other factors that you feel are responsible for the job abandonment (in general, not in your case)?

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Do you have any other observations, proposals for improvement to the questionnaire, comments to make?

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Thank you very much for your cooperation!

It has just contributed to the advancement of knowledge in this area and so that better human resources policies can be implemented in companies!