ACADEMIA MILITAR

People Analytics in the Portuguese Army

Aspirante de Administração Militar João Francisco Dantas Silva

Dissertação de Mestrado

Ciências Militares na Especialidade de Administração

Orientador: Professor Doutor Flávio Ivo Riedlinger de Magalhães

Coorientadora: Professora Doutora Elisabete Sofia Nabais de Oliveira de Freitas e Menezes

Júri

Presidente: Professora Doutora Sandra Luzia Esteves Oliveira de Almeida

Arguente: Professora Doutora Paula Cristina Pires Simões

Orientador: Professor Doutor Flávio Ivo Riedlinger de Magalhães

Diretor de Curso: Hélio de Jesus Branco Corguinho Fernandes

junho de 2025

ACADEMIA MILITAR

People Analytics in the Portuguese Army

Aspirante de Administração Militar João Francisco Dantas Silva

Dissertação de Mestrado

Ciências Militares na Especialidade de Administração

Orientador: Professor Doutor Flávio Ivo Riedlinger de Magalhães

Coorientadora: Professora Doutora Elisabete Sofia Nabais de Oliveira de Freitas e Menezes

Júri

Presidente: Professora Doutora Sandra Luzia Esteves Oliveira de Almeida

Arguente: Professora Doutora Paula Cristina Pires Simões

Orientador: Professor Doutor Flávio Ivo Riedlinger de Magalhães

Diretor de Curso: Hélio de Jesus Branco Corguinho Fernandes

junho de 2025

ACKNOWLEDGEMENTS

This dissertation marks the terminal stage of a five-year academic and professional journey, one made possible by the steadfast support, guidance, and encouragement of many individuals and institutions, to whom I am deeply grateful.

First and foremost, I extend my heartfelt thanks to Professor Dr. Flávio Ivo Riedlinger de Magalhães, my supervisor, for his exceptional dedication, scholarly guidance, and availability throughout the research process. His expertise and commitment were crucial in the successful completion of this work. I am equally indebted to Professor Dr. Elisabete Sofia Nabais de Oliveira de Freitas e Menezes, whose intellectual generosity and valuable perspectives significantly enriched the quality of this dissertation.

I also wish to express my sincere appreciation to Major Hélio Fernandes for the institutional support and academic orientation, which were vital throughout this endeavour.

Special thanks are due to the career management technician who kindly participated in the semi-structured interview and provided indispensable empirical insights for this research.

I am profoundly grateful to all the permanent staff members of the Portuguese Army who voluntarily took part in the PLACE survey. Their time and input were essential. My appreciation also goes to the PLACE Project coordinators, whose permission to access the dataset provided a crucial foundation for this study.

To my comrades, my second family during this academic journey, thank you for your companionship, solidarity, and shared ambition. Your support made this experience both intellectually stimulating and personally fulfilling.

Finally, I wish to acknowledge the unwavering support of my family. To my mother, especially, I offer my deepest gratitude for her constant encouragement, belief in my potential, and for always inspiring me to strive for excellence and personal growth.

RESUMO

Esta dissertação estuda a integração do People Analytics (PA) no quadro da Gestão de Recursos Humanos (GRH) do Exército Português, visando aumentar a eficiência da gestão de carreiras. People Analytics pode ser entendido como o uso sistemático de dados, métodos estatísticos e ferramentas analíticas para apoiar decisões de GRH, permitindo substituir abordagens baseadas apenas em intuição por processos fundamentados em evidência.

A investigação recorre a uma abordagem metodológica mista e a uma estratégia abdutiva, incorporando uma Revisão Sistemática da Literatura, um questionário e uma entrevista com um técnico responsável pela gestão de carreira. A análise quantitativa permitiu identificar cinco indicadores críticos da GRH: Ambiente Organizacional, Desenvolvimento de Carreira, Comunicação e Feedback, Estado Funcional Atual e Mobilidade e Colocação. A análise temática destacou desafios estruturais, como a estagnação na progressão profissional, a perceção de falta de confiança nas avaliações de desempenho e a ausência de estratégias de implementação baseadas em dados.

Abordando a questão central da investigação, "Como é que a implementação do método de PA melhora a eficiência da gestão de recursos humanos no Exército Português?", o estudo demonstra que o PA pode funcionar como uma ferramenta estratégica para alinhar competências individuais com os objetivos institucionais, promover uma progressão de carreira transparente e baseada no mérito e sustentar o desenvolvimento de talentos. Como contributo prático, evidencia-se que a utilização de PA permite monitorizar o ambiente organizacional em tempo real, identificar militares em risco de desmotivação ou estagnação, apoiar decisões de mobilidade e colocação mais justas e eficazes, e integrar métricas de desempenho e satisfação.

Com base nos resultados obtidos, é proposto um modelo conceptual que visa apoiar a tomada de decisões estratégicas e otimizar o planeamento da força de trabalho no contexto de organizações militares.

São reconhecidas várias limitações. A implementação do PA permanece numa fase inicial, condicionada por constrangimentos técnicos, fragmentação dos sistemas de dados e rigidez nas estruturas hierárquicas. Adicionalmente, a investigação restringiu-se ao efetivo do quadro permanente, excluindo o pessoal contratado, o que poderá comprometer a generalização dos resultados obtidos para a totalidade do contingente militar.

Com o objetivo de orientar futuras investigações, apresentam-se as seguintes recomendações: realizar estudos longitudinais que permitam avaliar o impacto da aplicação de ferramentas analíticas na gestão de recursos humanos, tanto em tempo real como a longo prazo; alargar o âmbito da investigação a outros ramos das Forças Armadas ou a países aliados da NATO, com vista à realização de análises comparativas; aprofundar a análise das implicações éticas associadas à tomada de decisão baseada em algoritmos; e desenvolver programas-piloto que permitam validar empiricamente o modelo conceptual proposto em unidades do Exército.

Palavras-chave: Exército Português; Gestão de Carreiras; Gestão de Recursos Humanos People Analytics

ABSTRACT

This dissertation studies the integration of *People Analytics* (PA) into the Human Resource Management (HRM) framework of the Portuguese Army, aiming to enhance career management efficiency. *People Analytics* can be defined as the systematic use of data, statistical methods, and analytical tools to support HRM decisions, replacing intuition-driven approaches with evidence-based processes.

The study employs a mixed-methods design and an abductive research strategy, combining a Systematic Literature Review, a survey, and an interview with a career management technician. The quantitative analysis identified five critical HRM indicators: Organizational Environment, Career Development, Communication and Feedback, Current Functional Status, and Mobility and Placement. The thematic analysis highlighted structural challenges, such as career stagnation, distrust in performance evaluations, and the absence of data-driven deployment strategies.

Addressing the central research question, "How can People Analytics enhance human resource management efficiency in the Portuguese Army?", the study demonstrates that PA can function as a strategic tool to align individual competencies with institutional goals, promote transparent and merit-based career progression, and support talent development. In practical terms, the findings show that PA enables real-time monitoring of organizational climate, early identification of service members at risk of stagnation or disengagement, more equitable and effective mobility and placement decisions, and the integration of performance and satisfaction.

Based on these findings, a conceptual framework is proposed to support strategic decision-making and optimize workforce planning in the military context.

Several limitations are acknowledged. The implementation of PA remains in an early stage, constrained by technical barriers, fragmented data systems, and rigid hierarchical structures. Moreover, the study was limited to Permanent Staff, excluding contract personnel, which may affect the generalizability of results.

To guide future research, the following recommendations are made: conduct longitudinal studies to evaluate the short- and long-term impacts of PA on HRM; broaden the research scope to include other military branches or NATO allies for comparative analysis; assess the ethical implications of algorithmic decision-making in HRM; and initiate pilot programs to empirically test the proposed conceptual framework in Army units.

Keywords: Portuguese Army; Career Management; Human Resource Management; People Analytics

INDEX

FIGURE INDEX

TABLE INDEX

LIST OF APPENDICES AND ANEXXES

LIST OF ABBREVIATIONS AND ACRONYMS

ADC	Career Development Support
AI	Artificial Intelligence
CFI	Comparative Fit Index
CQ	Central Question
DL	Deep Learning
DQ	Derived Question
EFA	Exploratory Factor Analysis
EMFAR	Statute of the Military of the Armed Forces
GDPR	General Data Protection Regulation
GO	General Objective
HR	Human Resource
HRM	Human Resource Management
KMO	Kaiser-Meyer-Olkin
KPI	Key Performance Indicators
L&D	Learning and Development
ML	Machine Learning
PA	People Analytics
PLACE	Content Development for the Army Career Information, Choices, and Support Platform
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SLR	Systematic Literature Review
SO	Specific Objective

INTRODUCTION

As part of the conclusion of the study cycle for the Master's Degree in Military Administration at the Military Academy, this dissertation, entitled “People Analytics in the Portuguese Army”, emerges within a context of rapid digital transformation and increasing demand for data-informed decision-making in public organizations.

People Analytics (PA) has gained significant traction in recent years as a strategic instrument for Human Resource Management (HRM), enabling organizations to collect, process, and interpret workforce-related data to support operational efficiency, talent retention, and strategic alignment (Irigaray & Stocker, 2023). The integration of PA within military institutions reflects a broader modernization effort, consistent with the adoption of Artificial Intelligence (AI), Big Data, and other emerging technologies for personnel and organizational process management (Kaluzny, 2021).

Despite these advancements, the application of PA in military HRM remains underexplored in the literature. Ethical concerns, such as data governance, employee privacy, and algorithmic transparency, pose substantial challenges to its implementation (Di Lauro et al., 2024). Considering these issues, this dissertation aims to identify and analyze the potential contributions of PA to HRM practices in the Portuguese Army, with a particular focus on career management processes.

A distinctive feature of this research lies in its methodological foundation in a Systematic Literature Review (SLR) that serves as the cornerstone of the theoretical framework. The SLR enables the rigorous identification, selection, and synthesis of the most relevant and recent knowledge on the topic, providing a solid and methodologically grounded basis for subsequent empirical developments (Snyder, 2019). Positioned at the start of the dissertation, the SLR constructs the conceptual frame that leads the following chapters, ensuring coherence among the research problem, objectives, and methodological choices. Moreover, this integrative approach refines the analytical focus and enhances the alignment between existing literature and the empirical proposition advanced in this study.

Thus, based on a mixed and abductive research strategy, this study aims to identify how PA can be applied to HRM procedures in the Portuguese Army, with a focus on career management. A conceptual application model was developed based on the analysis of data collected through the literature review, surveys, and interviews, reflecting the organizational context and aligned with the relevant literature.

Following the contextualization of the study, the Central Question (CQ) to be addressed is: "How can People Analytics enhance human resource management efficiency in the Portuguese Army?". The corresponding General Objective (GO) is "Comprehend the impact of People Analytics on the Portuguese Army".

To guide a logical and sequential approach, four Specific Research Objectives (SO) were defined, which are presented below in a sequential order (Table 1).

Table 1 - Specific research objectives.

SO1	Identify behavioral patterns and individual needs.
SO2	Identify the key metrics and indicators used in Human Resource Management in the Army.
SO3	Examine the impacts of Data Analytics on Decision-Making.
SO4	Develop a Conceptual Model for the Portuguese Army.

To achieve these objectives, this research work is divided into two parts (Table 2): one theoretical and the other practical. Part I presents the theoretical concepts that support the developed research, subdivided into three chapters: (1) Systematic Literature Review, (2) People Analytics Fundamentals, and (3) Human Resource Management. On the other hand, Part II corresponds to the practical part, encompassing the methodological framework and fieldwork, and is subdivided into: (4) Materials and Methods; (5) Results; (6) Discussion of Results, as well as the conclusions related to the research. The post-textual part serves as a complement to the topics covered, consisting of appendices and annexes.

Table 2 - Structure of Scientific Research Work.

<table>
<tr><th colspan="6">Scientific Research Work</th></tr>
<tr><td>Introduction</td><td>Part I - THEORETICAL FRAMEWORK</td><td>Chapter 1. Systematic Literature Review
Chapter 2. People Analytics Fundamentals
Chapter 3. Human Resource Management</td><td>Part II – PRACTICAL COMPONENT</td><td>Chapter 4. Materials and Methods
Chapter 5. Results
Chapter 6. Discussion of Results
Conclusions</td><td>POST-TEXTUAL PART (Appendices and Annexes)</td></tr>
</table>

CHAPTER 1 – SYSTEMATIC LITERATURE REVIEW

This chapter presents a systematic literature review on PA within the field of HRM. The purpose is to examine how data-driven approaches are influencing HR functions. By systematically identifying, evaluating, and analyzing scholarly sources, the review seeks to map current trends and identify gaps in the literature, thereby supporting future academic and practical developments in HRM.

1.1. Materials and Methods

Given the scope of the research topic, a SLR was conducted to examine the relationship between PA and HRM, following a structured and replicable protocol. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which provides standardized guidelines for the synthesis of empirical evidence (Page et al., 2021). The use of PRISMA ensured that all stages of the review process, from study identification and selection to inclusion and synthesis, complied with established academic standards (Berrang-Ford et al., 2015).

Although the initial scope of the review considered a broader publication range, the final inclusion criteria limited the review to studies published between 2022 and 2025. This decision was based on the recent increase in academic output regarding the integration of AI in organizational contexts, particularly in HRM. The rapid evolution of this field has reduced the applicability of earlier studies to the current research context. Therefore, recent literature was prioritized to align the theoretical foundation with the dissertation's thematic focus.

The PRISMA flow diagram was used to document the review process, including the search strategy, number of studies identified, and inclusion and exclusion decisions. It also provides justification for excluded articles, verifies eligibility, and records the final selection of studies included in the SLR (Hiebl, 2023).

The bibliographic search was conducted on 12 February 2025 using the Scopus database. This database was selected due to its coverage of scholarly publications in organizational behavior, data analytics, and HRM, which are relevant to the research topic.

The studies were evaluated based on the following inclusion criteria: studies published in English or Portuguese, peer-reviewed scientific articles, and publications between 2022 and 2025. Additionally, studies had to analyze the application, impact, or challenges of PA and examine the role of data-driven decision-making in HRM. However, the exclusion criteria were as follows: studies not published in English, books, book chapters, conference abstracts, or non-peer-reviewed articles, as well as studies published before 2022. Those not accessible in full text, and studies that did not focus on the application of People Analytics in HRM contexts, were also excluded.

1.2. Procedure

To initiate the process underlying a SLR, an independent bibliographic search was conducted to gain an idea of the keywords that should be used. Initially, the chosen databases were Web of Science and Scopus. After testing both options, Scopus was chosen for its comprehensive coverage.

The bibliographic search for this systematic literature review was conducted on 12 February 2025 using Scopus. The keywords used in the search were "People Analytics" and "Human Resource Management", which effectively filtered the literature focused on the central theme. The search identified a total of 259. Additionally, the following automated tools were applied: temporal period (2022–2025) and language of study (English). By restricting the temporal period and the language, 136 studies were selected, while 123 studies were discarded. Subsequently, the search was limited to the subject areas "Business, Management and Accounting" and "Social Sciences", resulting in 76 studies selected, with 60 studies discarded. Due to the large number of articles, it was necessary to narrow down the database. After testing several options, the inclusion of article-type documents was chosen, resulting in 30 studies selected and 46 studies removed. The identified studies were verified manually to address potential gaps, leading to the exclusion of nine studies that did not meet the topic criteria.

To illustrate the network of keywords used in the articles identified from the Scopus database, the VOSviewer[1] software tool (version 1.6.20) was employed. Subsequently, the VOSviewer tool was used, where the data from the RIS file was processed, and a map was created based on bibliographic data, specifically focusing on the occurrence of keywords. The network analysis of the keywords used in the articles identified by the Scopus database can be observed in Figure 1. The bibliometric analysis presents two groups of keywords: (1) data analytics, digital transformation, human resource management, information management, and risk management; (2) people analytics, big data, HR analytics, and human

[1] VOSviewer is a computer program for constructing and viewing bibliometric maps, with a focus on graphical representation (Van Eck & Waltman, 2010).

capital analytics. The bibliometric analysis conducted using VOSviewer aimed to explore the occurrence of keywords in the initial phase of the research, serving as an exploratory step in this systematic literature review.

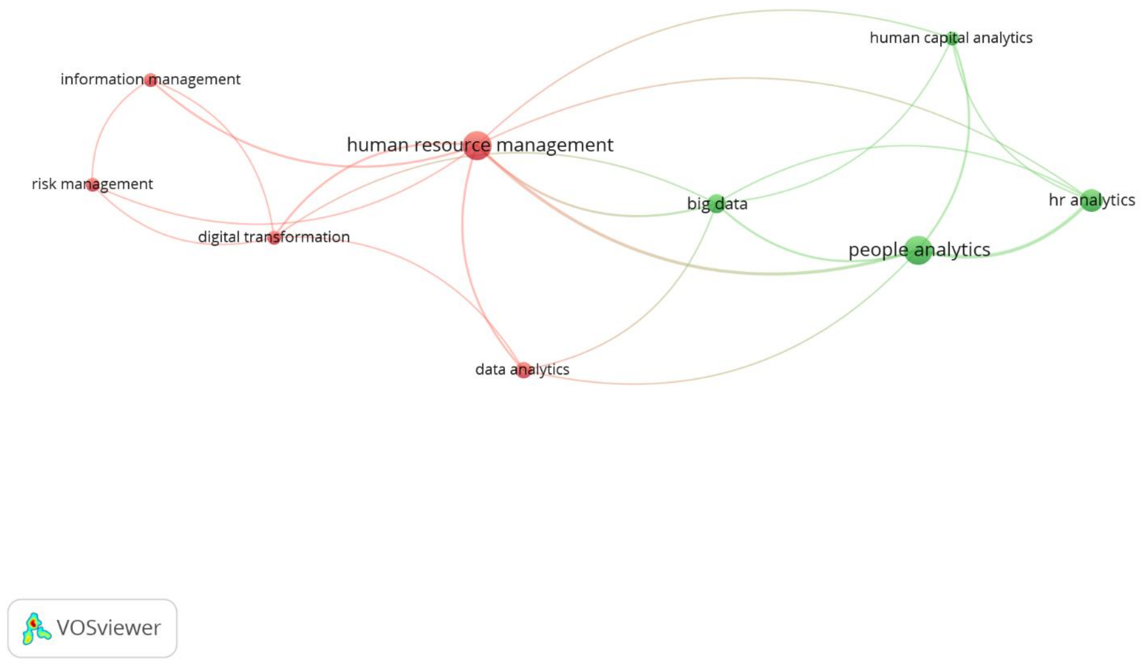


Figure 1 - Keyword network generated by VOSviewer.

After identifying the studies, the titles and abstracts underwent evaluation. Based on the exclusion and inclusion criteria, 21 papers were selected as relevant, while 9 were excluded, given that they did not address the relationship between PA and HRM. Throughout the selection and analysis of the publications, the previously mentioned inclusion and exclusion criteria were consistently applied. The selection process can be observed through the PRISMA flow diagram below (Figure 2).

Each of the articles was thoroughly examined to guarantee a rigorous and transparent selection process. The goal was to improve the review's reliability and reproducibility by systematically analyzing the quality and relevance of the selected literature. The process ended with 21 manuscripts included in the qualitative synthesis, with no further articles added beyond those obtained from the Scopus database.

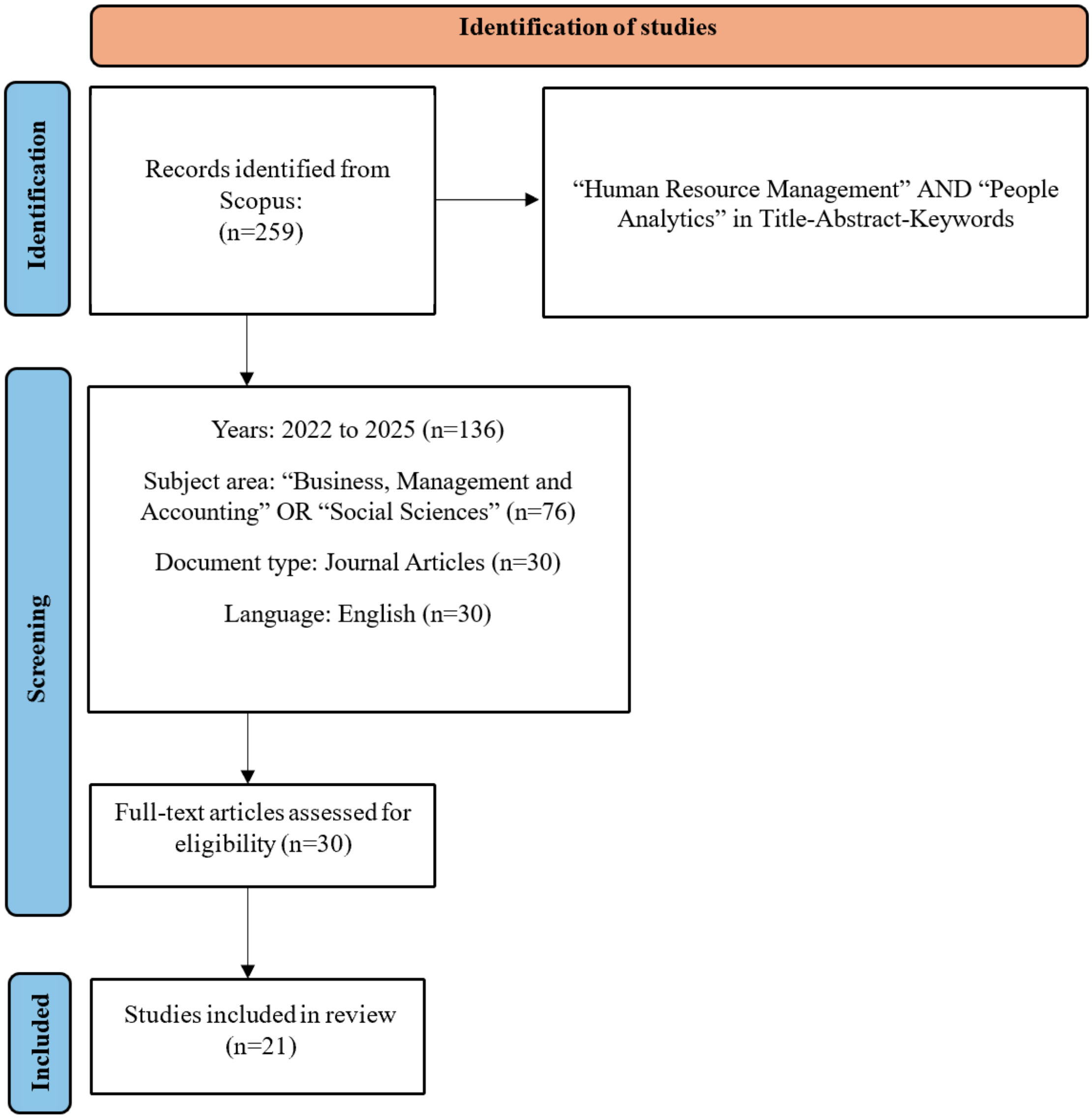


Figure 2 - PRISMA Flowchart.

1.3. Data Extraction and Synthesis

A rigorous systematic review aims to gather all pertinent data related to the research question, ensuring a comprehensive understanding of the existing literature (Petticrew & Roberts, 2006). In this study, data were primarily obtained from the Scopus database and processed using the PRISMA framework, which supports a structured synthesis of available evidence (Page et al., 2021). Synthesizing results from multiple studies helps identify both consistencies and discrepancies in findings across various contexts, contributing to a nuanced understanding of the research landscape (Pigott & Polanin, 2020).

A five-phase systematic review was conducted on 21 selected publications to enable a content analysis. The process began with multiple readings of each study to ensure familiarity with the material. Bibliographic data, including titles, authors, publication dates, and main findings, were documented in a structured database. Analysis then focused on identifying patterns and interrelationships in the data, which informed the development of initial thematic categories. These categories were subsequently refined to align with the study's research objectives. The final step involved synthesizing thematic insights to address the research questions. NVivo 14[2] software was employed to facilitate data management and support analytical procedures (Phillips & Lu, 2018).

1.4. Results

1.4.1. Decision-Making Optimization

In HRM, PA is utilized to optimize decision-making by applying data and quantitative methods to support strategic planning (McCartney & Fu, 2022). The integration of advanced analytics contributes to increased accuracy and operational effectiveness while reducing uncertainty and bias in HR processes (Larsson & Edwards, 2022). Techniques such as machine learning (ML) algorithms and predictive modeling are applied to support workforce planning, performance assessment, and talent acquisition (Graczyk-Kucharska et al., 2022).

Computational techniques such as artificial neural networks and multivariate adaptive regression splines have been used to detect complex relationships among variables and process large datasets (Graczyk-Kucharska et al., 2022). These methods support forecasting employee performance, thereby assisting HR professionals in making data-informed decisions regarding promotions, retention, and recruitment (McCartney & Fu, 2022).

PA also contributes to aligning human resource strategies with broader organizational objectives. Integrating econometric models with PA facilitates the development of structured frameworks for strategic decision-making (Larsson & Edwards, 2022). By using historical and real-time data, organizations can support managerial decisions that increase operational responsiveness (Belizón et al., 2024). Belizón et al. (2024) also present the Knowledge Discovery Process model, which outlines systematic stages of data collection, organization, algorithmic application, and outcome evaluation to identify workforce patterns.

The application of PA supports improved decision-making and contributes to the

[2] NVivo is a software for qualitative data analysis that allows users to store, manage, query, and analyze unstructured data (Phillips & Lu, 2018).

effectiveness of HRM. By employing data analysis and structured evaluation frameworks, organizations can enhance HR functions and align them with strategic goals (Larsson & Edwards, 2022). The adoption of PA can lead to operational efficiency, reduced uncertainty, and more effective workforce management, thereby promoting a data-centric organizational culture (McCartney & Fu, 2022).

1.4.2 Talent Development

Talent development involves supporting employee skill acquisition and aligning workforce capabilities with organizational objectives. As organizations adopt data-driven management, PA provides information to support talent identification, learning and development (L&D) programs, career progression planning, and succession management strategies (Suri & Lakhanpal, 2024).

The application of PA in L&D strategies allows organizations to design training programs tailored to workforce needs and organizational objectives. By analyzing employee performance data, training evaluations, and competency assessments, skill gaps can be identified, and development efforts optimized (Belizón et al., 2024). PA also enables forecasting of future skill requirements, aligning workforce development with changing industry demands.

Rigamonti et al. (2024) emphasize that HR analytics maturity models underscore the role of PA in advancing L&D functions beyond basic metrics toward strategic planning. Organizations also use PA to evaluate the return on investment in training, ensuring alignment between skill development and performance outcomes (Yoon et al., 2024).

Succession planning and career development processes benefit from the use of PA, which supports objective evaluations of leadership readiness and employee potential. While traditional approaches often rely on subjective judgments, PA incorporates data such as performance trends, leadership assessments, and engagement metrics to identify high-potential employees (Belizón et al., 2024).

Moreover, PA supports career pathing by analyzing historical career data and forecasting potential progression scenarios. Structured development pathways may increase employee engagement and retention by clarifying advancement opportunities (Rigamonti et al., 2024). PA’s role in HR Development is extensively explored in bibliometric studies, revealing a convergence of research on workforce planning, data-driven decision-making, and the application of analytics across HR functions (Suri & Lakhanpal, 2024).

Workforce planning and retention strategies are supported by PA and data mining techniques, which help organizations identify patterns related to satisfaction, performance, and turnover (Belizón et al., 2024). PA enables real-time monitoring of engagement metrics and satisfaction indicators. Machine learning models can be applied to predict employee attrition risk, supporting the implementation of targeted retention interventions (Rigamonti et al., 2024).

1.4.3. Ethical Considerations

The implementation of PA in HRM introduces ethical concerns regarding employee privacy, data governance, and the balance between organizational objectives and individual rights. As organizations apply AI and ML to workforce decision-making, challenges arise related to the collection, processing, and use of employee data (Di Lauro et al., 2024).

Data collection and employee monitoring are key ethical concerns in the application of PA. Passive surveillance, such as the analysis of social interactions and behavioral patterns, may compromise employee autonomy and foster an environment of continuous observation. These practices become more problematic when individuals lack control over their data or are not informed about its intended use (McCartney & Fu, 2022). This raises issues regarding consent and transparency, particularly when decisions based on such data affect employees' experiences and outcomes (Jörden et al., 2022). Additionally, algorithmic decision-making in recruitment, performance evaluation, and retention can reproduce and reinforce historical biases. Predictive models trained on past data may perpetuate discriminatory outcomes if not critically assessed and adjusted (Di Lauro et al., 2024). Furthermore, opacity in algorithmic criteria may lead to employee uncertainty, especially when evaluations are based on undisclosed metrics and lack avenues for appeal. These challenges underline the necessity of regulatory frameworks that guarantee employees the right to understand and contest algorithmic decisions (McCartney & Fu, 2022).

Regulatory frameworks such as the European Union’s General Data Protection Regulation (GDPR) establish explicit consent requirements and define limits for the use of personal data. However, implementation challenges persist, especially for multinational organizations operating under multiple legal systems (Jörden et al., 2022).

Employee trust in PA depends on the transparency of organizational practices. Perceptions of PA as a surveillance mechanism are associated with employee resistance and decreased engagement (Di Lauro et al., 2024). To mitigate this, organizations should adopt ethical policies that ensure access to personal data, clarify the purposes of data use, and allow employees to opt out of certain processes without adverse effects. The establishment of independent ethics committees may support the responsible and fair implementation of PA practices (McCartney & Fu, 2022).

Ethical considerations must guide the use of PA to ensure that technological applications align with both organizational goals and the protection of employee rights (Jörden et al., 2022). As a result, when applied within ethical boundaries, PA can function as a strategic resource that supports data-informed decision-making without undermining core principles of privacy and fairness.

1.5. Discussion

PA has reshaped HRM by enabling organizations to apply data-based strategies for decision-making, talent development, and employee retention. The combination of PA, ML algorithms, and econometric models supports efficiency improvements by minimizing uncertainty and bias in workforce planning, performance evaluations, and recruitment processes (McCartney & Fu, 2022).

Computational techniques such as artificial neural networks and multivariate adaptive regression splines help identify patterns in HR data, supporting proactive decision-making in areas like promotion, retention, and succession planning (Belizón et al., 2024). These data-driven methods assist organizations in responding to market changes while aligning HR functions with strategic goals. The Knowledge Discovery Process model, introduced by Belizón et al. (2024), outlines a systematic framework for collecting, organizing, and analyzing workforce data.

In addition to improving operational efficiency, PA contributes to talent development and career advancement. Data-informed learning and development initiatives enable organizations to tailor training programs, address skill deficiencies, and anticipate future workforce requirements (Suri & Lakhanpal, 2024). On the other hand, PA also enhances succession planning and career management by replacing subjective judgments with data-based evaluations, incorporating indicators such as engagement levels, leadership assessments, and performance trends (Rigamonti et al., 2024).

Historical career trajectory analysis supports structured career pathing by informing employee decisions, improving retention, and mitigating talent loss. As PA becomes more integrated into HRM, ethical concerns related to data privacy, monitoring, and algorithmic bias arise. Research highlights that limited transparency in data use may erode employee trust, emphasizing the need for regulatory compliance, transparent governance, and oversight through independent ethics committees (Di Lauro et al., 2024). Therefore, although PA enhances decision-making and workforce planning, its implementation should ensure alignment between organizational objectives and ethical responsibility.

1.5.1. Theoretical and Practical Implications

This study contributes to the literature on data-driven HRM by examining how PA applies computational and econometric models to enhance decision-making, workforce planning, and career development. Prior studies have shown that PA supports HR by identifying workforce trends, evaluating leadership potential, and forecasting employee performance (Larsson & Edwards, 2022).

As a result, the present analysis corroborates these findings by showing how PA facilitates a shift from reactive to proactive HR practices, enabling evidence-based decision-making. Furthermore, emphasizes the evolution of PA from descriptive analytics (e.g., reporting) to predictive and prescriptive approaches (e.g., strategic planning and forecasting).

From a practical perspective, the study provides key elements for HR professionals seeking to leverage PA to improve employee engagement, retention, and organizational performance. PA enables HR teams to monitor satisfaction indicators in real time, identify employees at risk of turnover, and implement retention strategies proactively (Belizón et al., 2024). Moreover, personalized L&D programs optimize employee skill development, ensuring that training investments grant measurable performance outcomes (Yoon et al., 2024).

Succession planning and career paths also benefit from PA, as HR departments can base decisions on objective metrics instead of subjective evaluations to assess leadership potential and career advancement opportunities (Rigamonti et al., 2024). However, ethical challenges require the implementation of transparent data governance frameworks. Compliance with GDPR and AI ethics regulations is crucial for maintaining employee autonomy and trust in PA systems (Di Lauro et al., 2024).

CHAPTER 2 – PEOPLE ANALYTICS FUNDAMENTALS

The expansion of HR metrics and workforce analytics in the 2010s, driven by the emergence of big data, AI, and ML, contributed to the evolution of HRM from an administrative role to a strategic, data-driven discipline (Tursunbayeva et al., 2018).

The application of these technologies in HRM involves analyzing behavioral patterns, interpersonal relationships, and individual characteristics. This methodology seeks to replace decision-making based on subjective experience, hierarchical structures, and risk avoidance with processes informed by data analysis (McCartney & Fu, 2022). According to DiClaudio (2019), unlike traditional HR practices that depend on intuition and personal judgment, PA enables trend analysis of employee data. Organizations apply predictive analytics to forecast attrition, prescriptive analytics to recommend interventions, and real-time data to enhance workforce management (Cho et al., 2023).

People Analytics continues to advance through the incorporation of technologies such as natural language processing for sentiment analysis and AI-based recruitment systems (Guo et al., 2024). As HRM increasingly adopts data-centric approaches, the use of analytics and algorithms in employee evaluation, control, and management introduces ethical and moral challenges with broad implications, particularly in comparison to other organizational domains (Giermindl et al., 2022).

2.1. Data Analytics

According to Ashwin Varghese et al. (2023), data analytics refers to the systematic process of analyzing, transforming, and interpreting large amounts of data to extract insights and make informed decisions. It involves techniques, methodologies, and tools that help organizations to uncover trends and correlations to obtain value from their data, which is why it is widely applied across industries such as healthcare, finance, marketing, and business intelligence to optimize operations, predict outcomes, and drive strategic initiatives (Simi & Nayaki, 2017).

Fitz-enz and Mattox (2014) classified data analytics into three categories, as presented in Table 3.

Table 3 - Types of Data Analytics.

Type of Analytics	Definition	Examples
Descriptive analytics	Disclose and describe relationships and data patterns.	Dashboards, scorecards, workforce segmentation, and periodic reports.
Predictive analytics	Uses statistics, modeling, and data mining to predict future outcomes based on historical data.	Models for increasing the probability of selecting the right people to hire, train, and promote.
Prescriptive analytics	Goes beyond predictions by recommending decision options.	Models for understanding how alternative learning investments impact business performance.

2.1.1. Descriptive analytics

Descriptive analytics, a core aspect of data analytics, involves the assessment of historical data to identify patterns and trends. According to Geetha and Sujatha (2024) , it offers a structured approach for summarizing large datasets by applying statistical methods and data visualization techniques, thereby generating insights into previous events and supporting evidence-based decision-making.

Data visualization plays a significant role in descriptive analytics by employing tools such as charts, tables, and graphs to present data in an accessible format. This method enables organizations to identify performance patterns, monitor developments over time, and support decisions based on historical information (Hurwitz et al., 2015).

According to Camm et al. (2021), descriptive analytics seeks to address questions such as those illustrated in Figure 3.

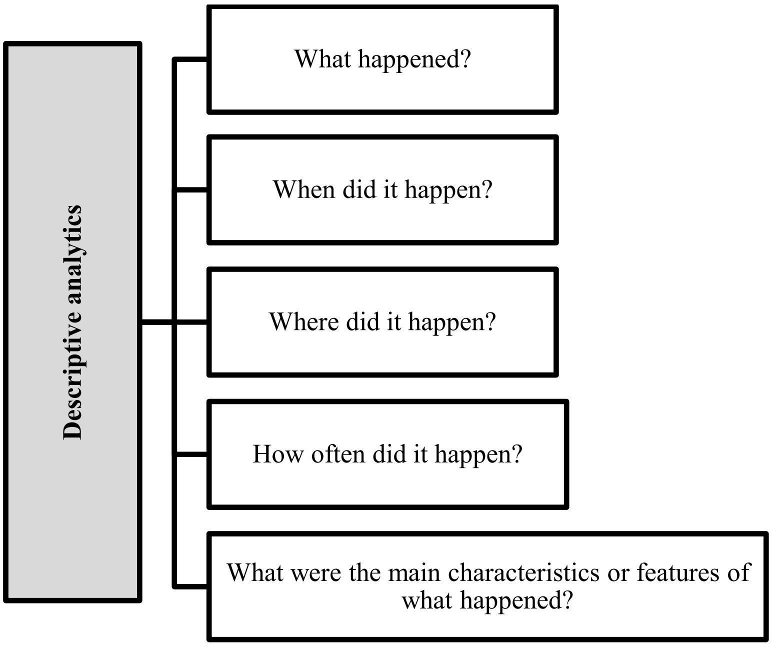


Figure 3 - Descriptive analytics questions.

Wolniak (2023) states that organizations across sectors apply descriptive analytics to support data-based decision-making by analyzing key performance indicators (KPIs) and historical records. This approach establishes a foundation for advanced analytics methods, such as predictive and prescriptive analytics, which contribute to strategic planning and operational process optimization.

2.1.2. Predictive analytics

Predictive analytics can be used to forecast future events and variable behavior, supporting the identification of risks and opportunities for individuals within an organization, including customers, employees, and managers (Vartak & Sapre, 2020). Therefore, applies statistical, data mining, ML, and AI techniques to current and historical data to generate such forecasts (Dejaeger et al., 2012).

These techniques are employed to construct predictive models, which detect patterns in data and utilize them to generate forecasts. N. Mishra and Silakari (2012) outline fundamental steps for developing such models, as shown in Table 4.

Table 4 - Predictive models steps.

Step	Description
1. Project Definition	Define the business problem and translate it into predictive analytics objectives.
2. Exploration	Analyze the source data to determine appropriate data and modeling approaches.
3. Data Preparation	Select, extract, and transform the data to build predictive models.
4. Model Building	Create, test, and validate models to ensure they meet project goals.
5. Deployment	Apply model results to business processes or decision-making tasks.
6. Model Management	Monitor, update, and manage models to improve performance and reduce redundancy.

As organizations increasingly emphasize decision support solutions, predictive models, such as neural networks, are being applied in HRM to enhance talent recruitment and retention with high accuracy (Mwaro et al., 2021).

2.1.3. Prescriptive analytics

Prescriptive analytics is considered the most advanced stage of analytical methods, as it builds upon descriptive, diagnostic, and predictive analytics (Niederhaus et al., 2024). Provides organizations with adaptive, automated, and time-sensitive recommendations to improve decision outcomes and mitigate risks (Soltanpoor & Sellis, 2016).

This kind of analytics is particularly applicable in domains with large amounts of data overseen by physical or mathematical laws, while areas involving human activities require further research (Moesmann & Pedersen, 2024). This challenge increases the complexity organizations face, which must develop competencies in analyzing and interpreting data and maintaining high data quality, and cultivating a workforce with the requisite technical expertise (Brandt et al., 2021).

Various prescriptive platforms have emerged to support data-driven decision-making, incorporating different data types, protocols, databases, and algorithms (Niederhaus et al., 2024). According to Soltanpoor and Sellis (2016), these systems possess two main features (Figure 4). First, they produce actionable outputs that deliver structured recommendations to guide organizational decisions. Second, they incorporate feedback mechanisms that track the implementation of recommended actions and monitor unexpected events (Soltanpoor & Sellis, 2016).

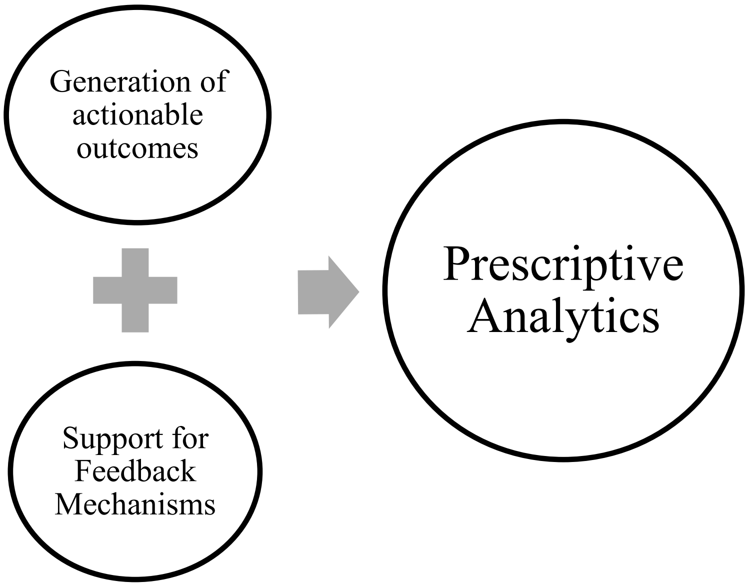


Figure 4 - Prescriptive Analytics Features.

2.1.4. Conclusive synthesis

Organizations seek to understand current conditions, anticipate future developments, and determine actionable strategies to achieve effective outcomes (Kaisler et al., 2014). As a result, there is an increasing effort to derive value from data and apply analytics to convert information into knowledge (Banerjee et al., 2013).

Large organizations possess extensive datasets and require effective methods to extract actionable insights. To capitalize on potential opportunities and mitigate risks, they must identify relevant data, develop targeted analytics models, and adapt organizational capabilities and culture to operationalize advanced analytics (Barton & Court, 2012).

Data analytics is mentioned as the new business analytics paradigm that helps organizations (Delen, 2015). According to Soltanpoor and Sellis (2016), business analytics can be divided into three primary stages (Table 5).

Table 5 - Business analytics stages.

	Descriptive analytics	Predictive analytics	Prescriptive analytics
Questions	- What has happened? - Why did it happen?	- What will happen? -Why will it happen?	- What should be done? - Why should it be done?
Techniques	- Statistical Analytics - Data Integration - Data Augmentation - Data Reduction	- Data Mining - Machine Learning	- Optimization - Simulation - Operations Research - Management Science
Outputs	- Reports on the historical data - Extracted insight from the raw data	- Future opportunities - Future risks	- Recommended business decisions - Optimal courses of action
Sophistication	− → +		

Advances in computer science, particularly through the development of big data, AI, and cloud computing, have enhanced data analytics by enabling real-time forecasting and adaptive decision-making (Vartak & Sapre, 2020).

According to Kumar & Garg (2018), developments in AI and ML have transformed computational methods through the application of intelligent algorithms, such as artificial neural networks. These advancements capture the necessity of engaging stakeholders effectively and prioritizing developing employee skills and leadership (Benabou & Touhami, 2025)

2.2. Artificial Intelligence and Big Data

The digital transformation has redefined how organizations operate and create value, driven by advanced technologies such as AI and Big Data. These innovations transform decision-making processes across industries, offering powerful tools for extracting valuable insights and solving complex problems (Pothuri & Reddy, 2019).

Russell and Norvig (2022) mention AI as the development of systems that mimic human intelligence, performing tasks that typically require human cognitive abilities, such as logical reasoning, learning, and problem-solving.

Several core technologies are included in AI. ML, for instance, enables computers to identify patterns in data without explicit programming. Deep Learning, a subset of ML, utilizes artificial neural networks to analyze large datasets and perform complex tasks (C. Mishra & Gupta, 2017).

AI facilitates the extraction of value from Big Data by supporting the automation and enhancement of descriptive, predictive, and prescriptive analytics (Mahanty and Mahanti, 2020). In the HR domain, AI is applied in multiple areas (Tewari & Pant, 2020) (Table 6).

Table 6 - AI Applications in HRM.

HRM Function	AI Applications	Benefits
Recruitment and Selection	- Automated resume screening. - AI chatbots for candidate engagement. - Video interview analysis. - Natural language processing for communication and scheduling.	- Faster hiring. - Reduced bias. - Lower costs. - Improved candidate experience.
Onboarding	- Customized onboarding programs. - Chatbots guiding new employees on policies, benefits, and roles.	- Efficient integration of new employees. - Higher adaptation and engagement.
Training and Development	- AI-supported e-learning platforms. - Training feedback analysis tools. - Personalized learning paths.	- Skill enhancement. - Improved learning outcomes. - Real-time performance tracking.
Employee Engagement	- Sentiment and mood analysis using facial recognition. - Predictive analytics for engagement levels.	- Improved employee satisfaction. - Better understanding of workplace dynamics.
Compensation Management	- Artificial neural networks for fair compensation evaluations. - Data-driven decisions.	- Transparent and equitable pay. - Enhanced motivation and retention.
Performance Management	- AI-based 360-degree feedback systems. - Automated and continuous performance tracking.	- Objective evaluations. - Real-time insights. - Increased efficiency.
Employee Retention	- Predictive analytics for identifying at-risk employees. - Monitoring digital behavior for early exit indicators.	- Proactive retention strategies. - Reduced employee turnover.

Big Data, on the other hand, represents innovative techniques and technologies to capture, store, distribute, manage, and analyze substantial and heterogeneous datasets (Kumari & Bhardwaj, 2019). Its definition is anchored to the “5Vs” (Figure 5): Volume, Velocity, Variety, Veracity, and Value (Monroe, 2013).

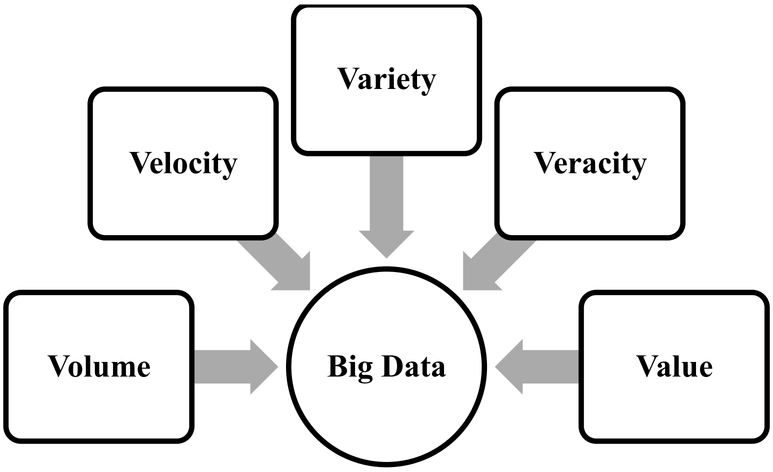


Figure 5 - Big Data 5Vs.

Big Data has become a significant concept in the digital age, influencing how organizations and societies manage and interpret information. As Machado (2018) outlines, the relevance of Big Data can be understood through five key dimensions, each of which plays a critical role in determining how data is collected, processed, and applied.

The first dimension, volume, pertains to the large and continuously increasing amounts of data generated daily by individuals, organizations, and systems globally. This data has only become manageable thanks to recent advances in storage and processing technologies, which have made it possible to work with such scale.

The second dimension, velocity, refers to the high speed at which data is generated and the associated demand for real-time analysis. Numerous contemporary applications, such as fraud detection and personalized marketing, require immediate data insights, rendering rapid processing essential.

The third dimension, variety, denotes the wide range of data types and formats. Today's data encompasses more than traditional spreadsheets and databases, incorporating emails, social media content, videos, sensor data, audio recordings, among others. This heterogeneity increases analytical complexity while enhancing the depth and breadth of possible analyses.

Veracity, the fourth dimension, points to the reliability and accuracy of data. Data sources vary in their trustworthiness; for example, user-generated content on social media may contain noise or inaccuracies, posing challenges for data validation and integrity.

The fifth dimension, value, emphasizes the extraction of meaningful insights from data. Regardless of its volume, velocity, or variety, data holds value only when it informs specific objectives. Without a defined analytical strategy, Big Data initiatives may become inefficient and misaligned. Aligning analysis with organizational goals is, therefore, essential for effective data utilization.

The evolving relationship between Big Data and AI is characterized by mutual reinforcement. AI techniques facilitate the analysis of large and complex datasets by identifying patterns and generating predictive models that exceed manual analytical capacities. Conversely, the scale and diversity of Big Data supply essential inputs for the development and refinement of AI systems, thereby expanding the capabilities of intelligent technologies (Reis et al., 2020).

2.3 Applications in the Public Sector

In the public sector, data-driven HRM is a strategic approach that aims to improve decision-making and policy development by systematically collecting, analyzing, and applying HR data, while addressing concerns related to privacy, security, equity, and ethics (Kim et al., 2024).

Public sector organizations are frequently motivated by a desire to serve citizens and the community. Therefore, they tend to prioritize data associated with public needs and taxpayer satisfaction (Cho et al., 2023). A notable trend is the gradual shift from descriptive to predictive and prescriptive analytics (Sousa et al., 2022). Predictive analytics, for instance, is increasingly used to forecast employee attrition and optimize recruitment strategies, thereby reducing talent gaps in critical areas (Shah et al., 2017).

Chowdhury et al. (2023) report that HR analytics is increasingly adopted by public and private organizations as they incorporate data-driven approaches into their operations. While some organizations aim to improve specific HR processes, others attempt to align HR analytics with broader organizational performance objectives (Margherita, 2022).

Cho et al. (2023) identify several successful applications of PA in the public sector (Table 7).

Table 7 - PA Applications in Public Sector.

Organization	Area of Use	How It Is Used	Objective
Australian Public Service	Workforce planning	Developed the Workforce Planning Capability Development Program to enhance the analytics skills of HR planners	Forecast future workforce needs and improve internal analytical capabilities
NSW Public Service Commission (Australia)	Diversity and inclusion policy development	Used data analytics to monitor and improve gender balance in leadership positions, targeting 50% female leaders by 2025	Promote diversity and inclusivity through measurable targets
Ministry of Energy (Mexico)	Strategic workforce planning in the energy sector	Analyzed economic variables (oil prices, exchange rates) to predict long-term labor and skills gaps in the oil and gas industry	Justify investment in national workforce development initiatives
Government of South Korea	Employee development and training	Developed an AI-powered HR open platform to personalize training based on performance data and learning history	Optimize training, reduce costs, and enhance job readiness and satisfaction
Global Affairs Canada	Talent acquisition and retention in data science roles	Created specific roles for data scientists in the public sector	Address talent shortages and build in-house analytics expertise
U.S. Office of Personnel Management (United States)	Workforce planning support across federal agencies	Provides standard guidelines, tools, and best practices for workforce analytics	Help agencies plan workforce needs aligned with government strategies

Despite these advancements, many public institutions face difficulties in data integration, maintaining data privacy, and cultivating analytical capabilities among HR professionals (Cho et al., 2023). Therefore, Kameswari et al. (2023) proposed a growing need for ethical guidelines and a framework that attends to the challenges brought by PA and AI, to ensure technologies adopted bring well-being to the employee.

CHAPTER 3 – HUMAN RESOURCE MANAGEMENT

HRM is a field concerned with managing personnel within organizations to support organizational performance, productivity, and employee outcomes (Peccei & Van De Voorde, 2019). Initially, HRM was primarily administrative, dealing with hiring, payroll, and compliance, but over time, it evolved into a strategic function that plays a crucial role in achieving business objectives (Marler, 2009).

Modern HRM combines traditional personnel administration and strategic workforce planning, focusing on talent acquisition, employee development, performance management, and organizational culture (Wang, 2024). This approach focuses on leveraging human capital as a source of sustainable competitive advantage, reinforcing the importance of employee engagement, leadership development, and performance measurement (Hamadamin & Atan, 2019).

According to Polzer (2022), an essential aspect of contemporary HRM is the integration of technology and data analytics, which has contributed to the rise of PA. The use of algorithms in employee-related decision-making introduces numerous research opportunities concerning cognitive, motivational, and social dynamics within organizations (Polzer, 2022). Despite its developments, HRM faces ongoing challenges, including ethical concerns, diversity and inclusion, and employee engagement in digital work environments (Du, 2024). As organizations adapt to technological and economic transformations, HRM is expected to remain a foundational element in sustaining organizational performance, innovation, and workforce viability.

3.1. Military HRM

Military HRM covers many of the same foundational functions as civilian HRM, such as recruitment and selection, training and development, performance management, compensation and benefits, and employee welfare (Offstein and Dufresne, 2007). Military HR systems often involve complex rule-based models that process large amounts of data, requiring specialized simulation environments such as “Right Person, Right Qualification, Right Place, Right Time Human Resources” (Okazawa, 2013, p. 2785).

The transition to a volunteer-based force has increased competition for personnel, necessitating strategic alignment between human resource management and military objectives (Mazari Abdessameud et al., 2022). However, the development of military HR managers is crucial to meet diverse operational demands, underscoring the need for multidimensional skills and innovative leadership development programs (Patrichi, 2015).

In military contexts, human resource management must support the development of resilience and adaptability among personnel. Given the unpredictable nature of military operations, it is necessary to sustain a high level of readiness and responsiveness (Rosinha et al., 2017). Continuous training programs are therefore required to maintain operational readiness, particularly among newer generations of service members (Gleiman and Zacharakis, 2016).

In an increasingly globalized world, a vital aspect is the effective management of diversity and inclusion in the military. According to Bailey (2019), the implementation of equal opportunities and anti-discrimination policies is essential to create a harmonious and cohesive work environment.

Nonetheless, one of the significant challenges in military HRM is balancing work-life well-being and operational readiness. Military careers frequently involve relocations, long-term deployments, and extended family separations, which can increase stress levels and attrition rates (Vuga and Juvan, 2013). Efforts to mitigate these effects include improved family support programs, flexible deployment policies, and enhanced mental health services (Graf and Kuemmel, 2022).

3.2. Military Career in the Portuguese Army

According to Article 27 of the Statute of the Military of the Armed Forces (EMFAR), the military career is structured as a hierarchical system of ranks organized into categories. These categories, as outlined in Article 28, include Officers, Sergeants, and Privates, each corresponding to specific functions and designated positions.

The military rank represents the hierarchical position within each category, determined by the function and qualification required. Positions, on the other hand, are defined spots in the structure of the Armed Forces or in state/international organizations, which correspond to specific military functions. In line with Article 34, these functions are grouped into Command, Direction or Leadership, General Staff, and Execution.

EMFAR regulates all military personnel, regardless of rank, service, or branch, and defines four forms of service: in the Permanent Staff, by Contract, Voluntarily, and by call or mobilization. However, the preamble outlines objectives such as maintaining structural balance in personnel distribution, promoting equitable career progression, establishing tenure limits for positions, and implementing norms to prevent unjustified advancement in the hierarchy.

Law No. 11/89 of June 1 establishes the General Bases of the Military Condition by defining the duties and rights of military personnel and outlining the fundamental principles of career development. It also guarantees, following article 11, the right to career progression, guided by principles such as valuing training, competence, adaptation to innovation, and balance between individual and institutional interests.

3.3. Portuguese Army Career Management Model

In 2017, the General Directorate of National Defense Resources conducted a study to identify the primary causes of high attrition rates and recruitment challenges among military personnel. The findings indicated an increase in the educational level of new entrants, alongside significant dissatisfaction with career development opportunities and the alignment between training and assigned duties. In response, the Army recognized the need to establish a Career Management Department within the Human Resources Administration Directorate (Jacinto, 2022).

According to Jacinto (2022), the department, which is exclusively responsible for Career Management, performs several functions. These include evaluating military personnel, planning career paths to support continuous development, offering guidance, identifying future educational and training requirements, and ensuring conditions favorable to promotion.

As a result, a career management model was created to facilitate communication among the administration, military personnel, and the chain of command. The purpose of this model is to provide career development guidance and to promote active and collaborative engagement by individuals in managing their careers. According to Jacinto (2022), the model contains six main phases (Table 8).

Table 8 - Career Management Model - Phases of the process.

Phases	Description
1. Self-knowledge	Carried out with psychological support to map values, skills, vocation, and fears of the military. Identification of opportunities.
2. Identification of opportunities	Assessment of acquired skills and possible career paths.
3. Goal setting	The military establishes its goals with the support of career managers.
4. Formulation of action measures	Definition of the necessary steps to achieve the objectives set.
5. Implementation of the actions	Placements, training, and practical experiences needed to fulfill the career plan.
6. Follow-up and monitoring	Continuous supervision for adjustments and improvements in the individual plan.

To support career managers, models have been developed to anticipate specific stages of training, specialization, and participation in international missions. These models facilitate the integration and visualization of various dimensions of military personnel's professional trajectories, guiding role assignments, and ensuring alignment with promotion criteria. Additionally, they enable the identification of career deviations and the implementation of corrective actions, which are subsequently validated by the respective branch councils (Jacinto, 2022).

Jacinto (2022) also mentions that an application with AI is under development to facilitate the predictive and prescriptive analysis of data, to optimize career management, and allow greater participation of the military in the process. This system seeks to align the decisions of the army command with organizational needs, encouraging the identification of talents and preparing service members for functions of greater responsibility.

CHAPTER 4 – MATERIALS AND METHODS

This chapter outlines the methodological structure of the research, detailing the strategic, methodological, and procedural decisions, as well as the techniques employed. It builds upon the foundation established in the preceding chapters.

Foote (2008) emphasizes that the Materials and Methods section of a scientific study must be described with precision to ensure replicability. This section typically includes elements such as materials, study design, population, measurement methods, and statistical analyses, serving as a conceptual framework aligned with the research objectives(Ghasemi et al., 2019). Therefore, based on the SLR and analysis of the PA and HRM presented in chapters 1, 2, and 3, this chapter presents a structured plan to address the research questions by outlining the methodologies and procedures used for data collection and analysis.

4.1. Definition of research objectives

Research objectives clarify the purpose of the study, guide the formulation of research questions, and inform the selection of appropriate methods (Alústiza Echeverría et al., 2012). Clearly defined objectives enable researchers to differentiate between relevant and irrelevant information, thereby maintaining focus during the study. In addition, clearly formulated objectives help readers understand the study's purpose and evaluate its results (James, 1948).

Table 9 - Structure of Research Objectives and Questions.

General Objective	Central Question	Specific Objectives	Derived questions
Comprehend the impact of People Analytics on the Portuguese Army.	How can People Analytics enhance human resource management efficiency in the Portuguese Army?	**SO1-** Identify behavioral patterns and individual needs.	**DQ1-** What are the main behavioral patterns and individual needs identified in the Portuguese Army?
		SO2- Identify the key metrics and indicators used in Human Resource Management in the Army.	**DQ2-** What are the main metrics and indicators used in human resources management in the Army?
		SO3- Examine the impacts of Data Analytics on Decision-Making.	**DQ3-** What are the impacts of using data analysis on decision making?
		SO4- Develop a Conceptual Model for the Portuguese Army.	**DQ4-** What is the viability of a Conceptual Model in the Portuguese Army?

The General Objective of this study is to examine the impact of People Analytics on the Portuguese Army. This objective will be addressed through the Central Question: "How can People Analytics enhance human resource management efficiency in the Portuguese Army?" To support the GO and answer the CQ, four Specific Objectives (SO) were established, each corresponding to a Derived Question (DQ) presented in Table 9. Alústiza Echeverría et al. (2012) emphasize the importance of aligning research questions, objectives, and statistical analyses throughout the research process.

4.2. Methodological Options

This research adopts a pragmatic philosophy to investigate and analyze the potential contributions of PA to HRM within the Portuguese Army. Pragmatism emphasizes the pursuit of knowledge through critical thinking and logical reasoning (Webb, 2007).

According to Saunders et al. (2023), the key methodological elements associated with these concepts are presented in Table 10.

Table 10 - Research philosophy and approach

Philosophy	**Pragmatism -** The choice of research philosophy should be guided by the research question itself. This ensures that the investigation is driven by the pursuit of practical and effective solutions to the problems under examination.
Method	**Abductive** - This approach alternates between inductive and deductive reasoning. It seeks to construct the most plausible explanation based on observations, iterating between theory and data to develop grounded insights that are later linked to existing literature.
Methodological Design	**Mixed methods** - Employs both quantitative and qualitative data collection and analysis. These can be conducted in parallel (simultaneously) or in sequence (one after the other), though not necessarily integrated, allowing for a more comprehensive understanding of phenomena.
Strategy	**Surveys** - Surveys can be employed in both descriptive and explanatory research. In descriptive studies, the use of surveys targeting attitudes, opinions, and organizational practices proves valuable in identifying and characterizing variability across different phenomena. In contrast, explanatory or analytical research enables the examination and interpretation of relationships between variables, using surveys and other data collection techniques.
Time Horizon	**Cross-sectional –** The research consists of the study of one or more phenomena at a specific point in time.
	Data collection and analysis

To analyze the object of study, a mixed methodological approach was adopted, which integrates quantitative and qualitative techniques. In addition, abductive thinking was used, which consists of inferring the most plausible explanation for the observed data.

4.3. Techniques and procedures

Following the clear definition of the research objectives and strategy, it becomes essential to establish the techniques, procedures, and resources to be employed throughout the data collection and analysis process. This stage is critical to ensure that the methodologies adopted are properly aligned with the research purposes and capable of yielding valid and reliable results.

4.3.1. Data collection techniques and measurement tools

The research began with a systematic literature review aimed at identifying trends in the application of PA in HRM, followed by a general literature review and analysis of relevant documents related to the research topic. This was essential, as it consolidated the key concepts and previous studies within this area of knowledge, including the appropriate framing of the military dimension.

To support this theoretical foundation, a semi-structured interview (Appendix E and Appendix F) was conducted with the HR Manager at the Career Development Support Division. The interview (Appendix G) provided contextual information regarding institutional practices and challenges in career management within the Portuguese Army, with a specific focus on the use of data-driven methods in HR decision-making. This interaction contributed to aligning the research instrument with organizational practices and informed the interpretation of both quantitative and qualitative data.

Data collection was conducted using a structured survey, which served as the primary instrument for obtaining both quantitative and qualitative data from military personnel. This method aligns with the study's methodological approach, which is based on a quantitative paradigm complemented by exploratory qualitative components. The survey was designed to explore patterns related to career satisfaction, professional aspirations, and organizational alignment within the Portuguese Army.

The survey adopted for this study (Annex I) was developed and validated as part of the project "Content Development for the Army Career Information, Choices, and Support Platform (PLACE) - A Scientific Approach." This initiative resulted from a collaboration between the Directorate of Human Resources Administration, specifically the Career Development Support Department of the Career Management Division, the Army Applied Psychology Center, and the Psychology Research Center at the School of Psychology, University of Minho. The instrument is pertinent to the present research due to its ability to produce data suitable for analytical and inferential statistical procedures.

The survey includes both closed-ended and open-ended questions, structured into thematic sections addressing: (1) current career placement and mobility intentions, (2) preferences for future assignments, (3) training needs and educational aspirations, (4) satisfaction with current duties and career trajectory, (5) work-life balance, (6) interest in international assignments, and (7) perceptions regarding leadership, organizational support, and career development mechanisms. Most closed-ended items employ Likert-type response formats, typically using five-point scales ranging from "Very dissatisfied" to "Very satisfied" or "Never" to "Very frequently," depending on the construct assessed.

In addition to standardized scales, the instrument includes several categorical and nominal variables that capture demographic characteristics and service conditions (e.g., current posting, type of function performed). The open-ended questions, although fewer in number, were designed to capture nuanced perceptions and concerns not fully addressed by the fixed-choice items. These responses were subjected to thematic analysis to uncover latent patterns relevant to strategic human resource management.

The deployment of the survey was facilitated by the chain of command and conducted anonymously to ensure confidentiality. Data collection occurred within a defined timeframe between March 2023 and February 2025.

4.3.2. Sampling: composition and justification

The survey "Contributions to Career Management" was directed exclusively to active-duty military personnel belonging to the Permanent Staff of the Portuguese Army. The target population covered 1,793 Officers and 2,682 Sergeants, totaling 4,475 eligible participants. However, specific hierarchical segments were excluded, namely Sergeant Majors, Colonels, and the General Officer Corps, as these categories are subject to distinct management frameworks and career structures.

4.3.3. Data processing

The data analyzed in this study were obtained through the PLACE project, resulting in a total of 1377 valid responses. These responses were collected via a comprehensive survey designed to assess perceptions and experiences related to career management within the military context. In addition to survey data, qualitative insights were gathered through a semi-structured interview, which provided further context for interpreting the findings and enriched the content analysis phase.

A multi-method approach was employed for data processing. Microsoft Excel was used for preliminary data handling. NVivo software facilitated qualitative content analysis, including the coding of open-ended survey responses and the transcription of the interview. For advanced statistical analyses, JAMOVI[3] version 2.3.26 was utilized.

As a preliminary step, the internal consistency of the survey instruments was evaluated using Cronbach's alpha, a widely accepted reliability measure for psychometric scales, as shown in Appendix B. All scales demonstrated high reliability, with Cronbach's alpha coefficients exceeding 0.80, following the standards suggested by Tavakol and Dennick (2011).

Subsequently, Exploratory Factor Analysis (EFA) was conducted to identify latent dimensions underlying the items related to perceived contributions to career management. The objective was to uncover a set of potential KPIs capable of capturing essential behavioral and organizational constructs. This step constitutes the core analytical focus of the present study.

In addition, descriptive statistics were computed for all key variables under investigation and are presented in Appendix A.

4.3.3.1. Operational Validation of Extracted KPIs: Normality and Inter-Factor Relationships

A statistical validation procedure was conducted to ensure the empirical robustness and operational reliability of the KPIs extracted through EFA. This validation represents a critical step in consolidating the factors as sound constructs capable of informing data-driven decisions within the scope of PA in the Portuguese Army.

The EFA was performed on the survey responses using the Varimax rotation method, aiming to enhance the interpretability of the factor structure. Factors were retained based on eigenvalues greater than 1 and a cumulative explained variance exceeding 50%, in line with

[3] Jamovi is a free, easy-to-use statistical software for social scientists, with an R-based interface and support for modules like meta-analysis and Bayesian statistics (ŞahiN & Aybek, 2020).

common standards (Hair et al., 2019).

Factor loadings were obtained and analyzed, ensuring that each item significantly loaded on a single factor. Subsequently, a regression method was applied to calculate the factor scores, thus enabling the transformation of the latent constructs into measurable variables. From this point forward, the extracted factors are referred to as KPI factors, as they are intended to serve as key performance indicators within the PA framework.

Although the items are based on Likert-type scales, typically treated as ordinal, each KPI factor score was derived as a composite of multiple items and treated as a continuous variable. This treatment is statistically justified by the Central Limit Theorem, given the large sample size ($n = 1{,}377$) and the nature of the regression-based computation of factor scores (Field, 2009).

To confirm the appropriateness of using parametric methods, the distributional properties of the KPI scores were examined. According to the criteria set by West et al. (1995), skewness within ±2 and kurtosis within ±7. The distributions of all five KPI were within acceptable limits, supporting the assumption of normality, as shown in Appendix A.

With the normality assumption validated, a Pearson correlation was computed to analyze the linear interrelationships among the KPI factors. This aims to assess both conceptual overlap and statistical dependence among the dimensions, providing a foundational understanding of their interaction. The interpretation of correlation coefficients followed Cohen`s (2013) benchmarks: negligible ($r < .10$), small ($.10 \leq r < .30$), moderate ($.30 \leq r < .50$), and strong ($r \geq .50$). The detailed correlation results can be found in Appendix C.

This phase extends beyond statistical validation by establishing a foundation for translating the constructs into operational metrics applicable to PA. The correlation patterns contribute to theoretical understanding and practical applications, including the selection of input variables for supervised ML models, the formulation of rules for digital career guidance systems, and the design of HR performance monitoring dashboards.

The validated KPI factors represent a consistent and interpretable set of metrics with potential for integration into AI-based tools that support HRM and strategic decision-making within the Portuguese Army, as simulated in the Annex A.

CHAPTER 5 – RESULTS

The results chapter of this study will present an analysis of the collected data using both quantitative and qualitative methods. The quantitative analysis will include descriptive statistics and factor analysis. The qualitative analysis will consist of a thematic analysis of the survey's open-ended question.

5.1. Characterization of Participants

The target population covered 1793 Officers and 2682 Sergeants, totaling 4475 eligible participants. From this defined population, 1377 valid responses were obtained, 631 from Officers and 746 from Sergeants (Figure 6).

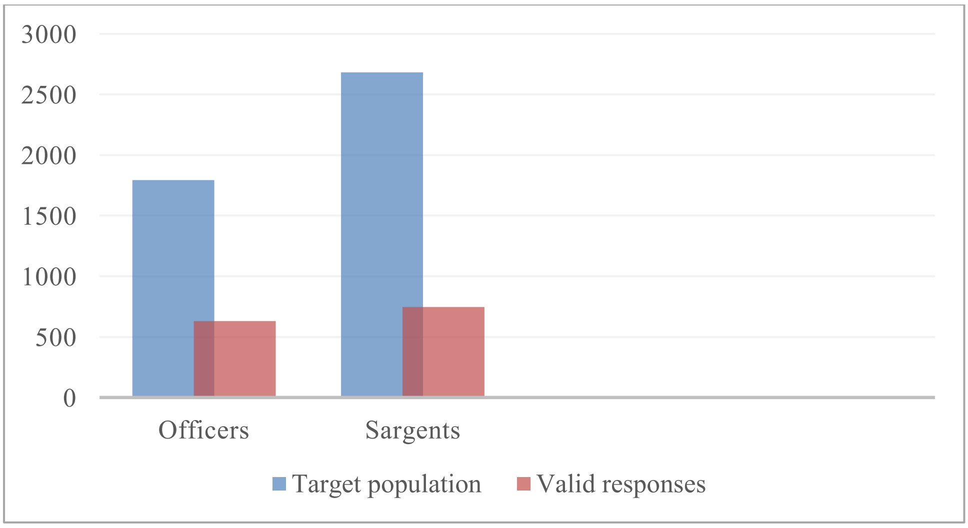


Figure 6 - Target Population vs. Responses by Category

This response rate reflects a significant engagement from the target population. These participants represent a broad cross-section of the active Permanent Staff, providing a reliable and representative sample.

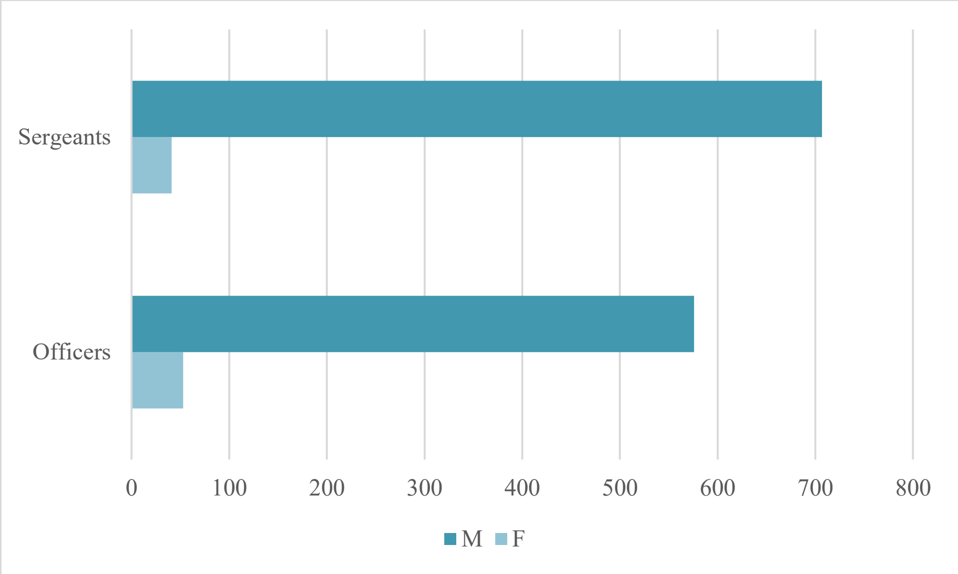


Figure 7 - Gender Distribution

The chart (Figure 7) shows that most respondents in both the Sergeant and Officer categories are male, while female representation remains limited in both groups. Furthermore, the total number of Sergeants exceeds that of Officers, regardless of gender, indicating a greater overall presence of Sergeants in the sample.

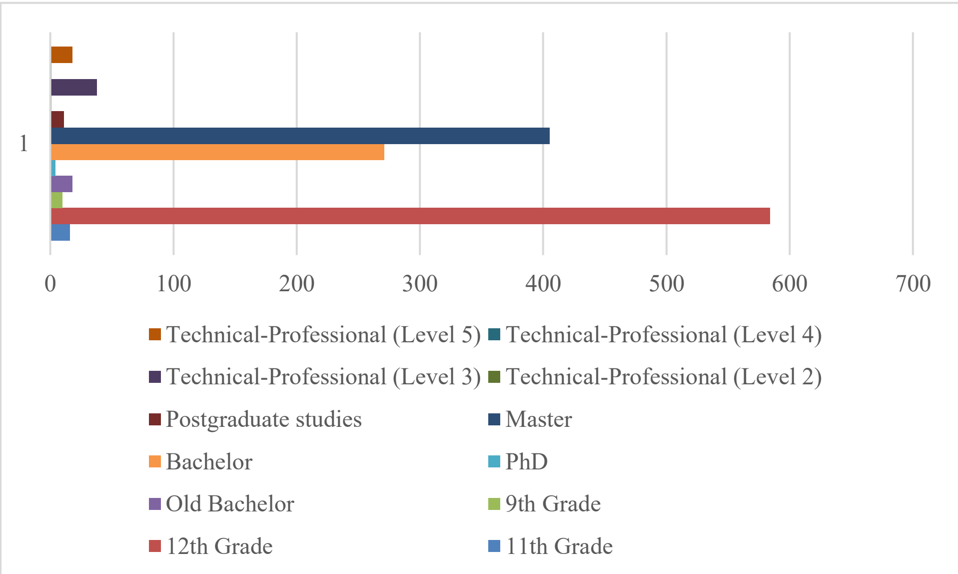


Figure 8 - Educational Background

Figure 8 indicates that 42.4% of participants completed secondary education (12th grade), representing the most frequently reported educational level. This is followed by

29.6% with a Master's degree and 19.4% with a Bachelor’s degree. Lower proportions were observed for other educational levels: Technical-Professional (Level 3) at 2.7%, postgraduate studies at 0.8%, and PhD at 0.4%. These data suggest a workforce primarily composed of individuals with upper-secondary education, with a notable subset holding advanced academic degrees.

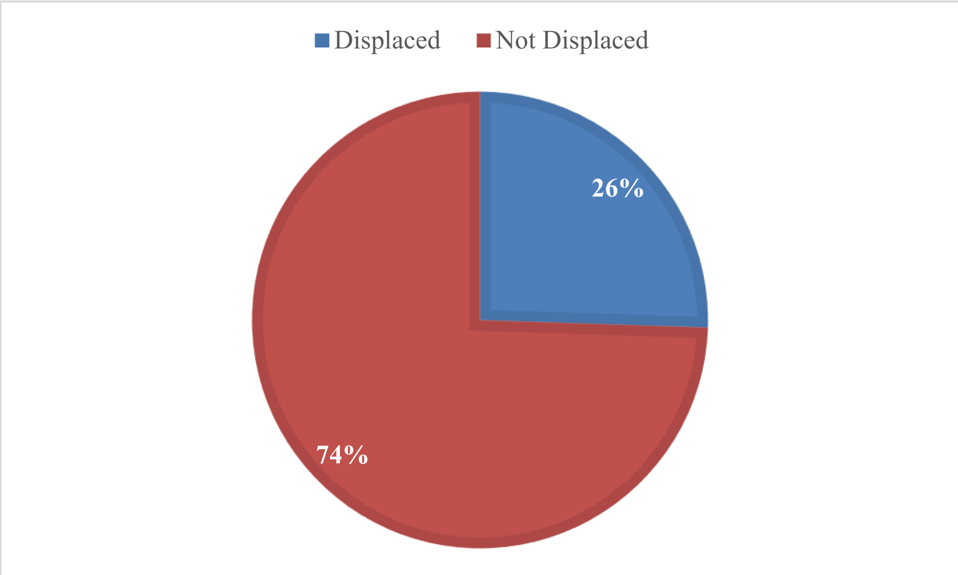


Figure 9 - Geographic Displacement Status

The chart (Figure 9) indicates that 26% of the participants are currently assigned to units or posts different from their original placement, while 74% remain in their initially designated locations.

This sampling approach ensured the collection of data from those most affected by institutional career policies, thus enhancing the relevance and applicability of the results to ongoing strategic HR initiatives within the Portuguese Army.

5.2. Factor Analysis

Prior to conducting the factor analysis, the internal consistency of the survey instruments was assessed using Cronbach’s alpha, as detailed in Appendix B. All scales demonstrated acceptable levels of internal consistency, thereby validating the reliability of the constructs measured.

This chapter outlines the analytical framework employed to identify key HRM indicators within the Portuguese Army (SO2), based on data from the survey “Contributions to Career Management." The identification of these indicators is instrumental in evaluating the effectiveness of Career Management practices and in guiding strategic decisions related to professional development, training initiatives, and personnel retention. The implementation of a rigorous factor analysis enhances the validity of the findings and contributes to a data-driven approach to improving military human capital management.

5.2.1. Metric qualities of Factor Analysis

A factor analysis was conducted to identify the latent structure underlying the survey items, corresponding to the core dimensions of Career Management. Before extraction, the reliability of the dataset for factor analysis was assessed through two standard statistical tests.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was employed to evaluate the proportion of common variance, with values above 0.90 deemed very suitable (Kaiser, 1974). In addition, Bartlett's test of sphericity was used to determine whether the correlation matrix was significantly different from an identity matrix, thus justifying the use of factor analysis (Bartlett, 1950). Only if both criteria were met was the factor extraction process initiated, in line with best practices recommended in multivariate analysis literature (Field, 2009).

The results of these preliminary tests (Table 11) confirmed the suitability of the data for exploratory factor analysis. These findings supported the application of EFA.

Table 11 - KMO statistical analysis and Bartlett's sphericity test.

Survey	KMO Statistic	Bartlett's Sphericity Test
Contributions to Career Management	0.901	$p<0.001$

After data validation by the KMO and Bartlett tests, the Varimax orthogonal rotation was applied to obtain independent factors, facilitating the interpretation of the factorial structure.

5.2.2. Factor Extraction and Interpretation of the Factor Structure

An EFA was conducted to identify the KPI factors through survey responses, to group interrelated items into dimensions related to career management. Data adequacy for factor analysis was confirmed using the KMO measure and Bartlett's test of sphericity.

Factors associated with the KPIs were extracted using the Maximum Likelihood method, which is appropriate for estimating latent variables and assessing the model's statistical adequacy. According to Hair et al. (2019), factors with eigenvalues greater than 1 should be retained, and a cumulative variance explained of at least 50% is generally acceptable in studies involving psychological or organizational constructs. Five factors were retained following these criteria, each with eigenvalues above 1, accounting for a cumulative 56.9% of the total variance[4]. This level of explained variance supports the adequacy of the factor structure, as detailed in Table 12

Table 12 - Variance Explained and Eigenvalues of the Extracted Factors

KPI Factor	Eigenvalue	% of Variance Explained	Cumulative %
1	2.42	16.11%	16.1%
2	1.64	10.92%	27.0%
3	1.62	10.83%	37.9%
4	1.53	10.19%	48.0%
5	1.33	8.85%	56.9%

To interpret the factor structure, a Varimax rotation was applied following the guidelines of Field (2009). This method increases the variance of squared loadings within each factor, resulting in clearer separation of variable groupings and reducing multicollinearity (Forina et al., 2005).

Items were retained based on communalities and factor loadings, with thresholds of 0.40 or higher, as recommended by Hair et al. (2019). Factor loadings of this magnitude are generally considered substantial, indicating that the items meaningfully contribute to the latent factors and support the construction of conceptually coherent dimensions.

The analysis retained items with communalities above 0.40, demonstrating an adequate proportion of variance explained by the extracted factors. These results are summarized in Appendix C.

The combination of substantial factor loadings and acceptable communality values indicates internal consistency and conceptual coherence in the extracted structure. These

[4] The table presents the explained variance values based on Jamovi's default output, which uses the Principal Component Analysis method. Although the factor extraction in this analysis used the Maximum Likelihood method, the figures serve as an interpretative approximation.

results support the potential use of the identified factors in developing KPIs for future data-driven applications in HRM.

The analysis of Appendix C resulted in the extraction and interpretation of five KPI factors (Table 13). The first factor, designated Organizational Environment, encompasses interpersonal and structural features of the professional setting that influence daily work life. It includes high factor loadings for Work Environment (0.767), Direct Management Relationship (0.702), and Interpersonal Relationship (0.703), reflecting the importance of relational dynamics and leadership quality. Additionally, although with lower loadings, items such as Roles and Responsibilities (0.403), Presentation of Problems (0.418), and Feedback (0.417) also contribute to this factor. Together, these variables highlight the relevance of communication, trust, and managerial support in shaping institutional climate and morale.

The second factor, labelled Career Development, addresses the perception of professional growth and future opportunities within the organization. It includes Overall Experience (0.476), Career Opportunities (0.498), and Roles and Responsibilities (0.476). These elements suggest that military personnel assess their career satisfaction based on the alignment between duties performed, the accessibility of advancement pathways, and the cumulative value of their professional journey. This factor reflects the extent to which the institution fosters structured and motivating development trajectories.

The third factor, Communication and Feedback, captures aspects related to internal communication mechanisms and institutional responsiveness. It includes Career to Present (0.837), Presentation of Problems (0.669), and Feedback (0.597). The prominence of the Career to Present item in this factor indicates that past and present career experiences shape how individuals evaluate the effectiveness and fairness of communication processes. This dimension underscores the importance of transparent dialogue, reliable feedback channels, and participatory management practices.

The fourth factor, defined as Current Functional Status, refers specifically to the respondent's present occupational context within the organization. It is primarily determined by a strong loading on Current Position (0.926), complemented by a moderate contribution from Current Placement (0.407). The high explanatory power of this factor suggests that current job assignments significantly influence individual perceptions of stability, engagement, and institutional alignment. This factor provides a static but impactful view of the professional present, distinct from broader developmental or relational concerns.

The fifth factor, named Mobility and Placement, addresses themes related to geographic deployment and career allocation. It includes Geographic Distance (0.697), Current Placement (0.536), and Career Opportunities (0.436). These items collectively describe the logistical and locational aspects that affect job satisfaction, particularly in a military context where mobility and reassignments are common. This dimension reflects how placement conditions intersect with individual preferences and institutional planning, influencing both operational efficiency and quality of life.

In the process of validating the factorial model, three variables were excluded due to not meeting the established psychometric thresholds. These were Training for the Current Position (communality = 0.1986), Conflict (0.3063), and Unpaid Leave/Resignation (0.2998). Their removal enhanced the internal consistency of the factor structure and ensured conceptual clarity in the interpretation.

Table 13 - Distribution of Questions by Factor.

KPI Factor	Questions		Factor Load	Designation
1	Q27	Work Environment	76.7%	Organizational Environment
	Q28	Direct Management Relationship	70.2%	
	Q29	Interpersonal Relationship	70.3%	
	Q31	Roles and responsibilities	40.3%	
	Q33	Presentation of problems	41.8%	
	Q32	Feedback	41.7%	
2	Q26	Overall Experience	47.6%	Career Development
	Q32	Career Opportunities	49.8%	
	Q24	Career to present	83.7%	
3	Q31	Roles and responsibilities	47.6%	Communication and Feedback
	Q32	Career Opportunities	43.6%	
	Q33	Presentation of Problems	66.9%	
	Q34	Feedback	59.7%	
4	Q20	Current Placement	40.7%	Current Functional Status
	Q22	Current Position	92.6%	
5	Q20	Current Placement	53.6%	Mobility and Placement
	Q30	Geographic Distance	69.7%	

5.3. Thematic Analysis

This section presents the thematic analysis of qualitative responses provided in the open-ended section of the PLACE survey. The objective is to explore behavioral patterns and individual needs (SO1) and examine the impact of data analytics on human resource decision-making processes (SO3) in the Portuguese Army.

Thematic analysis was conducted following Braun and Clarke's (2006) six-step approach: familiarizing with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report.

Frequency estimates were calculated to reflect the relative salience of each theme, based on the valid responses analyzed (Table 14).

Table 14 - Relative Frequency of Emergent Themes.

Theme	Objective	Relative Frequency (%)
Career Stagnation and Disengagement from Institutional Progression	SO1	42%
Distrust in Evaluation and Promotion Systems	SO1 + SO3	35%
Functional Misallocation and Absence of Data-Informed Deployment	SO3	23%

5.3.1. Theme 1: Career Stagnation and Disengagement from Institutional Progression

Aligned with SO1, this theme emerged in approximately 42% of all qualitative responses, making it the most frequently reported. Participants consistently described prolonged stagnation in rank and a lack of concrete opportunities for career advancement. These experiences contributed to decreased motivation, widespread frustration, and growing emotional disengagement from the institution.

Several respondents reported long periods of service with minimal career progression. One participant stated, “I have 15 years as a 1st Sergeant, 10 as a Staff Sergeant, and only months as Chief Sergeant after almost 30 years of service.” Others indicated that their performance efforts were not acknowledged in formal evaluations. As one respondent noted, “Despite years of exceeding expectations, my evaluations never reflect the reality of my work.”

The behavioral patterns associated with this theme were consistent across responses. A significant number of participants expressed resignation and reduced initiative. As one participant stated, “I no longer invest in training or preparation, there’s no return.”

Emotional detachment was frequently mentioned, as reflected in one respondent’s statement: “My pride in the institution has eroded completely.” Additionally, numerous participants advocated systemic changes, particularly in the career structure, emphasizing the need for more flexible and horizontally oriented progression models. One participant remarked, “There must be horizontal career options and specialized paths.”

5.3.2. Theme 2: Distrust in Evaluation and Promotion Systems

This theme, which relates to both SO1 and SO3, emerged in 35% of the responses, indicating dissatisfaction with institutional mechanisms for performance evaluation, promotion criteria, and the assignment of training value. Respondents highlighted inconsistencies, lack of standardization, and procedural opacity as primary concerns. For instance, one participant stated, "The evaluation system is unfair and causes too many leapfrogging cases." Others cited the unpredictable valuation of training credits as a barrier to long-term planning, as reflected in the comment: "Course values change without justification, making career planning impossible." This sense of systemic disregard was also expressed in the statement: "My international deployment wasn't even included in my performance evaluation."

The reported mistrust has led to notable behavioral consequences. Several respondents expressed skepticism toward institutional development programs, indicating that they had discontinued participation in training due to a perceived lack of benefit for career advancement. One respondent remarked, "I stopped applying to courses. The benefit isn't worth the effort." Another noted the perceived disconnection between performance and promotion, stating, "Promotions depend on politics, not performance." These perceptions suggest a weakening of merit-based principles and underscore the consequences of inconsistent and non-transparent use of HR data.

5.3.3. Theme 3: Functional Misallocation and the Absence of Data-Informed Deployment

This theme, aligned exclusively with SO3, was identified in 23% of the responses and centers on personnel dissatisfaction with the assignment of roles that do not correspond to their qualifications, prior experience, or individual circumstances. Respondents frequently reported being placed in positions without regard to their skill sets or career paths, suggesting a structural deficiency.

Several participants indicated that they felt misused or improperly placed in their functional roles. One respondent stated, "I'm doing the job of a higher rank without the title or pay," while another noted, "Despite my background in health sciences, I was assigned to logistics. It doesn't make sense." Additional comments reflected perceptions that assignment decisions are arbitrary and disconnected from institutional memory, as one participant observed: "Assignments seem arbitrary; no data or history is being considered."

These examples underscore several structural issues: ineffective alignment of roles with individual skills, limited transparency and consultation in personnel placement processes, and the lack of mechanisms to record or utilize service history and individual competencies in decision-making.

CHAPTER 6 – DISCUSSION OF RESULTS

This chapter integrates the quantitative and qualitative findings of the study to address the central question: "How can People Analytics enhance human resource management efficiency in the Portuguese Army?" and fully respond to the four SO and their DQ defined in the research design.

6.1. Discussion of Qualitative Analysis Results

The thematic analysis identified three predominant themes, each strongly aligned with SO1 (Identify behavioral patterns and individual needs) and SO3 (Examine the impacts of data analytics on decision-making), thereby responding to DQ1 and DQ3, respectively.

6.1.1. Career Stagnation and Disengagement from Institutional Progression

The most frequently reported theme, cited by 42% of respondents, was a persistent sense of stagnation and demotivation due to perceived immobility within the organizational career structure. For example, statements such as "I stopped investing in training, there is no return" illustrate behavioral withdrawal, reflecting emotional disengagement and reduced discretionary effort. These findings closely reflect constructs identified in the interview, where the need to realign individual aspirations with institutional career trajectories was emphasized as a foundational principle of effective career management.

This theme corroborates the findings of Belizón et al. (2024), who argue that PA enables early detection of disengagement signals, allowing institutions to develop timely interventions based on behavioral data.

Moreover, the interview emphasizes that the Portal ADC was conceived precisely to mitigate these issues by creating individualized career paths and integrating training, deployment history, and personal preferences. However, as the interview reveals, the platform's predictive and prescriptive functionalities are still under development, delaying the full realization of proactive career management.

6.1.2. Distrust in Evaluation and Promotion Systems

Approximately 35% of respondents reported a lack of transparency in performance evaluations and promotion criteria as a factor contributing to demotivation and perceptions of unfairness. Statements such as "Promotions depend on politics, not performance" and

"Course values change without justification, making career planning impossible" suggest institutional inconsistency and the perceived erosion of merit-based advancement.

These accounts support existing research regarding the importance of algorithmic fairness and transparency in human resource management systems. According to Di Lauro et al. (2024), non-transparent decision-making reduces employee trust and impedes the effective implementation of performance appraisal tools.

Interview data corroborate these findings by indicating that inconsistent recognition of training and operational experiences, including international deployments, has compromised effective career planning. Although the Army has introduced feedback and satisfaction mechanisms, the resulting data are not yet integrated into a centralized analytics system that can systematically inform promotion decisions.

This gap reveals the need to improve interoperability between HR systems and decision-making tools. McCartney and Fu (2022) suggest that the integration of structured feedback mechanisms into PA platforms can increase institutional accountability and enhance perceptions of procedural justice among employees.

6.1.3. Functional Misallocation and Absence of Data-Informed Deployment

The third theme, identified in 23% of the responses, highlights a misalignment between military personnel's competencies and their assigned roles. For example, one respondent stated, "Despite my background in health sciences, I was assigned to logistics," illustrating a broader institutional failure to align individual qualifications with organizational needs. This mismatch contributes to operational inefficiencies, reduced morale, and underutilization of talent.

This theme aligns with SO3 and supports the argument for implementing prescriptive analytics in HR deployment strategies. Prescriptive analytics can optimize workforce allocation by integrating variables such as educational background, prior deployments, and psychological profiles to recommend suitable positions (Rigamonti et al., 2024).

The interview indicates ongoing efforts to modernize career management infrastructure through the Portal do ADC, which integrates survey data, performance evaluations, and training records. However, the lack of real-time decision-support tools and AI-based matching algorithms constitutes a significant operational limitation. The interviewee acknowledged this shortcoming and mentioned that the PLACE project is being developed to enhance the platform's prescriptive capabilities.

These findings support the conclusions of Belizón et al. (2024), who argue that aligning personnel functions with institutional demands improves organizational efficiency and increases personnel retention.

6.2. Discussion of Quantitative Analysis Results

The quantitative analysis identified five statistically significant latent dimensions that shape perceptions of career management within the Portuguese Army: Organizational Environment, Career Development, Communication and Feedback, Current Functional Status, and Mobility and Placement. These dimensions directly address SO2 and DQ2 by revealing key indicators currently shaping HRM practices.

The Organizational Environment factor presented the highest salience, with high factor loadings for Work Environment (76.7%), Interpersonal Relationship (70.3%), and Direct Management Relationship (70.2%), alongside moderate loadings for Presentation of Problems (41.8%), Feedback (41.7%), and Roles and Responsibilities (40.3%). These results suggest that interpersonal conditions and supervisory relationships significantly affect institutional satisfaction. Interview data support these patterns, indicating a triadic interaction among the individual, the chain of command, and the administration, mediated by the career manager.

The Career Development factor was characterized by high loadings for Career to Present (83.7%), Career Opportunities (49.8%), and Overall Experience (47.6%), underscoring the influence of cumulative career trajectory and advancement potential on perceived career quality. Interview findings reinforce these results by emphasizing the importance of individualized career planning through the PLACE platform, designed to align institutional goals with individual aspirations. In this context, predictive analytics facilitates the identification of potential mismatches and supports timely interventions (Belizón et al., 2024).

The Communication and Feedback factor includes Presentation of Problems (66.9%), Feedback (59.7%), Roles and Responsibilities (47.6%), and Career Opportunities (43.6%). Although communication mechanisms are in place, the moderate loadings indicate inconsistencies or limited perceived effectiveness. The PLACE survey is designed to assess these perceptions, functioning as a diagnostic instrument for institutional responsiveness. However, the results underscore a gap between structural provision and perceived utility, echoing Giermindl et al. (2022) caution about the ethical and psychological impacts of opaque feedback systems.

An important insight emerges from the Current Functional Status factor, primarily influenced by Current Position (92.6%) and Current Placement (40.7%). This indicates that personnel assessments of institutional support are closely tied to their immediate functional contexts. Interview data confirm that, although individuals report satisfaction with their current roles, structural barriers limit alignment with long-term career goals. These findings support the development of PA systems that transition from static evaluations to real-time predictive analytics capable of modeling career trajectories (Rigamonti et al., 2024).

The Mobility and Placement factor, composed of Geographical Distance (65.4%) and Current Placement (53.6%), reflects the psychosocial effects of physical displacement and assignment mismatches. Interview findings indicate that family disruption and logistical burdens represent key challenges in military HRM. Prescriptive analytics that integrate service history, skill profiles, and individual preferences are being developed to improve future personnel placements, as outlined in the PLACE project.

These five dimensions exhibit strong psychometric validity and are consistent with qualitative findings, indicating robust triangulation across data sources. This enhances the reliability of the KPIs and supports their integration into digital HRM platforms such as the Portal do ADC. More broadly, these dimensions represent a viable foundation for supervised ML models and AI-based decision support systems, enabling a shift from reactive to proactive personnel management (Rasmussen et al., 2024).

6.2.1. Application of the extracted factors in AI and PA systems

The EFA conducted in this study identified five KPI factors related to the perceptions of the military about the institutional environment, interpersonal relationships, leadership, intention to remain, and opportunities for professional development.

To explore the practical applicability of these factors within the strategic HRM framework of the Portuguese Army, a simulation was conducted to integrate factor scores into decision support systems based on AI and PA technologies. The simulation was developed in a controlled environment using the GPT language model, which generated plausible use-case scenarios presented in Appendix D.

The simulation consisted of five application modules, each corresponding to one of the identified KPI factors, as detailed in Table 15.

Table 15 - Application Scenarios

KPI Factor	Application
Organizational Environment	Monitor morale and organizational climate across different units. If scores drop significantly, audits or psychosocial support can be activated.
Career Development	Identify military personnel with low satisfaction regarding career progression and automatically enroll them in mentoring programs or targeted training.
Communication and Feedback	Evaluate the effectiveness of communication between commanders and subordinates. Persistent issues may justify leadership interventions or structured feedback sessions.
Current Functional Status	Quickly identify personnel assigned to roles misaligned with their background, for instance, an engineer placed in a logistics function.
Mobility and Placement	Support planning of geographical movements, ensuring military personnel are preferably assigned near their residence areas, whenever operationally feasible.

These examples illustrate how extracted factors can be integrated into supervised or unsupervised AI systems and used in interactive dashboards to support strategic decision-making. The approach facilitates the alignment of psychosocial perceptions with administrative data, enabling proactive, evidence-based management.

This simulation is not intended to serve as a functional prototype, but rather as a proof of concept within the domain of talent retention and career development. It identifies potential directions for future research and institutional implementation.

6.3. Proposed Conceptual Framework

According to Jabareen (2009), a conceptual framework is a structured approach defined as a network of interrelated concepts that guides thinking about a problem or study. In response to SO4 and addressing DQ4, this section presents a structured framework for integrating data-driven approaches into military career management. Grounded in theoretical and empirical insights, the framework seeks to align institutional objectives with individual aspirations, enhancing efficiency, transparency, and engagement in HR practices.

This framework is grounded in the tripartite model of HR analytics (descriptive, predictive, and prescriptive), which guides data interpretation, forecasting, and strategic action (Fitz-enz & Mattox, 2014). Key moderating factors such as organizational culture, digital maturity, and ethical governance are considered, reflecting the specific demands of military contexts (Peeters et al., 2020).

6.3.1. Model Dynamics and Flow

The conceptual framework consists of five interdependent components (Figure 10), arranged in a feedback loop that connects data collection processes to strategic outcomes. It begins with diverse data sources, including performance evaluations, training and mission records, psychosocial and demographic variables, and indicators of engagement and mobility preferences. These datasets, partially integrated through internal platforms such as the Portal do ADC, form the analytical foundation of the model.

The central component is PA, which includes descriptive analytics for identifying behavioral and satisfaction patterns, predictive analytics for estimating turnover risk and leadership potential, and prescriptive analytics for generating recommendations regarding career development, mobility, and promotion planning.

The analytical outputs are applied in military HRM through mechanisms such as individualized career planning, performance evaluations aligned with KPIs, and data-supported decisions regarding talent allocation and succession planning. Additionally, the model further supports alignment between human capital strategies and operational objectives.

The implementation of the framework is influenced by moderating factors, such as the hierarchical structure of the Army, compliance with ethical and data governance standards (e.g., GDPR), and the institution's digital maturity, particularly regarding infrastructure and digital literacy.

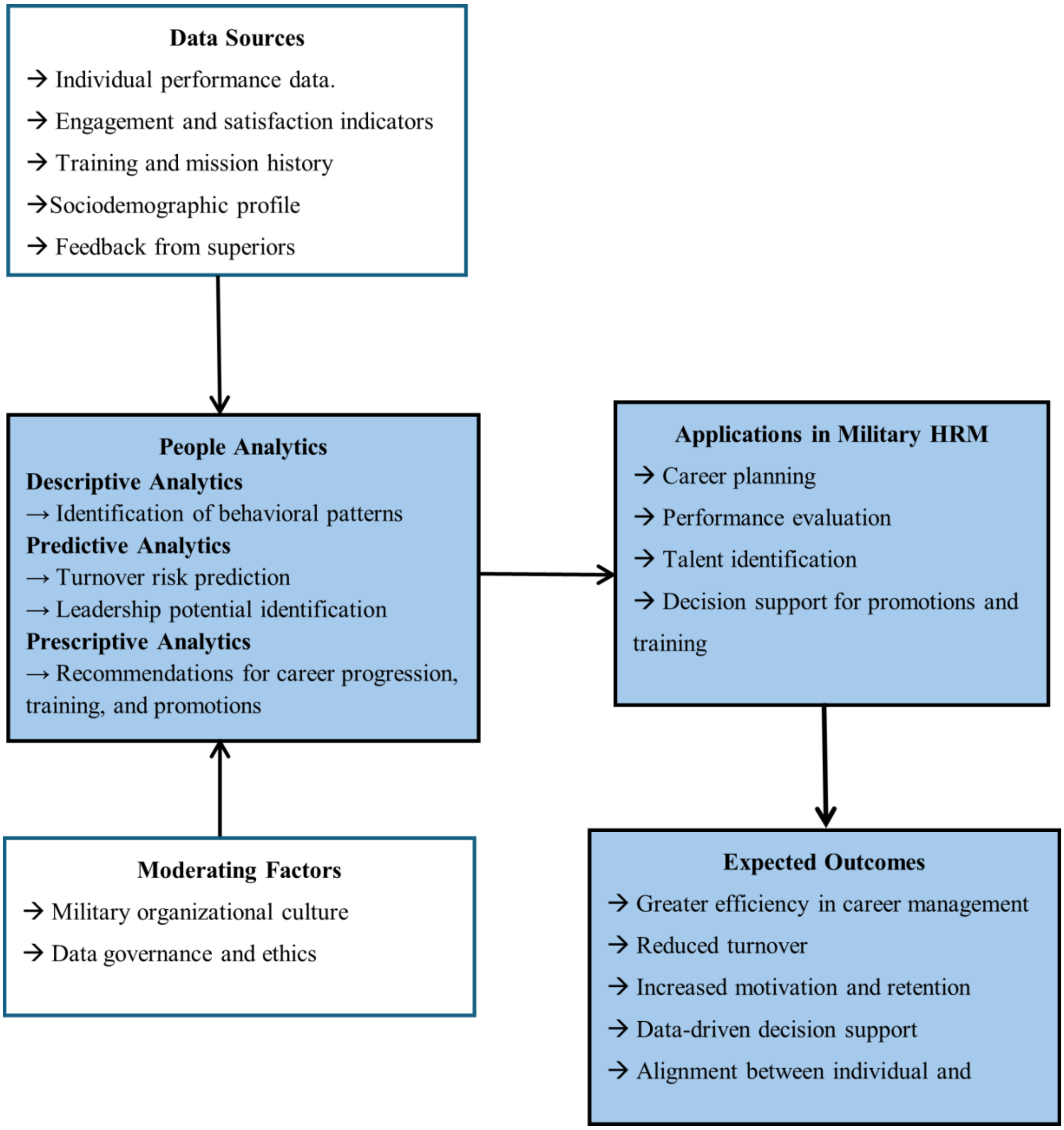


Figure 10 - Proposed Conceptual Framework.

CONCLUSION

This final chapter consolidates findings from a theoretical literature review, a quantitative analysis of PLACE survey responses, and qualitative insights from open-ended questions and a semi-structured interview with the career manager technician of the Career Development Support Division. The central objective is to assess how PA can support the efficiency and strategic alignment of HRM in the Portuguese Army, with emphasis on career management.

The theoretical foundation, established through a SLR, identified the potential of PA to improve HRM systems. Current research emphasizes the role of descriptive, predictive, and prescriptive analytics in supporting evidence-based decision-making, promoting transparency, and strengthening strategies for talent development and retention. These analytic approaches were examined in both organizational and military contexts to evaluate their relevance to the Portuguese Army's HRM challenges.

The quantitative analysis of 1377 responses to the PLACE survey identified five statistically significant latent constructs: Organizational Environment, Career Development, Communication and Feedback, Current Functional Status, and Mobility and Placement. These constructs, obtained through EFA and supported by high internal consistency, offer a valid basis for developing KPIs in military HRM. They encompass relational and operational dimensions of career satisfaction, including structural, interpersonal, and geographic factors affecting the professional military experience.

In addition to the quantitative findings, the qualitative analysis identified three emergent themes: career stagnation and disengagement, distrust in evaluation and promotion systems, and functional misallocation. These themes indicate systemic misalignments between individual expectations and institutional frameworks. Reports of limited advancement opportunities, inconsistent evaluation criteria, and inappropriate job assignments underscore areas where PA-based systems may reduce inefficiencies, enhance procedural fairness, and strengthen trust in career development mechanisms.

Addressing DQ 1, "What are the main behavioral patterns and individual needs identified in the Portuguese Army?", the findings reveal consistent behavioral trends across ranks, particularly a demand for professional recognition, advancement opportunities, and alignment between individual competencies and assigned roles. The recurring sentiment of demotivation, especially among sergeants, shows the relevance of implementing dynamic and personalized career pathways.

In response to DQ 2, “What are the main metrics and indicators used in HRM in the Army?”, the factor analysis confirmed five key dimensions influencing HRM: Organizational Environment, Career Development, Communication and Feedback, Current Functional Status, and Mobility and Placement. These dimensions serve as operational indicators for assessing institutional performance and serve as input variables for future AI-based decision support systems.

In response to DQ 3, “What are the impacts of using data analytics on decision making?”, the findings provide empirical evidence of PA’s contribution to decision-making processes. When incorporated into HRM systems, PA supports functions such as turnover prediction, satisfaction monitoring, assessment of leadership effectiveness, and mobility planning. Nonetheless, the implementation of these tools is currently hindered by fragmented data infrastructures and limited interoperability across core platforms (e.g., Portal do ADC and SIG), which restricts the use of real-time analytics and prescriptive decision-making.

In response to DQ 4, “What is the viability of a conceptual model in the Portuguese Army?”, the findings suggest that the proposed framework applies to the military context. The model integrates descriptive, predictive, and prescriptive analytics and relies on institutional platforms such as the Portal do ADC. It enables personalized career planning, data-based assignment decisions, and advancement linked to performance indicators. However, its effective implementation depends on resolving challenges related to data governance, system interoperability, and organizational data literacy.

This study acknowledges several limitations. First, the implementation of PA in the Portuguese Army remains in an early stage and is constrained by technical barriers, fragmented systems, and a hierarchical decision-making structure. Second, the proposed model has not yet undergone longitudinal testing, and therefore, its practical effectiveness remains theoretical. Third, the analysis was limited to the Permanent Staff, excluding contract personnel, which may affect the generalizability of the results.

Based on these findings, the following recommendations are proposed for future research: (1) conduct longitudinal studies to evaluate both real-time and long-term impacts of PA on HRM effectiveness; (2) expand the scope to include other military branches or NATO member states for comparative analysis; (3) assess the ethical implications and governance frameworks associated with algorithmic decision-making in HRM; and (4) implement pilot programs to experimentally test the proposed model in selected Army units.

In conclusion, and in response to the CQ, “How can People Analytics enhance human resource management efficiency in the Portuguese Army?", the study finds that PA can function as a strategic instrument to improve HRM practices. It enables alignment between individual competencies and institutional demands, supports transparent career progression, and informs talent development. Therefore, these findings underline the importance of investing in ethical data infrastructure, promoting organizational data literacy, and ensuring inclusive career planning.

REFERENCES

Alústiza Echeverría, J. M., Salvador Pardo, E., & Castiella Eguzkiza, A. (2012). Cómo establecer la hipótesis y los objetivos de un proyecto de investigación en Radiología? *Radiología*, *54*(1), 3–8. https://doi.org/10.1016/j.rx.2011.09.002

Ashwin Varghese, Chris Sajimon Joseph, Maria Binoy, Rosmi Jacob, & Anu Joseph. (2023). Unleashing the Power of Data Analytics: A Pathway to Insightful Decision-Making. *International Journal of Engineering Technology and Management Sciences*, *7*(4), 433–437. https://doi.org/10.46647/ijetms.2023.v07i04.057

Bailey, A. K. (2019). Inclusion in the American Military: A Force for Diversity. *Contemporary Sociology: A Journal of Reviews*, *48*(1), 96–97. https://doi.org/10.1177/0094306118815500ii

Banerjee, A., Bandyopadhyay, T., & Acharya, P. (2013). *Data Analytics: Hyped Up Aspirations or True Potential? Vikalpa: The Journal for Decision Makers*, *38*(4), 1–12. https://doi.org/10.1177/0256090920130401

Bartlett, M. S. (1950). Tests of Significance in Factor Analysis. *British Journal of Statistical Psychology*, *3*(2), 77–85. https://doi.org/10.1111/j.2044-8317.1950.tb00285.x

Barton, D., & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review*, *90*(10), 78–83, 128.

Belizón, M. J., Majarín, D., & Aguado, D. (2024). Human resources analytics in practice: A knowledge discovery process. *European Management Review*, *21*(3), 659–677. https://doi.org/10.1111/emre.12605

Benabou, A., & Touhami, F. (2025). Empowering human resource management through artificial intelligence: A systematic literature review and bibliometric analysis. *International Journal of Production Management and Engineering*, *13*(1), 59–76. https://doi.org/10.4995/ijpme.2025.21900

Berrang-Ford, L., Pearce, T., & Ford, J. D. (2015). Systematic review approaches for climate change adaptation research. *Regional Environmental Change*, *15*(5), 755–769. https://doi.org/10.1007/s10113-014-0708-7

Brandt, T., Wagner, S., & Neumann, D. (2021). Prescriptive analytics in public-sector decision-making: A framework and insights from charging infrastructure planning. *European Journal of Operational Research*, *291*(1), 379–393. https://doi.org/10.1016/j.ejor.2020.09.034

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Camm, J. D., Cochran, J. J., Fry, M. J., & Ohlmann, J. W. (2021). *Business analytics: Descriptive, predictive, prescriptive* (Fourth edition). Cengage.

Cho, W., Choi, S., & Choi, H. (2023). Human Resources Analytics for Public Personnel Management: Concepts, Cases, and Caveats. *Administrative Sciences*, *13*(2), 41. https://doi.org/10.3390/admsci13020041

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences* (0 ed.). Routledge. https://doi.org/10.4324/9780203771587

Dejaeger, K., Verbeke, W., Martens, D., & Baesens, B. (2012). Data Mining Techniques for Software Effort Estimation: A Comparative Study. *IEEE Transactions on Software Engineering*, *38*(2), 375–397. https://doi.org/10.1109/TSE.2011.55

Delen, D. (2015). *Real-world data mining: Applied business analytics and decision making*. Pearson Education.

Di Lauro, S., Tursunbayeva, A., Antonelli, G., & Moschera, L. (2024). Disrupting human resource management with people analytics: A study of applications, value, enablers and barriers in Italy. *Personnel Review*. https://doi.org/10.1108/PR-11-2023-0927

DiClaudio, M. (2019). People analytics and the rise of HR: How data, analytics and emerging technology can transform human resources (HR) into a profit center. *Strategic HR Review*, *18*(2), 42–46. https://doi.org/10.1108/SHR-11-2018-0096

Du, J. (2024). Ethical and Legal Challenges of AI in Human Resource Management. *Journal of Computing and Electronic Information Management*, *13*(2), 71–77. https://doi.org/10.54097/83j64ub9

Field, A. (2009). *Discovering Statistics Using SPSS* (3 ed). Sage Publications.

Fitz-enz, J., & Mattox, J. R. (2014). *Predictive analytics for human resources*. John Wiley & Sons, Inc.

Foote, M. (2008). Materials and Methods. *Chest*, *133*(1), 291–293. https://doi.org/10.1378/chest.07-2382

Forina, M., Armanino, C., Lanteri, S., & Leardi, R. (2005). Methods of varimax rotation in factor analysis with applications in clinical and food chemistry. *Journal of Chemometrics*, *3*(S1), 115–125. https://doi.org/10.1002/cem.1180030504

Geetha, V., & Sujatha, N. (2024). An Overview of Descriptive Analytics and Data Visualization. *2024 5th International Conference on Smart Electronics and Communication (ICOSEC)*, 1158–1163. https://doi.org/10.1109/ICOSEC61587.2024.10722273

Ghasemi, A., Bahadoran, Z., Zadeh-Vakili, A., Montazeri, S. A., & Hosseinpanah, F. (2019). The Principles of Biomedical Scientific Writing: Materials and Methods. *International Journal of Endocrinology and Metabolism*, *In Press*(In Press). https://doi.org/10.5812/ijem.88155

Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: Reviewing the perils for organisations and employees. *European Journal of Information Systems*, *31*(3), 410–435. https://doi.org/10.1080/0960085X.2021.1927213

Gleiman, A., & Zacharakis, J. (2016). Continuing Professional Education in the Military. *New Directions for Adult and Continuing Education*, *2016*(151), 81–90. https://doi.org/10.1002/ace.20197

Graczyk-Kucharska, M., Olszewski, R., Golinski, M., Spychala, M., Szafranski, M., Wilhelm Weber, G., & Miadowicz, M. (2022). Human resources optimization with MARS and ANN: Innovation geolocation model for generation Z. *Journal of Industrial and Management Optimization*, *18*(6), 4093. https://doi.org/10.3934/jimo.2021149

Graf, T. A., & Kuemmel, G. (2022). The Achilles Heel of Recruiting Women: Perceived Gender Equality as a Key Determinant of the Military's Employer Attractiveness Among Women. *Armed Forces & Society*, *48*(4), 936–960. https://doi.org/10.1177/0095327X211035818

Guo, F., Gallagher, C. M., Sun, T., Tavoosi, S., & Min, H. (2024). Smarter people analytics with organizational text data: Demonstrations using classic and advanced NLP models. *Human Resource Management Journal*, *34*(1), 39–54. https://doi.org/10.1111/1748-8583.12426

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (Eighth edition). Cengage.

Hamadamin, H. H., & Atan, T. (2019). The Impact of Strategic Human Resource Management Practices on Competitive Advantage Sustainability: The Mediation of Human Capital Development and Employee Commitment. *Sustainability*, *11*(20),

5782. https://doi.org/10.3390/su11205782

Hiebl, M. R. W. (2023). Sample Selection in Systematic Literature Reviews of Management Research. *Organizational Research Methods*, *26*(2), 229–261. https://doi.org/10.1177/1094428120986851

Hurwitz, J., Bowles, A., & Kaufman, M. (2015). *Cognitive computing and big data analytics*. John Wiley & Sons. https://doi.org/10.1002/9781119183648

Irigaray, H. A. R., & Stocker, F. (2023). Leadership with data: Improving people management through People Analytics, leadership, and Workforce Planning. *Cadernos EBAPE.BR*, *21*(6), e90281. https://doi.org/10.1590/1679-395190281x

Jabareen, Y. (2009). Building a Conceptual Framework: Philosophy, Definitions, and Procedure. *International Journal of Qualitative Methods*, *8*(4), 49–62. https://doi.org/10.1177/160940690900800406

Jacinto, A. (2022, December). A Gestão de Carreiras no Exército. *Jornal Do Exército*. https://assets.exercito.pt/SiteAssets/JE/Jornais/2022/Dez/725.pdf

James, P. E. (1948). Formulating Objectives of Geographic Research. *Annals of the Association of American Geographers*, *38*(4), 271–276. https://doi.org/10.1080/00045604809351985

Jörden, N. M., Sage, D., & Trusson, C. (2022). 'It's so fake': Identity performances and cynicism within a people analytics team. *Human Resource Management Journal*, *32*(3), 524–539. https://doi.org/10.1111/1748-8583.12412

Kaiser, H. F. (1974). An Index of Factorial Simplicity. *Psychometrika*, *39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kaisler, S. H., Espinosa, J. A., Armour, F., & Money, W. H. (2014). Advanced Analytics—Issues and Challenges in a Global Environment. *2014 47th Hawaii International Conference on System Sciences*, 729–738. https://doi.org/10.1109/HICSS.2014.98

Kaluzny, B. L. (2021). Data analytics in military human performance: Getting in the game. *Journal of Science and Medicine in Sport*, *24*(10), 970–974. https://doi.org/10.1016/j.jsams.2021.04.003

Kameswari, J., Palivela, H., Settur, S., & Solanki, P. (2023). Identification, Assessment and Optimisation of Key Impact Variables in People Analytics Using AI. In P. Tyagi, N. Chilamkurti, S. Grima, K. Sood, & B. Balusamy (Eds.), *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A* (pp. 245–282). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80382-027-920231013

Kim, P., Cho, W., & Yang, I. (2024). Workplace Disruption in the Public Sector and HRM Practices to Enhance Employee Resilience. *Review of Public Personnel Administration*, *44*(1), 86–115. https://doi.org/10.1177/0734371X221095399

Kumar, V., & Garg, M. L. (2018). Predictive Analytics: A Review of Trends and Techniques. *International Journal of Computer Applications*, *182*(1), 31–37. https://doi.org/10.5120/ijca2018917434

Kumari, S., & Bhardwaj, Dr. N. (2019). A Review paper on Big Data. *International Journal of Mobile Computing and Application*, *6*(2), 1–3. https://doi.org/10.14445/23939141/IJMCA-V6I2P101

Larsson, A.-S., & Edwards, M. R. (2022). Insider econometrics meets people analytics and strategic human resource management. *The International Journal of Human Resource Management*, *33*(12), 2373–2419. https://doi.org/10.1080/09585192.2020.1847166

Machado, F. N. R. (2018). *Big Data O Futuro dos Dados e Aplicações*. Érica.

Mahanty, R., & Mahanti, P. K. (2020). Unleashing Artificial Intelligence onto Big Data: A Review: In I. R. Management Association (Ed.), *Cognitive Analytics* (pp. 1682–1697). IGI Global. https://doi.org/10.4018/978-1-7998-2460-2.ch087

Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, *32*(2), 100795. https://doi.org/10.1016/j.hrmr.2020.100795

Marler, J. H. (2009). Making human resources strategic by going to the Net: Reality or myth? *The International Journal of Human Resource Management*, *20*(3), 515–527. https://doi.org/10.1080/09585190802707276

Mazari Abdessameud, O., Van Utterbeeck, F., & Guerry, M.-A. (2022). Military Human Resource Planning through Flow Network Modeling. *Engineering Management Journal*, *34*(2), 302–313. https://doi.org/10.1080/10429247.2021.1900660

McCartney, S., & Fu, N. (2022). Promise versus reality: A systematic review of the ongoing debates in people analytics. *Journal of Organizational Effectiveness: People and Performance*, *9*(2), 281–311. https://doi.org/10.1108/JOEPP-01-2021-0013

Mishra, C., & Gupta, D. L. (2017). Deep Machine Learning and Neural Networks: An Overview. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *6*(2), 66. https://doi.org/10.11591/ijai.v6.i2.pp66-73

Mishra, N., & Silakari, D. S. (2012). Predictive Analytics: A Survey, Trends, Applications, Oppurtunities & Challenges. *International Journal of Computer Science and Information Technologies*, *3*(3), 4434–4438.

Moesmann, M., & Pedersen, T. B. (2024). *Data-Driven Prescriptive Analytics Applications: A Comprehensive Survey* (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2412.00034

Monroe, B. L. (2013). The Five Vs of Big Data Political Science Introduction to the Virtual Issue on Big Data in Political Science *Political Analysis*. *Political Analysis*, *21*(V5), 1–9. https://doi.org/10.1017/S1047198700014315

Mwaro, P. N., Ogada, K., & Cheruiyot, W. (2021). Neural Network Model for Talent

Recruitment and Management for Employee Development and Retention. *2021 IEEE AFRICON*, 1–6. https://doi.org/10.1109/AFRICON51333.2021.9571014

Niederhaus, M., Migenda, N., Weller, J., Schenck, W., & Kohlhase, M. (2024). Technical Readiness of Prescriptive Analytics Platforms: A Survey. *2024 35th Conference of Open Innovations Association (FRUCT)*, 509–519. https://doi.org/10.23919/FRUCT61870.2024.10516367

Offstein, E. H., & Dufresne, R. L. (2007). Building strong ethics and promoting positive character development: The influence of HRM at the United States Military Academy at West Point. *Human Resource Management*, *46*(1), 95–114. https://doi.org/10.1002/hrm.20147

Okazawa, S. (2013). A discrete event simulation environment tailored to the needs of military human resources management. *2013 Winter Simulations Conference (WSC)*, 2784–2795. https://doi.org/10.1109/WSC.2013.6721649

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Systematic Reviews*, *10*(1), 89. https://doi.org/10.1186/s13643-021-01626-4

Patrichi, M. E. (2015). General Military Human Resource Management and Special Forces Human Resource Management. A Comparative Outlook. *Journal of Defense Resources Management*, *6*(2), 75–82.

Peccei, R., & Van De Voorde, K. (2019). Human resource management–well-being–performance research revisited: Past, present, and future. *Human Resource Management Journal*, *29*(4), 539–563. https://doi.org/10.1111/1748-8583.12254

Peeters, T., Paauwe, J., & Van De Voorde, K. (2020). People analytics effectiveness: Developing a framework. *Journal of Organizational Effectiveness: People and Performance*, *7*(2), 203–219. https://doi.org/10.1108/JOEPP-04-2020-0071

Petticrew, M., & Roberts, H. (2006). *Systematic Reviews in the Social Sciences: A Practical Guide* (1st ed.). Wiley. https://doi.org/10.1002/9780470754887

Phillips, M., & Lu, J. (2018). A quick look at NVivo. *Journal of Electronic Resources Librarianship*, *30*(2), 104–106. https://doi.org/10.1080/1941126X.2018.1465535

Pigott, T. D., & Polanin, J. R. (2020). Methodological Guidance Paper: High-Quality Meta-Analysis in a Systematic Review. *Review of Educational Research*, *90*(1), 24–46. https://doi.org/10.3102/0034654319877153

Polzer, J. T. (2022). The rise of people analytics and the future of organizational research. *Research in Organizational Behavior*, *42*, 100181. https://doi.org/10.1016/j.riob.2023.100181

Pothuri, V. R. V., & Reddy, U. M. (2019). AI and Big Data: Harnessing the Power of Data-Driven Decision Making. *International Journal of Advanced Research in Science, Communication and Technology*, 63–71. https://doi.org/10.48175/IJARSCT-9974B

Rasmussen, T. H., Ulrich, M., & Ulrich, D. (2024). Moving People Analytics From Insight to Impact. *Human Resource Development Review*, *23*(1), 11–29. https://doi.org/10.1177/15344843231207220

Reis, T., Bornschlegl, M. X., & Hemmje, M. L. (2020). Big Data Analysis, AI, and Visualization Workshop: Road Mapping Infrastructures for Artificial Intelligence Supporting Advanced Visual Big Data Analysis. *Proceedings of the International Conference on Advanced Visual Interfaces*, 1–2. https://doi.org/10.1145/3399715.3400860

Rigamonti, E., Gastaldi, L., & Corso, M. (2024). Measuring HR analytics maturity:

Supporting the development of a roadmap for data-driven human resources management. *Management Decision*, *62*(13), 243–282. https://doi.org/10.1108/MD-11-2023-2087

Rosinha, A. P., Matias, L. J. S., & De Souza, M. A. (2017). Leadership in Extreme Conditions and Under Severe Stress: Case Study Analysis. In M. Holenweger, M. K. Jager, & F. Kernic (Eds.), *Leadership in Extreme Situations* (pp. 93–112). Springer International Publishing. https://doi.org/10.1007/978-3-319-55059-6_6

Russell, S. J., & Norvig, P. (with Chang, M., Devlin, J., Dragan, A., Forsyth, D., Goodfellow, I., Malik, J., Mansinghka, V., Pearl, J., & Wooldridge, M. J.). (2022). *Artificial intelligence: A modern approach* (Fourth edition, global edition). Pearson.

ŞahiN, M., & Aybek, E. (2020). Jamovi: An Easy to Use Statistical Software for the Social Scientists. *International Journal of Assessment Tools in Education*, *6*(4), 670–692. https://doi.org/10.21449/ijate.661803

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2023). *Research methods for business students* (Ninth edition). Pearson.

Shah, N., Irani, Z., & Sharif, A. M. (2017). Big data in an HR context: Exploring organizational change readiness, employee attitudes and behaviors. *Journal of Business Research*, *70*, 366–378. https://doi.org/10.1016/j.jbusres.2016.08.010

Simi, M. S., & Nayaki, K. S. (2017). Data analytics in medical data: A review. *2017 International Conference on Circuit ,Power and Computing Technologies (ICCPCT)*, 1–4. https://doi.org/10.1109/ICCPCT.2017.8074337

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Soltanpoor, R., & Sellis, T. (2016). Prescriptive Analytics for Big Data. In M. A. Cheema,

W. Zhang, & L. Chang (Eds.), *Databases Theory and Applications* (Vol. 9877, pp. 245–256). Springer International Publishing. https://doi.org/10.1007/978-3-319-46922-5_19

Sousa, M. J., Ferraz, D., Sacavém, A., & Gomes, J. S. (2022). Human Governance Analytics for Public Organizations. In S. R. Mondal, F. Di Virgilio, & S. Das (Eds.), *HR Analytics and Digital HR Practices* (pp. 217–241). Springer Nature Singapore. https://doi.org/10.1007/978-981-16-7099-2_9

Suri, N., & Lakhanpal, P. (2024). People Analytics Enabling HR Strategic Partnership: A Review. *South Asian Journal of Human Resources Management*, *11*(1), 130–164. https://doi.org/10.1177/23220937221119599

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tewari, I., & Pant, M. (2020). Artificial Intelligence Reshaping Human Resource Management: A Review. *2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI)*, 1–4. https://doi.org/10.1109/ICATMRI51801.2020.9398420

Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics—A scoping review of conceptual boundaries and value propositions. *International Journal of Information Management*, *43*, 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002

Van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Vartak, S., & Sapre, A. (2020). An Overview of Predictive Analysis: Techniques and Applications. *International Journal for Research in Applied Science and*

Engineering Technology, *8*(11), 652–662. https://doi.org/10.22214/ijraset.2020.32250

Vuga, J., & Juvan, J. (2013). Work–family conflict between two greedy institutions – the family and the military. *Current Sociology*, *61*(7), 1058–1077. https://doi.org/10.1177/0011392113498881

Wang, A. (2024). Advancing Organizational Effectiveness Through Strategic Workforce Planning and Technology Integration. *Advances in Economics, Management and Political Sciences*, *121*(1), 107–112. https://doi.org/10.54254/2754-1169/121/20242362

Webb, J. L. (2007). "Pragmatisms (Plural) Part 1: Classical Pragmatism and Some Implications for Empirical Inquiry." *Journal of Economic Issues*, *41*(4), 1063–1086. https://doi.org/10.1080/00213624.2007.11507087

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables. In *Structural equation modeling: Concepts, issues, and applications* (pp. 56–75). Sage Publications.

Wolniak. (2023). The concept of descriptive analytics. *Scientific Papers of Silesian University of Technology Organization and Management Series*, *2023*(172). https://doi.org/10.29119/1641-3466.2023.172.42

Yoon, S. W., Han, S., & Chae, C. (2024). People Analytics and Human Resource Development – Research Landscape and Future Needs Based on Bibliometrics and Scoping Review. *Human Resource Development Review*, *23*(1), 30–57. https://doi.org/10.1177/15344843231209362

Other Sources

Ministério da Defesa Nacional [MDN] (2015). Decreto-Lei n.º 90/2015: Aprova o Estatuto dos Militares das Forças Armadas. Diário da República, n.º 104/2015, Série I.

Assembleia da República (1989). Lei n.º 11/89: Bases gerais do estatuto da condição militar. Diário da República n.º 125/1989, Série I.

APENDICES AND ANNEXES

APPENDIX A - STATISTICAL EVALUATION OF DATA

Through the survey, the 1377 responses of the Permanent Staff of the Portuguese Army were explored through statistical procedures. The variables were all measured using Likert scales with five response categories, coded from 1 to 5.

Table 16 - Descriptive statistics.

Variable	Mean ± Standard deviation	Median	Minimum	Maximum	Skewness	Kurtosis
Training for the Current Position	3.90 ± 0.905	4	1	5	-0.998	1.022
Conflict	2.77 ± 0.928	3	1	5	-0.152	-0.273
Current Placement	4.02 ± 1.021	4	1	5	-1.156	0.965
Current position	3.99 ± 0.939	4	1	5	-1.04	1.015
Overall Experience	3.66 ± 0.773	4	1	5	-0.683	1.031
Work Environment	4.08 ± 0.885	4	1	5	-1.103	1.468
Direct Management Relationship	4.22 ± 0.860	4	1	5	-1.209	1.585
Interpersonal Relationship	4.40 ± 0.724	5	1	5	-1.448	3.257
Geographic Distance	3.59 ± 1.414	4	1	5	-0.604	-0.974
Roles and responsibilities	3.84 ± 0.879	4	1	5	-0.841	0.954
Career Opportunities	3.10 ± 1.110	3	1	5	-0.297	-0.603
Presentation of problems	3.72 ± 0.954	4	1	5	-0.682	0.269
Feedback	3.68 ± 0.956	4	1	5	-0.637	0.193
Career to present	3.38 ± 1.098	4	1	5	-0.531	-0.61
Unpaid Leave/Resignation	3.62 ± 1.342	4	1	5	-0.484	-1.031

Table 16 presents the descriptive statistics for the variables measured in the survey, all based on a Likert-type scale ranging from 1 to 5. These variables capture a range of dimensions related to military personnel's perceptions of their career.

Overall, the mean values range from 2.77 to 4.40, indicating generally positive perceptions across most dimensions. Median values are generally equal to or close to the means, indicating a relatively symmetric distribution of responses across most variables.

Standard deviations (SD) range from 0.724 to 1.414, suggesting varying levels of response dispersion.

To assess the distributional characteristics of the data, skewness and kurtosis were examined. Skewness values range between −1.448 and −0.152, reflecting a slight to moderate negative skew in most variables, that is, a tendency for respondents to select more positive ratings on the scale. Kurtosis values range from −1.031 to 3.257, with most variables exhibiting values close to zero, suggesting distributions similar in shape to the normal curve. The only notable exception is Interpersonal Relationship, which presents a kurtosis of 3.257, indicating a more peaked distribution with a concentration of responses at the high end of the scale.

According to the guidelines proposed by West et al. (1995), skewness values within ±2 and kurtosis values within ±7 are considered acceptable for assuming normality in social science research. Based on these criteria, none of the variables demonstrates severe deviations from normality. Therefore, the data are deemed appropriate for the application of parametric statistical techniques, including correlation analyses, regression models, and factor analysis.

APPENDIX B - RELIABILITY OF SURVEYS

Field (2009) states that the standard way to analyze reliability is represented in the idea that individual items (or a set of items) should produce similar results. Thus, the internal consistency of the survey was analyzed through Cronbach's alpha coefficient (α) analysis (Table 17).

According to Tavakol and Dennick (2011), the values of the alpha coefficient can be interpreted as follows: Unacceptable: if the value is less than or equal to 0.6; Weak: if the value is between 0.6 (exclusive) and 0.7 (inclusive); Reasonable: if the value is between 0.7 (exclusive) and 0.8 (inclusive); Good: if the value is between 0.8 (exclusive) and 0.9 (inclusive) and Excellent: if the value is equal to or greater than 0.9.

Table 17 - Internal consistency values.

Cronbach's alpha		
Training for the Current Position	0.879	Good
Conflict	0.877	Good
Current Placement	0.868	Good
Current position	0.868	Good
Overall Experience	0.870	Good
Work Environment	0.867	Good
Direct Management Relationship	0.870	Good
Interpersonal Relationship	0.875	Good
Geographic Distance	0.889	Good
Roles and responsibilities	0.867	Good
Career Opportunities	0.867	Good
Presentation of problems	0.866	Good
Feedback	0.867	Good
Career to present	0.874	Good
Unpaid Leave/Resignation	0.877	Good

Cronbach's alpha value was 0.880, indicating acceptable internal consistency, as described by Tavakol and Dennick (2011). This suggests that the items are consistently measuring a common underlying construct, and the instrument can be considered reliable for this study.

Additionally, the effect of each individual item on the overall internal consistency was examined. The Cronbach’s alpha values, if individual items were removed, ranged from 0.866 to 0.889. This range indicates that no single item negatively affected the overall reliability of the scale. These findings support the suitability of the instrument for data collection within the scope of this dissertation.

APPENDIX C - SURVEY FACTORS

In this appendix, the results of the factor analysis performed on the survey are presented. This analysis aimed to identify the KPI factors underlying this dimension of the study, using the VARIMAX rotation, which, according to Field (2009), seeks to maximize the dispersion of loads within the factors, resulting in more interpretable groupings of variables (Table 18).

Table 18 - Survey KPI factors.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness	Communalities
Training for the Current Position (Q12)						0.80138	0.19862
Conflict (Q18)					0.491	0.6937	0.30630
Current Placement (Q20)				0.407	0.536	0.40483	0.59517
Current position (Q22)				0.926		0.005	0.99500
Career to present (Q24)		0.837				0.24282	0.75718
Overall Experience (Q26)		0.476				0.54699	0.45301
Work Environment (Q27)	0.767					0.25775	0.74225
Direct Management Relationship (Q28)	0.702					0.33167	0.66833
Interpersonal Relationship (Q29)	0.703					0.46292	0.53708
Geographic Distance (Q30)					0.697	0.50567	0.49433
Roles and responsibilities (Q31)	0.403		0.476			0.43569	0.56431
Career Opportunities (Q32)		0.498	0.436			0.43346	0.56654
Presentation of problems (Q33)	0.418		0.669			0.27623	0.72377
Feedback (Q34)	0.417		0.597			0.36754	0.63246
Unpaid Leave/Resignation (Q35)						0.7002	0.29980

Following the EFA, a Pearson correlation matrix was calculated to examine the linear interrelations among the KPI dimensions and support the factor structure validation.

Table 19 - Pearson correlation

KPI Factor	Mean	SD	1	2	3	4	5
1	3.99	0.699	-----				
2	3.38	0.816	0.605	-----			
3	3.58	0.805	0.899	0.758	-----		
4	4.01	0.873	0.580	0.515	0.579	-----	
5	3.80	1.038	0.373	0.345	0.379	0.684	-----

Table 19 displays the Pearson correlation coefficients between the five factors identified through the factor analysis. All correlations are statistically significant, indicating a strong internal consistency and meaningful relationships among the latent dimensions assessed.

The results show a very strong positive correlation between Factor 1 and Factor 3 ($r = 0.899$), suggesting that these two constructs are closely related and may capture highly overlapping aspects of the participants' perceptions. Similarly, Factor 2 also correlates strongly with Factor 3 ($r = 0.758$), and moderately with Factor 1 ($r = 0.605$), which may reflect interconnected themes such as leadership, communication, or professional development.

Factor 4 demonstrates moderate correlations with Factors 1 ($r = 0.580$), 2 ($r = 0.515$), and 3 ($r = 0.579$). These values indicate that this factor is also well integrated into the broader construct measured by the instrument, although with slightly less intensity than the relationships observed among the first three factors.

Finally, Factor 5 presents the lowest correlations across the matrix, ranging from $r = 0.345$ (with Factor 2) to $r = 0.684$ (with Factor 4). Despite being statistically significant, these correlations are weaker compared to those observed among the other factors, suggesting that Factor 5 may represent a somewhat more distinct dimension, potentially reflecting attitudes or intentions less directly related to the core constructs captured by the remaining factors.

The mean scores of the factors range from 3.38 (Factor 2) to 4.01 (Factor 4), suggesting generally favorable perceptions across dimensions, with Factor 2 possibly reflecting the most critical or least endorsed area among participants. Standard deviations range from 0.699 to 1.038, indicating varying degrees of dispersion in responses, with Factor 5 showing the greatest variability.

Overall, the correlation matrix confirms the conceptual coherence among the identified factors, while also highlighting meaningful distinctions between them. These results support the internal structure of the instrument and reinforce the adequacy of using these factors in subsequent analyses.

APPENDIX D - SIMULATION OF PRACTICAL USE SCENARIOS FOR KPI FACTORS

This appendix presents a conceptual simulation demonstrating how the five KPI factors extracted from the PLACE survey may be operationalized within AI-based decision support systems for application in the Portuguese Army. Each use case is grounded in statistical methodology, aligned with institutional objectives, and informed by established practices in literature.

The proposed simulations offer an opportunity to enhance operational efficiency while supporting institutional goals and individual well-being. Full implementation through platforms such as the Portal do ADC would represent a significant advancement in HRM.

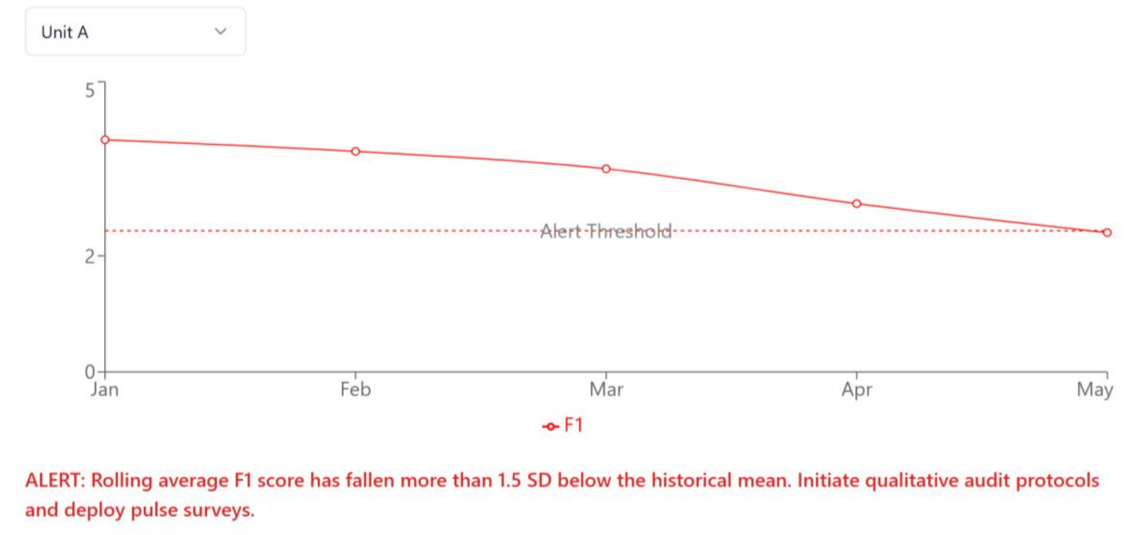
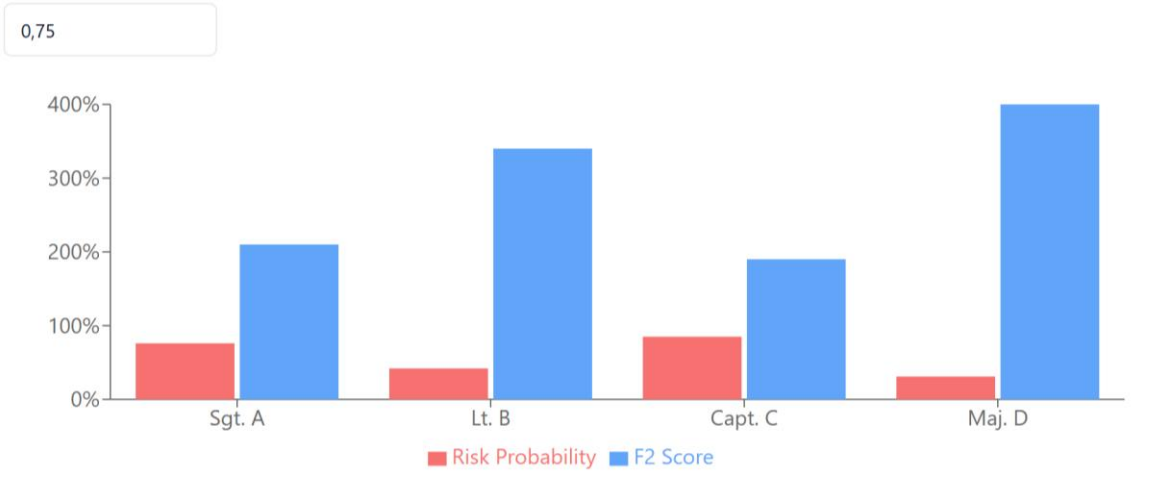


Figure 11 - Dashboard for KPI Factor 1 – Organizational Environment

Figure 11 presents a data-driven early warning system designed to monitor the KPI factor “Organizational Environment” (F1). The graph shows a declining trend in the rolling average F1 score for Unit A over five months (January to May). An alert is automatically triggered when the average score falls more than 1.5 standard deviations below the historical mean, surpassing the predefined alert threshold.

This simulation represents an AI-supported mechanism for real-time monitoring of organizational climate. When the threshold is exceeded, the system initiates automated interventions, including the implementation of qualitative audits and the deployment of pulse surveys to identify potential underlying issues. This case illustrates the operationalization of latent constructs from survey-based diagnostics within the Portuguese Army's decision support infrastructure to enable proactive management of HR.



Personnel	F2 Score	Misalignment	Years in Role	Training	Risk Probability
Sgt. A	2.1	Yes	8	Basic	76.0%
Lt. B	3.4	No	4	Advanced	42.0%
Capt. C	1.9	Yes	10	None	85.0%
Maj. D	4	No	3	Intermediate	31.0%

Trigger Actions:

- Sgt. A: Enrolled in mentorship and L&D. Career path simulation initiated via Markov Chain.
- Capt. C: Enrolled in mentorship and L&D. Career path simulation initiated via Markov Chain.

Figure 12 - Dashboard for KPI Factor 2 – Career Development

Figure 12 demonstrates the application factor “Career Development” (F2). The bar chart compares F2 scores (blue) and corresponding risk probabilities (red) for four personnel profiles: Sgt. A, Lt. B, Capt. C, and Maj. D. These probabilities are generated by a predictive algorithm that incorporates variables such as tenure in current role, training level, and career-role alignment.

The system identifies Sgt. A and Capt. C as high-risk case due to low F2 scores, long time in current roles (8 and 10 years, respectively), and limited or no training. Consequently, these individuals were automatically enrolled in mentorship and L&D programs, and their career paths were simulated to evaluate potential transitions and improve alignment with institutional pathways.

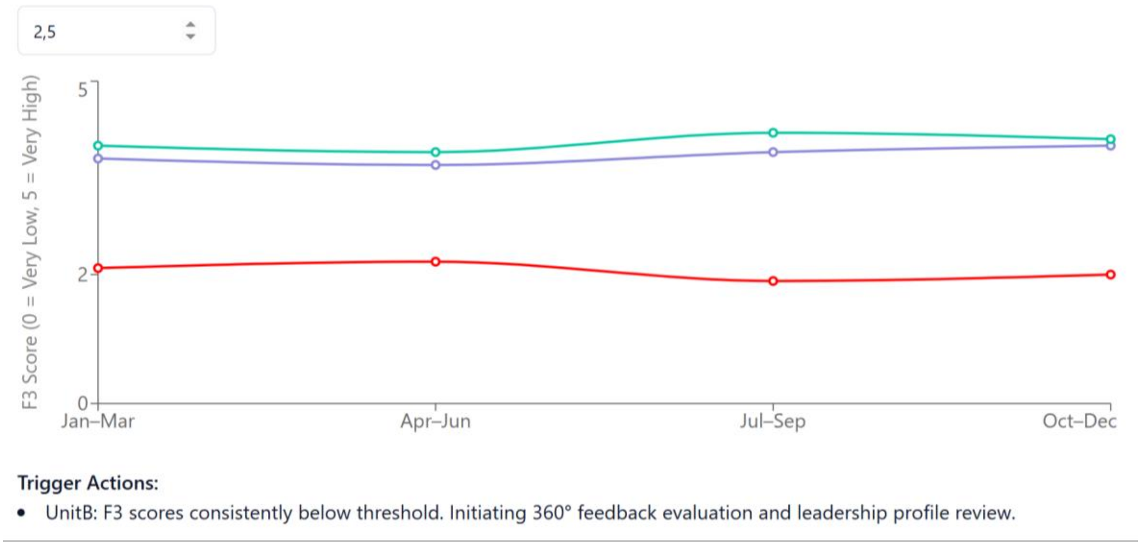


Figure 13 - Dashboard for KPI Factor 3 – Communication and Feedback

Figure 13 displays a simulated dashboard for the KPI factor "Communication and Feedback" (F3), which monitors quarterly trends in perceived leadership quality across organizational units. Scores for F3 range from 0 (Very Low) to 5 (Very High). The data indicates that, while most units maintain scores above the established threshold of 2.5, Unit B consistently reports values below this benchmark throughout all measured quarters.

In response to this pattern, the system has triggered targeted interventions for Unit B, including the launch of a 360° feedback process and a leadership profile audit. These measures aim to identify specific performance gaps and leadership development needs. The goal is to enhance command climate, communication practices, and overall leadership impact through evidence-based review processes.

0,7

Personnel	F4 Score	Distance (km)	Role Misalignment	Exit Risk (12 mo)
Sgt. A	3.9	80	No	42.0%
Lt. B	2.3	150	Yes	76.0%
Capt. C	1.9	200	Yes	83.0%
Maj. D	4.2	30	No	21.0%

Trigger Actions:

- Lt. B: High attrition risk detected. Recommend relocation, tailored training, or hybrid assignment.
- Capt. C: High attrition risk detected. Recommend relocation, tailored training, or hybrid assignment.

Figure 14 - Dashboard for KPI Factor 4 – Current Functional Status

This dashboard (Figure 14) simulates a system for monitoring F4 "Current Functional Status" that reflects the probability of voluntary departure over a 12-month horizon. The model integrates survey-based F4 scores with operational data such as geographic distance from home base and role misalignment to compute individualized exit risk probabilities.

The dashboard identifies Lt. B (76%) and Capt. C (83%) as high-risk individuals due to low F4 scores, extended commute distances (150–200 km), and confirmed role misalignment. These conditions exceed the defined risk threshold of 0.70, prompting automated alerts and tailored retention interventions. Recommended actions include relocation options, tailored L&D plans, or reassignment to more compatible roles.

This use case demonstrates how attrition risk can be dynamically predicted using a combination of perceptual and operational data.

Q1 2025

Personnel	F5 Score	Current Location	Preferred Location	Qualified	Feasible	Recommendation
Sgt. A	3.2	Braga	Porto	Yes	Yes	Move to Porto (preferred)
Lt. B	2.1	Lisbon	Faro	No	No	Stay in Lisbon (no qualified positions in preferred region)
Capt. C	4.1	Évora	Lisbon	Yes	Yes	Transfer to Lisbon
Maj. D	2.5	Portalegre	Coimbra	Yes	No	Remain in Portalegre (logistical constraints)

Figure 15 - Dashboard for KPI Factor 5 – Mobility and Placement

Figure 15 simulates the application KPI factor 5, "Mobility and Placement". The dashboard integrates personnel preferences, qualification status, and logistical probability to generate mobility optimization recommendations aligned with institutional needs and individual preferences.

The system evaluates four individuals based on their F5 scores and operational attributes. For example, Sgt. A, who is currently in Braga and prefers Porto, is both qualified and logistically feasible for transfer; the system recommends relocation to the preferred location. Capt. C, based in Évora, is also eligible and aligned for transfer to Lisbon. In contrast, Lt. B is not qualified nor logistically feasible to relocate to Faro and is thus recommended to remain in Lisbon. Similarly, Maj. D remains in Portalegre due to logistical constraints, despite being qualified.

APPENDIX E - DECLARATION OF CONSENT

INFORMED CONSENT PROTOCOL

This protocol is established between João Francisco Dantas Silva, a student at the Military Academy researching the theme "People Analytics in Portuguese Army", and the participant ____ through the interview method.

The researcher and the scientific supervisor undertake to:

a) Conduct research by the quality parameters recommended by the scientific community of the specialty.
b) Discuss and negotiate other case-specific aspects relating to the confidentiality of information, if requested by the participant.
c) Prevent any disclosure of information regarding the participants outside the research team without the prior consent of all those involved.
d) Deliver a descriptive summary of the results to the participants via email.
e) Keep participants up to date with the work being developed, namely about data analysis, whenever they request it.
f) To provide the participants in the process with all the clarifications requested during the investigation.
g) Comply with the Code of Ethics of the American Psychological Association when conducting research.
h) Eliminate all audio recordings after the course of the investigation and the public defense of the thesis.

Participants undertake to:

a) Provide information about their experience in the case under study and their professional experience.
b) Be interviewed at a time agreed between the researcher and the participant.
c) Authorize the audio recording of the interview, at the request of the investigator.
d) Decide to mention or omit their participation in the project in professional contexts in which they consider it appropriate to do so.

e) Allow the publication of the result of the study, with omission of their identity, namely in the following situations:

I. Master's Thesis to be presented to the Military Academy.

II. Communications at scientific-professional congresses.

III. Scientific publications in journals and/or in specialized books.

Signatures:

____

(Participant)

____

(Researcher)

Place and Date:

____

APPENDIX F - INTERVIEW

Your Excellency's answers are fundamental to achieving the objectives of the investigation, so it is requested that they be as complete as possible. Your answers will serve solely and exclusively as an object of study for research. If it is your intention, they will be provided to you, along with the final work, as soon as it is approved.

Part I – Questionnaire "Contributions for Career Management"

1. Could you indicate the target population of the "Contributions to Career Management" survey?

2. What was the main objective of this questionnaire in the context of career management?

3. Was the questionnaire developed based on any theoretical framework or specific career management model? If so, which one?

4. What are the key performance indicators (KPIs) that were extracted from the analysis of the data collected?

5. What are the main results and practical implications obtained based on the application of the questionnaire?

Part II – Career Management in the Career Management Division

6. How is the management of military careers in the Portuguese Army currently operationalized?

7. Does the Career Management Division use any specific system or software to support career management? - If yes: Which platform is used? Was it developed internally or acquired externally?

8. What are the main functionalities or modules of this system that support individual development and career progression?

9. What types of data are collected and processed in the context of career management? Is there integration with other data sources (performance evaluation, training, mobility)?

10. What indicators are monitored to assess the effectiveness of the career management model?

11. Is the integration of People Analytics functionalities planned, as proposed in the PLACE project? If so, what stage of development are you in?

12. What challenges and opportunities do you identify in the transition to a more analytical and data-centric model in managing careers in the Army?

APPENDIX G - INTERVIEW ANALYSIS

Table 20 - Interview Analysis

	QUESTION	ANSWER
PART I	Q1	The questionnaire was distributed to all active-duty Permanent Staff military personnel of the Portuguese Army, except those holding the ranks of Sergeant-Major, Colonel, and General Officers. There are plans to extend the questionnaire to enlisted personnel and contract military members.
	Q2	To identify individual career development needs and interests, align them with institutional goals, facilitate strategic decision-making, and create a database to support human resource allocation and gap analysis. It also aimed to measure satisfaction and organizational commitment.
	Q3	Yes, it was developed through a partnership involving DARH, the Army's Applied Psychology Center, and the University of Minho's Psychology Research Center, using validated psychometric tools grounded in scientific literature.
	Q4	KPIs highlighted issues such as satisfaction and commitment, supporting interventions to increase engagement, motivation, and retention within the institution.
	Q5	High satisfaction with current roles and strong intent to remain in current units. Interest in international roles, good training adequacy. Challenges include work-life balance, especially among sergeants. Measures proposed include better communication, skill-role alignment, relocation support, and social support initiatives.
PART II	Q6	Career Development Support is a dynamic process involving the individual, command chain, and administration. It includes communication, information gathering, counselling, and targeted recruitment, differentiated by contract regimes.
	Q7	Yes, the "Portal do ADC" was developed internally by the Army's Directorate of Communications and Information. It supports digital career management processes securely and efficiently.
	Q8	Accessible via intranet, it includes Career Development Support presentation, registration, profile consultation, and response to questionnaires. For management, it allows process administration and strategic decision support. More modules are planned.
	Q9	Data is collected via LimeSurvey and integrated into the Portal ADC with other systems (e.g., SIG). It complies with GDPR, supporting decision-making and trend analysis. Further integration with performance and training systems is planned.
	Q10	Metrics include Portal ADC enrollment numbers, processing times, retention rates, and satisfaction surveys. These enable continuous improvement of the processes.
	Q11	Yes, development is ongoing. Integration will enable predictive insights, trend anticipation, and improved decision-making, aligning human capital needs with

		institutional goals.
	Q12	Challenges include data integration, quality, and cultural resistance to change. Opportunities include more assertive decisions, proactive talent management, personalized support, and process optimization, aligning the Army with international best practices.

ANNEX A - PROJECT PLACE SURVEY

Survey – Contributions to Career Management

Taking the current year as a time reference, it should be noted:
1.What is your status regarding your Original Placement? Displaced Not displaced
2.In the current year, have you completed two or more years of displacement? Yes No
3.What is your intention? (If answered out of place) Extend the Offset in the same placement Extend the Offset to a different placement Return to my original placement
4.What is your intention? (If answered, not displaced) Extend the Offset in the same placement Extend the Offset to a different placement Return to my original placement
5.Indicate by priority up to three U/E/O (1/2/3 in the comment box) where you would like to provide service. All Army U/E/O and Off-Branch
6.Indicate by priority up to three Military Garrisons (1/2/3 in the comment box, which may include the abbreviated designation of the preferred U/E/O) where you would like to serve: All Garnishes
7.Their preference as to the Military Function of the position to be performed. Command Direction or Leadership General Staff Implementation (Includes teaching and research activities)
8.Your preference as to the Nature of the Position to be performed. Operational Territorial Training
Degree of interest in:
9.Integrate international missions. With interest It has no interest

10.Indicate the typologies of international missions. CDD END FND
11.Integrate international positions. Yes No
12.How do you evaluate the suitability of the training you have for the performance of the current position? Very inappropriate Inappropriate Neither adequate nor inappropriate Proper Very suitable
13.Are you interested in additional military training? Yes No
14.Indicate the preferred Training area. See Annex A
15.Are you interested in obtaining additional civil training? Yes No
16.Indicate the preferred Training area. See Annex B
17.Indicate the reason(s) why you are interested in obtaining civil training. Not applicable Acquire skills for future job performance Acquire/develop skills for application in the position/function you perform. Apply for positions/missions abroad Personal appreciation Develop activity outside the Institution Other (please specify)
18.To what extent have you found it difficult to reconcile the spheres of Professional, Personal, and Family life? Never Rarely Occasionally Frequently Very often

19.Indicate the main reasons. Performing tasks after normal working hours High frequency of service scale(s) The geographical distance between the placement and the area of residence Misalignment between the idealized career project and the current position Low remuneration is incompatible with the financial burden Accumulation of positions/functions Overload of work and commitments High turnover when traveling
Indicate your degree of satisfaction regarding:
20.To the current position in the U/E/O? Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
21.Indicate the main reasons for dissatisfaction. Accumulation of positions/functions Misalignment between the skills required for the position and those that the military has The geographical distance between your placement and your area of residence Duration of the performance of the position Lack of working conditions Lack of prospects for career development Lack of staff Lack of recognition Other
22.To the position you currently hold? Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
23.Indicate the main reasons for dissatisfaction. Accumulation of positions/functions Misalignment between the skills required for the position and those that the military has Misalignment between the performance of the position and the expectations of the military Duration of the performance of the position Lack of identification with the leadership practiced Lack of prospects for career development Lack of recognition Other

24.Your career so far? Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
25.Indicate the main reasons for dissatisfaction. Accumulation of positions/functions Misalignment between the military's competencies and the performance of the position High number of trips during the career Lack of identification with the leadership practiced Lack of opportunity to join a Detached National Force Lack of prospects for career development Lack of recognition Career progression Remuneration Other
Indicate your degree of satisfaction with each of the following aspects associated with the provision of military service:
26.Overall experience Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
27.Working environment in the current placement Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
28.Interpersonal relationship with the direct manager Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
29.Interpersonal relationships with peers Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied

Very satisfied
30.Geographical distance of the current placement from the area of residence Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
31.Definition of the duties and responsibilities of the position Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
32.Career development opportunities Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
33.Opportunity to present problems that affect your work Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
34.Feedback on your performance Very dissatisfied Unsatisfied Neither satisfied nor dissatisfied Satisfied Very satisfied
35.Taking last year as a time reference, how often did you consider requesting an Unpaid Leave or Resignation? Never Rarely Occasionally Frequently Very often

36.Indicate the main reasons. Insufficient remuneration More advantageous job offers High turnover Lack of prospects for career development Lack of recognition High working volume Insufficient training for the position Difficulty in reconciling professional and personal life Not identifying with the leadership practiced Failure to identify with the organization's culture and values Other (please specify)
37.Are you aware of NAT 03.02.70? "Advice on the Career of the Military", of the Personnel Command? Yes No
38.Your opinion is important to us. **Use this space to share any career concerns that have not been addressed in this survey (limited to 250 characters).**
39.Would you like to be contacted in the context of Career Development Support? Yes No
40.Please indicate the contact (telephone and/or electronic) through which you would like to be contacted by the Career Managers Section.

Annex A

Staff	01	Human Resources - Management
	02	Human Resources - Salaries
	03	Human Resources - Recruitment
	04	Human Resources - Justice
	05	Training - Training Methodologies
	06	Training - Training with Animals
	07	Training - Physical Training and Shooting
	08	Training - Conducting Training Activities
	09	Support Service - Occupational Health and Safety
	10	Support Service - Social Support
	11	Support Service - Religious Support

Social and Behavioral Sciences	01	Psychological Counseling
	02	Orientation
	03	Organizational Psychology
	04	Forensic Psychology
Legal Support	01	
Information	01	
Safety	01	
Geospatial	01	
Operations	01	Light Infantry Operations
	02	Medium/Heavy Infantry Operations
	03	Special Ops
	04	Air-Ground Operations
	05	Tank Operations
	06	Reconnaissance Operations
	07	Army Police Operations
	08	Field Artillery Operations
	09	Anti-Aircraft Artillery Operations
	10	Engineering Operations - Combat
	11	Operations Engineering - Bridges
	12	Operations Engineering - Explosives
	13	Engineering Operations - NBQR
	14	Operations - Rotary Wing Means
	15	Operations - Military Emergency Support
	16	Operations - Security
	17	Psychological Operations
	18	Operations - Equipment and Air Supply
	19	Battlefield Surveillance Operations
	20	Operations - Information
CIMIC		
Plans		
Training and Doctrine		
Logistics	01	Refueling (Reab)

	02	Maintenance - Vehicles
	03	Maintenance - Light Armament
	04	Maintenance - Heavy Weaponry
	05	Maintenance - Heat / Cold
	06	Maintenance - Optics and Optronics
	07	Movements and Transportation (MT)
	08	Services - Food Support
	09	Services - Baths / Latrines Support
	10	Services - Laundry Support
	11	Services - General Support
	12	Services - Accommodation Support
	13	Infrastructures - Heritage
	14	Infrastructures - Constructions
	15	Infrastructures - Management
	16	Acquisition, contracting and disposal
Finance	01	Budget Planning and Control
	02	Financial Execution
Health	01	Management
	02	Health - Assistance
	03	Health - Operational
	04	Pharmacy - Clinical Analysis
	05	Pharmacy - Toxicology
	06	Pharmacy - Hospital Pharmacy
	07	Pharmacy - Pharmaceutical Industry
	08	Veterinary - Equines and Canids (clinical area)
	09	Veterinary - Food Safety and Epidemiological Surveillance
Environmental Protection		
Informatics and Business Intelligence	01	Development
	02	System maintenance support
Communications	01	Tactical Communications
	02	Fixed/Operational Communications
	03	Security, control and management
	04	Tm Maintenance

Information Systems	01	Information Systems for Operations
	02	Management Information Systems
	03	Security, control and management
Information War	01	Operations in Cyberspace (tactical level and operational level) – Cyber Defense
	02	Information Security/SIC
	03	Electronic Warfare
Information and knowledge management	01	Planning, Auditing, Standardization
Teaching and Research	01	Teaching and Research
	02	Technological Experimentation
Advice		
Communication and Public Relations		
Administrative Support		
Dissemination and Preservation of Military Culture	01	Disclosure
	02	Image and Audiovisual
	03	Museology
	04	Archive and librarianship
	05	Music Support
Inspection and Audit		

Annex B

Education	01	Teacher training/trainers and educational sciences
Arts and humanities	01	Arts
	02	Humanities
Social sciences, commerce and law	01	Social and behavioral sciences
	02	Information and journalism
	03	Business sciences
	04	Law
Science, math, and computer science	01	Life Sciences
	02	Physical sciences

	03	Mathematics and statistics
	04	Computer science
Engineering, Industries Transformers and construction	01	Engineering and related techniques
	02	Manufacturing
	03	Architecture and construction
Agriculture	01	Agriculture, forestry, and fisheries
	02	Veterinary Sciences
Health and social protection	01	Health
	02	Social Services
Services	01	Personal Services
	02	Transportation Services
	03	Environmental protection
	04	Security Services
Not specified	01	Not specified