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An Empirical Comparative Study of AI and Human Decision-Making in Candidate Selection

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Master's in Business Administration

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Department of Marketing, Operations and General Management

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Resumo

A crescente adoção da Inteligência Artificial nos processos de recrutamento tem levantado questões críticas sobre a fiabilidade, a equidade e a consistência da tomada de decisão algorítmica em comparação com os recrutadores humanos. Este estudo procura comparar empiricamente os resultados da triagem de CVs efetuada por IA e por profissionais de Recursos Humanos, com foco na consistência da decisão. Com base em dados de recrutamento de uma empresa multinacional de construção em Portugal, foram analisadas três categorias de funções — Analista Financeiro, Especialista de Marketing e Diretor de Gestão de Projetos — recorrendo ao coeficiente Phi e a testes do qui-quadrado. Os resultados revelam uma consistência negligenciável e estatisticamente não significativa entre IA e RH nos níveis júnior e especialista, mas uma associação fraca a moderada, estatisticamente significativa, ao nível de gestão sénior. A análise de casos ilustra ainda que a IA se aproxima mais das decisões dos RH quando os perfis dos candidatos são altamente estruturados e explícitos, enquanto surgem divergências em situações que exigem interpretação contextual ou conhecimento específico do setor. Estes resultados sugerem que os sistemas de IA são mais adequados como ferramentas complementares, em vez de substitutos dos recrutadores humanos. O estudo contribui para o debate académico e para a prática organizacional ao clarificar as condições em que as ferramentas de recrutamento baseadas em IA podem melhorar a consistência das decisões, salientando a necessidade de supervisão humana em contextos de contratação complexos.

Palavras-chave: Inteligência Artificial, Recursos Humanos, Recrutamento e Seleção, Triagem de CV, Consistência da Tomada de Decisão

Códigos JEL: M12, O33

Abstract

The increasing adoption of Artificial Intelligence (AI) in recruitment has raised critical questions about the reliability, fairness, and consistency of algorithmic decision-making compared to human recruiters. This study aims to empirically compare AI- and HR-based CV screening outcomes, focusing on decision-making consistency. Drawing on recruitment data from a multinational construction company in Portugal, three job categories were analyzed—Finance Analyst, Marketing Specialist, and Head of Project Management—using Phi coefficient correlation and Chi-square tests. The findings reveal negligible and statistically insignificant consistency between AI and HR at the junior and specialist levels, but a weak-to-moderate, statistically significant association at the senior managerial level. Case study analysis further illustrates that AI aligns with HR when candidate profiles are highly structured and explicit, while divergences arise in cases requiring contextual interpretation or domain-specific expertise. These results suggest that AI systems are more suitable as complementary tools rather than substitutes for human recruiters. The study contributes to both scholarly debate and organizational practice by clarifying the conditions under which AI recruitment tools enhance fairness and consistency, while highlighting the necessity of human oversight in complex hiring contexts.

Keywords: Artificial Intelligence, Human Resources, Recruitment and Selection, CV Screening, Decision-Making Consistency

JEL Codes: M12, O33

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Chapter 1 Introduction

Recruitment constitutes a core process within Human Resource Management (HRM), where the fundamental objective is to attract and select candidates who are both qualified and suited for specific job roles. While recruitment is concerned with generating a pool of eligible applicants, selection focuses on identifying the most suitable individual from that pool. Traditionally, both recruitment and selection have relied heavily on human judgment, drawing on recruiters' expertise, contextual knowledge, and organizational experience. However, the rise of Artificial Intelligence (AI) has significantly reshaped these practices, raising both opportunities and concerns for organizations.

AI has become particularly prominent in CV screening, the first and most fundamental stage of the recruitment process. Through automated parsing, scoring, and ranking of CVs, AI tools promise faster, standardized, and ostensibly more objective evaluations compared to human recruiters (Ling et al., 2024). Yet, this efficiency is not without limitations. Whereas AI systems predominantly depend on structured data, keyword detection, and algorithmic rules, human recruiters also incorporate nuanced contextual interpretations, implicit signals, and tacit organizational knowledge. This divergence highlights a central dilemma for organizations: to what extent can AI replicate or replace human recruiters, and in which contexts might AI function better as a complementary rather than a substitutive tool?

Existing research on AI in recruitment has concentrated primarily on issues of fairness and bias, with particular emphasis on demographic characteristics such as gender and ethnicity (Oman et al., 2024). These debates remain essential for ensuring equity in recruitment practices, but they represent only part of the broader picture. Far less attention has been devoted to the decision-making differences between AI systems and HR recruiters. Most prior studies either examine AI adoption from the perspective of recruiters (Li et al., 2021) or discuss fairness in abstract, theoretical terms. As a result, there is a notable lack of empirical evidence examining whether AI and HR recruiters reach convergent or divergent decisions when evaluating the same candidate pool. For organizations considering the adoption of AI, this gap is particularly consequential: without understanding the extent of overlap or divergence, it is difficult to evaluate the reliability of AI as a recruitment tool.

Against this backdrop, the central research question guiding this dissertation is: In real-world recruitment processes, how do AI recruitment systems and human recruiters compare in terms of consistency in candidate selection?

Beyond examining outcome consistency, this study also investigates the underlying decision-making logics employed by AI and HR recruiters when determining candidate suitability. Whereas AI decisions are typically based on quantifiable features such as keyword frequency, educational qualifications, and work experience parsed from CVs, HR recruiters draw upon broader evaluative criteria, including contextual interpretations, implicit signals, and judgments of cultural fit. By comparing not only the final outcomes but also the reasoning processes that lead to those outcomes, the study provides deeper insights into how AI and HR construct "candidate suitability." This dual-level analysis—outcomes and logics—enables a more comprehensive evaluation of AI's role in recruitment, clarifying both the extent to which AI mirrors human decisions and the contexts in which human judgment remains uniquely valuable.

This study is conducted within the context of a large international construction company based in Portugal. The study focuses on the practices and outcomes of the company's recruitment process, specifically at the CV screening stage, where both AI tools and the Human Resources department are involved. CV screening represents the first and most critical step in recruitment, as it determines whether candidates advance to the interview stage. Therefore, analyzing the differences between AI and HR in this phase is essential for assessing whether AI can replace or complement human recruiters.

This study specifically leverages recruitment data from three distinct job positions within the company:

- Finance Analyst (Junior-level)
- Marketing Specialist (Senior-level)
- Head of Project Management (Senior-level)

These positions were purposefully selected due to their varied requirements, seniority levels, and distinct job functions. Conducting this analysis across multiple positions provides an ideal opportunity to investigate potential biases comprehensively and enhances the generalizability of our findings.

For this study, the dataset includes approximately 117 CVs for the junior-level Finance Analyst position, 119 CVs for the senior-level Marketing Specialist position, and about 228 CVs for the senior-level Head of Project Management role.

Moreover, this study incorporates AI-based decision-making data from Manatal, a well-established recruitment platform. Manatal has developed an intuitive and user-friendly AI-powered applicant tracking system designed to streamline the entire recruitment process. Over the years, the company has expanded its global presence and formed partnerships with more than 10,000 organizations worldwide. Its broad adoption and strong online visibility further reinforce Manatal's credibility and suitability as a reference point in this study.

The primary contribution of this dissertation lies in the development of an empirically grounded framework for understanding AI versus HR recruitment decisions. By analyzing both convergences and divergences at the levels of outcomes and logics, the study clarifies the conditions under which AI is most effective and identifies contexts in which human judgment remains indispensable. This framework contributes to scholarly debates on AI in HRM and provides actionable guidance for organizations seeking to integrate AI into recruitment processes.

To guide this study, the following main study question was formulated:

To what extent do AI recruitment systems and human recruiters produce consistent candidate selection outcomes in real-world recruitment processes?

To achieve this objective, the study could be divided into the following research questions:

- Research question 1: Do AI and HR recruiters differ significantly in their candidate selection outcomes?
- Research question 2: What factors explain the divergences between AI- and HR-based recruitment decisions?

These questions guide the empirical analysis of the study and form the foundation for the following chapters.

Finally, this dissertation is structured as follows. The Introduction outlines the research objectives, research questions, and overall structure. It presents the contextual background of

the study, explaining the motivation, practical relevance, research objectives, and research questions, while also providing an overview of the methodological approach. Chapter 1 expands on the research context by detailing the organizational setting and the problem that motivates the investigation. Chapter 2 provides the literature review, examining the development of AI in CV screening, consistency in recruitment decisions, fairness frameworks, bias in AI-based screening, and related strategies and challenges. It concludes with a summary and the identification of the research gap. Chapter 3 presents the conceptual framework and discusses how the research questions guide the analysis of AI and HR-based recruitment decisions. Chapter 4 contextualizes the study, describing the organizational setting and recruitment processes, while Chapter 5 details the research methodology, including data collection procedures and the application of the Phi coefficient analysis. Chapter 6 reports the empirical findings and discussion, organized across three job categories—Financial Analyst, Marketing Specialist, and Head of Project Management—with each section analyzing both the correlation between AI- and human-based decisions and the reasoning underlying them. Finally, Chapter 7 concludes the dissertation by summarizing the main contributions, limitations, and recommendations for future research, followed by the bibliographical references consulted throughout the study.

Chapter 2 Literature Review

2.1 Artificial Intelligence in Recruitment and Selection

From the First to the Fourth Industrial Revolution, technological innovations have continuously reshaped the nature of work. Particularly notable is the Fourth Industrial Revolution, characterized by most influential technologies such as big data and artificial intelligence (Zhang & Chen, 2023). Those are significantly enhancing capabilities in information processing, problem-solving, and decision-making (Raveendra et al., 2020). With increasing digitalization and timeliness in technological applications, AI systems are expected to achieve more sophisticated levels of implementation in the future (Beneduce, 2020).

The simplest way to understand Artificial Intelligence (AI) is to separately examine the meanings of the two words "Artificial" and "Intelligence." Although the concept of AI has existed for a long time, there is still no universally accepted definition (Legg & Hutter, 2007). Many scholars, when defining AI, focus more on the term "Intelligence", as it is far more difficult to define than "Artificial." The meaning of "Artificial" is relatively clear and requires little explanation. According to the *Oxford Dictionary* (2019), "Artificial refers to something made or produced by human beings rather than occurring naturally, especially as a copy of something natural." Therefore, "artificial" can be understood as something created by humans to imitate natural phenomena. The truly challenging part lies in defining "Intelligence."

Human Resource Management (HRM), traditionally a key organizational function responsible for talent management and growth facilitation, has been profoundly transformed by modern technologies, including AI, leading to enhanced organizational performance (Hmoud & Várallyai, 2019). Recruitment, in particular, stands out as a domain substantially impacted by AI technologies. By employing AI, organizations gain different insights into talent, by comparing thousands and millions of CVs, to analyze their competitive advantage in the market. Many recruitment tasks, such as receiving, organizing, and initially screening resumes, are repetitive and time-consuming, requiring minimal specialized skills. Therefore, these routine tasks present ideal opportunities for AI-driven automation.

Compared to humans, AI is capable of rapidly analyzing extensive datasets with high accuracy, establishing itself as a dependable tool for decision-making processes (Akinnagbe,

2024). AI can process and analyze data far beyond human analytical capacity, subsequently generating informed recommendations (Hao et al., 2025).

Despite growing scholarly and industry attention to these issues, there remains a notable paucity of direct comparative analyses between AI systems and human recruiters regarding decision-making consistency—specifically, the degree to which both approaches identify and prioritize the same candidates from a shared applicant pool.

Consistency focuses on whether different screening agents, namely AI systems and human recruiters, make similar selection decisions when evaluating the same pool of candidates under equivalent conditions. High consistency would indicate strong alignment in evaluation standards and prioritization between the two, whereas low consistency may reveal divergences in information interpretation, weighting of factors, or implicit preferences. At present, comparative studies examining the consistency of candidate selection between AI and human recruiters are scarce. This lack of evidence limits our ability to assess the extent to which AI outcomes can substitute for or complement human decision-making, as well as to evaluate the stability and reliability of AI systems in cross-domain recruitment contexts.

While increasing evidence suggests AI systems are more objective than typically perceived, AI and algorithmic processes can still lead to unfair employment outcomes, especially when accountability mechanisms are insufficient. Therefore, to effectively harness the advantages of AI in recruitment, organizations should carefully select their systems, promote responsible algorithm usage, and foster greater diversity in technology companies.

Addressing this gap, the present study undertakes a systematic comparison of AI- and human-led CV screening processes, with a focus on the degree of convergence or divergence in candidate selection. In so doing, it seeks to provide robust empirical evidence to inform the theoretical discourse and practical considerations surrounding the role of AI in promoting fairness and reliability in recruitment.

2.2 Development of AI and Its Application in CV Screening

Since 1956, theories related to AI have evolved steadily, supported by remarkable advances in computing technology (Cohen & Feigenbaum, 2014). Although scholars and industry experts provide various definitions of AI, it is generally understood as machines capable of simulating human cognitive functions (McGettigan, 2016) and adapting to complex situations to make

informed decisions (Malik et al., 2021). Additionally, AI equips enterprises with diverse decision-support tools (Bader & Kaiser, 2019), assisting managers in improving their decision-making processes through enhanced data analysis, intuitive reasoning, and situational comprehension (Kar et al., 2022). In recent years, notable progress has been made in areas such as data processing, algorithm optimization, and computational power (Messner, 2022). AI leverages machine-learning algorithms to analyze raw data, generating valuable insights (Althati et al., 2024). These technological improvements have enabled AI to transition from theoretical concepts to practical organizational applications, including within HRM.

Specifically, within corporate human resource management, it is widely recognized that AI-powered chatbots hold great potential for improving efficiency, streamlining recruitment processes, and enhancing employee experiences. Although academic definitions regarding the specific applications of AI in HR may vary, there is broad consensus that AI and conversational systems can enhance the efficiency and fairness of processes such as recruitment, employee evaluation, and training through automation and intelligent tools (Tilmes, 2022). By integrating conversational AI technology, HR departments can offer more personalized support and services to employees, significantly reducing repetitive tasks involved in HR management. This reflects a shift in HRM from administrative labor execution toward data-driven decision support.

While AI has demonstrated value across various HR functions, its impact has been particularly significant in recruitment, a process that remains highly demanding and resource-intensive for organizations. Recruitment encompasses all the activities undertaken to identify and attract new employees. To build an ideal candidate pool and make effective hiring decisions, companies must compete for top talent — especially in today's increasingly competitive labour market (Parry & Wilson, 2009; Parry & Olivas-Luján, 2011). Thus, recruitment becomes a strategic task rather than a purely administrative one.

Traditional recruitment processes were often lengthy, time-consuming, and burdened with extensive paperwork. However, with the widespread adoption of online recruitment, this situation is gradually changing (O'Donovan, 2019). Today, job applicants can submit their résumés online through company websites, and the advantages brought by technology and the Internet include more efficient candidate screening and matching mechanisms, as well as significant improvements in cost, time, candidate pool size, and feedback quality (Panayotopoulou et al., 2007). Yet, digitalisation alone has not eliminated the human workload of screening large candidate pools.

Therefore, researchers have begun to focus on how technology can be used to make the recruitment process smoother and more efficient (Galanaki et al., 2018). The application of Artificial Intelligence (AI) in HRM and recruitment has been described as “the new era of HR”, as AI is reshaping the recruitment industry by taking over repetitive tasks that were previously performed by humans (Upadhyay & Khandelwal, 2018). AI becomes a natural response to recruitment scalability challenges.

At present, most recruitment processes are still led by human recruiters, who are responsible for screening candidates from a large number of CVs, online portfolios, and other sources. Recruiters also handle initial communications, send rejection feedback, and conduct interviews (O'Donovan, 2019). In addition, the impact of new technologies on Human Resource Management (HRM) remains unclear and recruiters are still uncertain whether these efficient tools represent opportunities or challenges (Bondarouk & Brewster, 2016). Since the current literature continues to exhibit the same research gaps as before, it is therefore necessary to explore this topic in greater depth, particularly now that new technologies have increasingly become an integral part of recruiters’ daily work. This coexistence of manual and automated screening leads to uncertainty regarding decision alignment.

One of the most common AI applications in recruitment is automated CV scoring, where algorithms evaluate candidate profiles based on extracted features such as skills, education and experience. These scoring systems are powered by AI algorithms, while human recruiters provide the training data that enables the models to learn how to evaluate and rank candidates (Faliagka et al., 2012). According to Upadhyay and Khandelwal (2018), AI is neutral and evaluates résumés more equitably, thereby providing equal opportunities for all candidates. Therefore, CV screening has become the most widespread stage of AI integration in recruitment, making it crucial to understand how AI-generated decisions differ from or align with human evaluations — the primary focus of this dissertation.

2.3 Consistency in Recruitment Decisions

Consistency in recruitment decisions is critical for ensuring the reliability and credibility of hiring outcomes. When different decision-makers, whether human recruiters or AI-based systems, evaluate the same pool of candidates, the degree of overlap in their choices reflects the robustness of the selection process (Tippins et al., 2021). High consistency suggests that similar evaluation standards and criteria are being applied, which increases the trustworthiness

and repeatability of the process. Conversely, low consistency may indicate divergent interpretations of candidate information or implicit biases influencing decision-making, raising concerns about the fairness and stability of recruitment outcomes (Whysall, 2017). In the context of AI recruitment tools, assessing consistency is particularly relevant, as it helps determine whether algorithmic decision-making aligns with or diverges from human judgment.

To evaluate consistency scientifically, recruitment research frequently relies on statistical indicators of inter-rater agreement. These metrics quantify the level of similarity in the decisions made by different evaluators (Yun, 2023). Common measures include Cohen's Kappa and Fleiss' Kappa for categorical decisions, and correlation coefficients when ranking or scoring is involved (Landis & Koch, 1977). In cases where binary screening outcomes are used—such as "selected" vs. "not selected" at the CV screening stage—the Phi coefficient (ϕ) serves as an appropriate and widely adopted indicator of association between two decision-makers (J. Salkind, 2010). A higher φ value indicates a stronger alignment between selections, while lower values reflect divergent decision patterns. Therefore, the assessment of consistency through such statistical measures is fundamental to determining whether AI can be considered a reliable complement—or substitute—for human recruiters.

Chapter 3 Conceptual Framework

The purpose of this chapter is to establish the conceptual and theoretical foundations for comparing AI-driven and human-driven CV screening. The framework not only examines whether differences in decisions occur but also why such divergences may arise. By connecting the research questions to clear theoretical perspectives, this chapter provides a logical structure that guides the empirical analysis.

Recruitment decision-making involves a complex cognitive evaluation process. Importantly, AI systems and human recruiters rely on fundamentally different mechanisms when assessing candidate suitability:

AI-based decision-making relies primarily on structured information, keyword extraction, rule-based matching, and quantifiable indicators present in CVs (e.g., job titles, certifications, and years of experience).

Human-based decision-making incorporates subjective interpretation, contextual judgement, tacit knowledge, and implicit information such as narrative coherence, candidate motivation, and perceived organizational fitness.

As a result, the two agents—AI and HR—may reach similar outcomes when evaluating standardized qualifications but differ when contextual interpretation or qualitative judgement plays a larger role.

Building on these distinctions, this study proposes a dual-path evaluation logic:

1. Candidate CVs enter the screening process simultaneously
2. AI and HR independently evaluate candidates using different decision rules
3. Their decisions are compared to assessing the degree of consistency
4. Divergences are then further interpreted based on differences in decision-making logic

This approach recognizes that consistency alone does not indicate superiority; rather, inconsistency may reveal areas where human judgement remains critical or where AI may require improvement.

This conceptual framework provides a clear structure for systematically analyzing and comparing AI-driven and HR-driven recruitment decisions. Guided by the research questions, the study aims to clarify the extent to which AI can replicate or complement human decision-making and to identify the conditions under which AI may serve as a reliable recruitment tool. The major contribution lies in offering an empirically informed and practically relevant framework that organizations can use to better understand the strengths and limitations of AI in recruitment, as well as to determine how AI technologies can be effectively integrated alongside human judgment to create more balanced and efficient hiring systems.

Chapter 4 Methodology

This study adopts a quantitative research approach to evaluate the consistency between AI-based and human-based CV screening decisions. The primary statistical tool applied is the Phi coefficient (ϕ), which measures the degree of association between two sets of binary selection outcomes (i.e., selected vs. not selected). Specifically, the Phi coefficient is used to determine the extent to which AI and HR simultaneously select or reject the same candidates, thereby providing an objective numerical indicator of alignment between the two decision-making processes.

In addition to statistical correlation analysis, this study also incorporates a comparative assessment of CV features to investigate the underlying sources of divergence. The analysis is conducted from two perspectives:

On the one hand, the study examines the decision-making logic of HR recruiters. In screening CVs, HR professionals often look beyond hard criteria such as educational qualifications, professional background, and years of experience. They also consider implicit requirements in the job description as well as the coherence and completeness of a candidate's career trajectory. For example, HR recruiters are more likely to interpret the timeline of employment, evaluate the rationality of job changes, and assess indications of professional stability conveyed through the candidate's wording, thereby applying subjective judgment and experiential insights.

On the other hand, the study investigates the decision-making logic of AI systems. AI-based CV screening primarily relies on predefined algorithmic rules and keyword matching, placing greater emphasis on explicit information relevant to the job requirements, such as educational level, numeric ranges of work experience, and the frequency of specific skills. Since AI judgments are based on structured data and algorithmic logic, these systems often lack the ability to interpret implicit information or contextual expressions embedded in resumes.

The Phi coefficient (ϕ) was selected to evaluate the correlation and similarity between the recruitment decisions of the AI-driven recruitment software (Manatal) and human HR professionals. The Phi coefficient (shown as formular 4.1) is a measure commonly used in statistical analysis to quantify the degree of association between two categorical variables, making it ideal for analyzing relationships between two decision-making outcomes in recruitment.

Formula 4.1 Phi coefficient calculation (Adapted from (Pearson, 1992))

$$\phi = \frac{ad - bc}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$$

In this formula:

- a represents the number of candidates simultaneously selected by both AI and human recruiters.
- b represents the number of candidates selected by AI but not by humans.
- c represents the number of candidates selected by humans but not by AI.
- d represents the number of candidates rejected by both AI and humans.

The Phi coefficient provides insight into how closely AI-driven recruitment aligns with human decision-making, offering an initial understanding of similarities and differences in selection patterns, the detail interpretation shown in table 4.1.

Table 4.1 Interpretation of Phi Coefficient Values (Adapted from (Akoglu, 2018))

Phi Coeffiient (ϕ)	Interpretation of Relationship Strength
0.00–0.10	Negligible (Very weak)
0.10–0.30	Weak
0.30–0.50	Moderate
0.50–0.70	Strong
0.70–1.00	Very strong

In addition to calculating the Phi coefficient as a measure of effect size, its statistical significance was further evaluated using the chi-square test of independence applied to the 2 × 2 contingency table.

Finally, the resulting p-value was compared against the conventional significance threshold of 0.05. A p-value below this level would indicate that the association between AI and HR recruitment decisions is statistically significant, whereas a p-value above this level suggests no significant association.

This procedure enables the simultaneous reporting of both the strength of association ϕ and its statistical significance (p-value), thereby providing a more comprehensive understanding of whether the observed similarity between AI and human recruitment decisions is meaningful beyond random variation.

To better understand the basis of AI-driven decision-making in this study, it is essential to outline the operational procedure of the Manatal recruitment platform. The system applies natural language processing techniques to automatically parse candidates' CVs, extracting structured information such as education, work experience, job titles, technical and soft skills, languages, certifications, and career seniority. Job descriptions are processed in a similar way, allowing the platform to identify expected qualifications, required skills, and experience levels.

At this stage, the system recognizes different CV file formats (such as .pdf, .doc, .doc, .docx, and txt) as well as various layout templates. It then extracts key information from different sections of each résumé, including Personal Information, Educational Qualifications, Skills, Work Experience, and Achievements.

Following this parsing process, Manatal computes a matching score for each candidate–job pair, ranging from 0 to 100. The score reflects the degree of similarity between the candidate's profile and the job description, particularly in terms of skills, education, and professional experience. According to the platform's documentation, a candidate is recommended for a role only when two conditions are met: at least three skills must overlap between the CV and the job description, and at least two additional structured fields—such as education level, job title, or experience—must also match.

This rules-based mechanism demonstrates that Manatal's recommendation engine primarily depends on textual overlap across structured fields, rather than on a deeper contextual understanding of candidates' career trajectories. Therefore, when critical information is communicated implicitly rather than explicitly in CVs, divergences between AI-based and HR-based decisions may arise (Upadhyay & Khandelwal, 2018).

Chapter 5 Obtained results, findings and discussion

For the Financial & Accounting Analyst (Junior-level) position, a total of 117 applications were received. Of these, 96 candidates were Portuguese and 21 were foreign nationals from countries such as Brazil, Ukraine, Russia, and France. Notably, 71% of the foreign applicants did not meet the language proficiency requirement. Approximately 90% of the candidates fell within the expected junior age range of 26–28 years. In terms of gender distribution, the pool consisted of 39 female candidates (33%) and 78 male candidates (67%).

For the Marketing Specialist (Senior-level) position, the applicant pool comprised 166 CVs, the vast majority from Portuguese nationals. Around 90% of the candidates fell within the expected age range of 30–40 years. The gender breakdown included 30 female candidates (18%) and 136 male candidates (82%).

For the Head of Project Management (Senior-level) position, a total of 228 applications were received. More than 90% of the candidates were Portuguese nationals. Approximately 80% of applicants clustered around the age of 40, reflecting the senior nature of the role. The gender distribution included 43 female candidates (19%) and 185 male candidates (81%).

5.1 Financial Analyst

The Junior-level Financial Analyst position requires a bachelor's or master's degree in Finance, Economics, Accounting, or a related field, together with one to three years of relevant professional experience, preferably with exposure to real estate development. Strong candidates may also include recent graduates who demonstrate solid academic knowledge in these areas. Applicants are expected to have a sound understanding of accounting and financial reporting principles, as well as skills in data analysis and forecasting; proficiency in financial modeling is considered an asset. The role further demands strong analytical ability and attention to detail, with the capacity to interpret financial data, identify trends, and provide actionable insights. Effective communication and interpersonal skills are also essential, enabling collaboration with cross-functional teams and the ability to convey complex financial concepts to non-financial stakeholders. In addition, candidates must demonstrate advanced proficiency in MS Excel and PowerPoint for analytical and reporting purposes, alongside adaptability and resilience to thrive in a fast-paced, entrepreneurial environment.

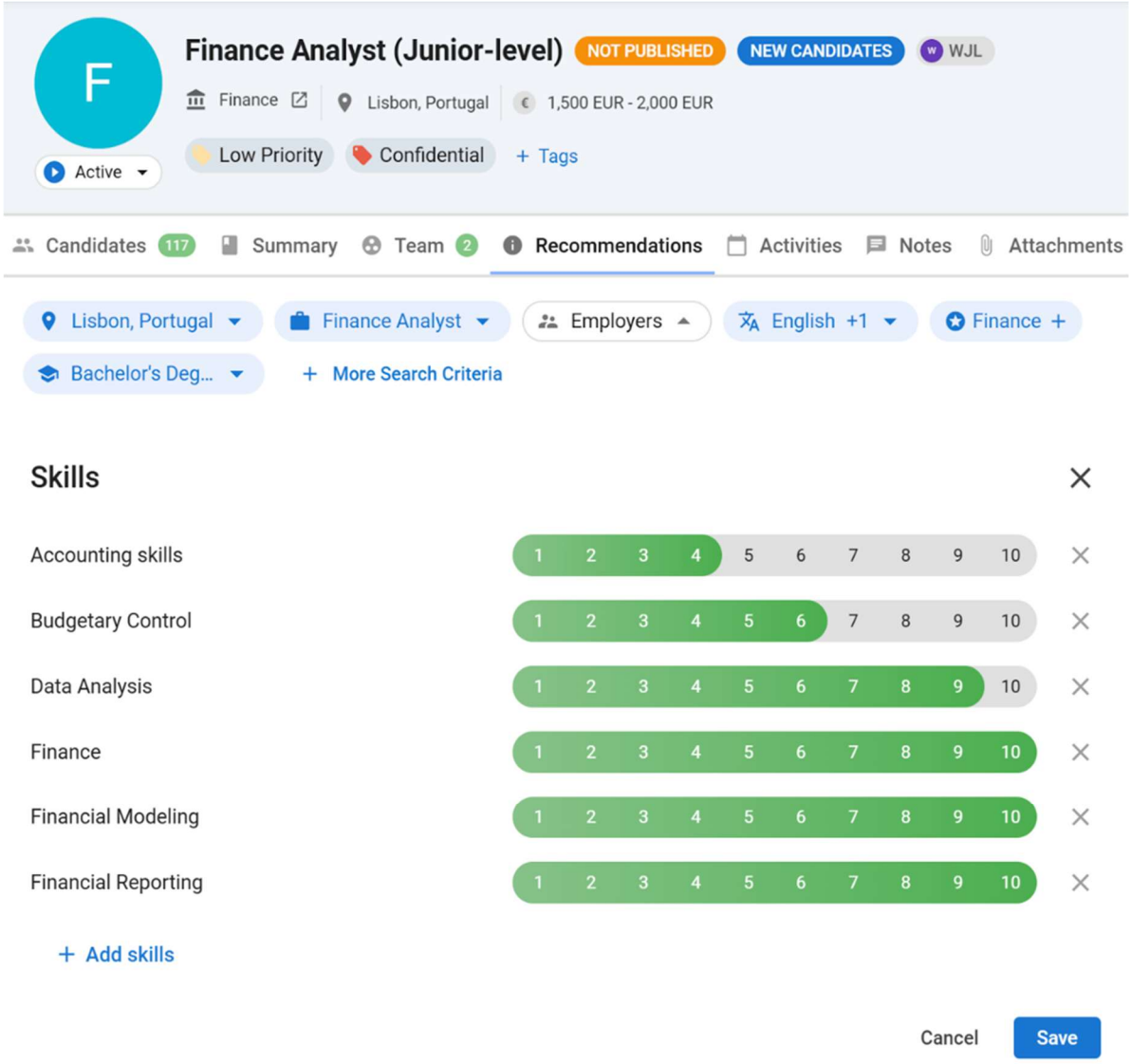
Based on the job description and discussions with the company's HR representatives, the skills weighting interface for this position within the Manatal recruitment system is presented (see Figure 5.1). This weighting structure not only reflects the technical requirements of the Financial Analyst role but also aligns with HR's practical decision-making logic during the initial screening stage. For junior-level finance positions, organisations aim to identify candidates who can quickly adapt to job responsibilities while demonstrating strong potential for future development. Therefore, HR professionals place priority on competencies that are explicitly linked to core responsibilities—such as financial reporting, data analysis, and quantitative modelling—since these are fundamental to handling analytical deliverables and assessing financial information effectively.

From an HR perspective, early-stage screening focuses on determining whether candidates possess the essential technical capabilities required by the role (must-have competencies), whether they demonstrate a solid foundation of knowledge and trainability for further professional growth, and whether their CV expresses noticeable financial data literacy and analytical reasoning skills. These competencies are highly explicit, verifiable and quantifiable in CVs, enabling HR to efficiently evaluate candidates' suitability during initial screening.

In contrast, competencies such as budgetary control or broader accounting responsibilities, while relevant, are often regarded by HR as experience-dependent capabilities that can be strengthened through organizational training or accumulated in practice. As such, these skills receive moderate weightings (4–6), since junior candidates are not expected to fully master them before entering the position.

According to HR competency models for junior financial roles, the primary assessment dimensions include strong technical ability centered on finance knowledge and quantitative analysis; solid business understanding reflected in the ability to interpret financial reports and indicators; and a foundational level of work exposure that can be further developed on the job. Managerial thinking or supervisory capability is not a key requirement at this stage, since the role is positioned at the early career level. These expectations collectively explain why structured, technical skills dominate the weighting configuration applied by the AI system.

Figure 5.1 Skills assessment for Financial Analyst position.



Note. Screenshot from the Manatal recruitment platform, captured by the author (2025).

5.1.1 Coefficient Analysis Between AI and Human Decisions

To assess the similarity or divergence between AI and human recruitment decisions, a Phi coefficient analysis was performed. The cross-tabulation of AI and HR recruitment decisions for the financial analyst position is presented in Table 5.1.

To examine the degree of alignment between AI-driven recruitment decisions and human recruitment outcomes for the financial analyst position, a cross-tabulation was performed (Table 5.1). Based on this contingency table, the Phi coefficient (ϕ) was calculated to assess the strength of association between the two decision-making approaches. By applying the formular

4.1, the resulting value was $\phi = 0.071$, which falls within the "negligible" range according to established benchmarks (Akoglu, 2018).

Table 5.1 Cross-Tabulation of AI and HR Recruitment Decisions for Financial Analyst Position

	HR selected	HR not selected	Total
AI selected	5	16	21
AI not selected	16	80	96
Total	21	96	117

Note. Created by the author using recruitment selection data (2025).

In addition to effect size estimation, a chi-square test of independence was conducted to examine whether the relationship between AI and HR recruitment decisions was statistically significant. The hypotheses tested were:

H_0 : AI and HR recruitment decisions are independent (no association).

H_1 : AI and HR recruitment decisions are not independent (there is an association).

A chi-square test of independence was conducted to evaluate whether the observed relationship between AI and HR recruitment decisions was statistically significant. The results indicated no significant association between the two methods, p-value = 0.646. This finding reinforces the interpretation of the Phi coefficient, suggesting that AI and HR recruitment decisions are largely independent of each other and demonstrate minimal consistency.

Together, these results highlight a substantial divergence in decision-making patterns between AI and human recruiters, with negligible correlation and non-significant statistical evidence of overlap.

5.1.2 Cases of Selection

To ensure consistency and transparency in the manual evaluation of candidates, a codebook was developed for the Finance Analyst position. The evaluation dimensions were divided into primary dimensions (must-have) and secondary dimensions (nice-to-have). The primary

dimensions included educational background (Bachelor's or Master's degree in Finance, Accounting, Economics, or a related field), relevant professional experience of 1–3 years (including internships), and full professional proficiency in English. Secondary dimensions included familiarity with accounting principles and tools (e.g., SAP, QuickBooks), analytical thinking skills, and communication and presentation abilities.

Each CV was coded using a binary scale: a score of 1 indicated that the skill or qualification was explicitly present, while a score of 0 indicated absence or lack of clarity. Based on this coding, candidates were categorized into three groups: *Recommend* (all three primary dimensions plus at least two secondary dimensions), *Borderline* (two primary dimensions and one secondary dimension), and *Not Recommend* (missing one or more primary dimensions).

The prioritization of these dimensions was informed by an interview with a company HR professional. Although accounting tools and data interpretation are important, they were classified as secondary dimensions because the role targets junior-level candidates, many of whom are recent graduates. The company provides structured training programs to strengthen such competencies during onboarding, meaning that these skills were regarded as beneficial but not eliminatory.

To illustrate how the AI system evaluates candidates, the case of one applicant CV1 is presented. This candidate was selected by both the human recruiter and the AI tool.

From the recruiter's perspective, the candidate fulfilled all three primary dimensions: a Master's degree in Finance and a Bachelor's in Management from TOP 5 national Business Schools, two years of experience at Bank institution is plus a current analyst role at another Bank institution, and certified English proficiency at an advanced level (TOEFL 90/120). In addition, the candidate demonstrated all three secondary dimensions, including reporting and Excel expertise, evidence of financial modeling (DCF, ROI, market analysis), and strong communication skills (daily reporting to the board, case workshop participation). Accordingly, the candidate was classified in the *Recommend* category.

From the AI perspective, the Manatal system identified matches across the structured fields of education, experience, and English proficiency, thereby satisfying its formal recommendation criteria. Furthermore, through keyword matching and NLP extraction, the system detected at least five relevant skills explicitly mentioned in the CV1, including financial reporting, cash flow monitoring, financial modeling, Excel certification, analytical thinking,

and communication skills. Since the candidate exceeded the minimum threshold of three matched skills, the AI also classified him as a suitable recommendation.

As a contrasting case, another candidate CV2 was classified as *Recommended* by the human recruiter but was not shortlisted by the AI system.

From the HR perspective, the candidate satisfied all three primary dimensions: a Master's degree in Finance, an exchange semester at abroad, and a Bachelor's degree in International Business; relevant professional experience as a Deal Advisory Analyst at the Big Four accounting firms since 2023, along with prior internships in M&A and Planning & Control; and clear evidence of English proficiency listed in the CV2. In addition, the candidate also fulfilled all three secondary dimensions, including accounting knowledge (analyzing accounting procedures and preparing planning/control reports at the Big Four), analytical thinking (conducting due diligence, competitor analysis, and market profiling), and communication and presentation skills (preparing reports under tight deadlines and collaborating with multiple stakeholders during M&A processes). Accordingly, the HR evaluation rubric placed this candidate in the *Recommend* category.

From the AI perspective, however, Manatal did not classify the CV2 as recommended. While the education requirement was correctly detected, the experience field (Deal Advisory Analyst at the Big Four, October 2023–present) may not have been recognized as "1–3 years of relevant experience" due to the ongoing nature of the role. English proficiency, although clearly stated, may not have been identified as full professional proficiency because no standardized labels (e.g., TOEFL, CEFR) were included. Regarding skills, the CV2 contained relevant evidence of financial reporting, accounting knowledge, due diligence, market analysis, and stakeholder communication; however, financial modeling was not explicitly mentioned, and Excel proficiency was presented without certification or emphasis. As a result, the AI likely detected only a limited number of structured fields and skills, falling short of the thresholds required for formal recommendation.

5.1.3 Summary of Comparative Analysis

The analysis of the financial analyst position reveals two key findings. First, the Phi coefficient ($\phi = 0.071$) indicates that the correlation between AI and HR recruitment decisions is negligible and not statistically significant. This suggests that AI and HR recruiters rely on substantially

different decision-making criteria, resulting in largely independent candidate selection outcomes.

Taken together, the two cases highlight the conditions under which AI and HR decisions converge or diverge. In the case of CV1, both systems reached the same outcome because the candidate's profile explicitly aligned with the structured requirements and skill keywords detectable by the AI, while also meeting the broader evaluative criteria considered by HR. By contrast, in the case of CV2, the divergence stemmed from differences in interpretive logic: HR recruiters contextualized the candidate's ongoing role, professional trajectory, and implicit signals of competence, whereas the AI system failed to fully recognize these elements due to its reliance on explicit field labels and keyword matches. These examples underscore that while AI can replicate human decisions when information is presented in a structured and explicit manner, it remains limited in cases requiring contextual interpretation, thereby reinforcing its role as a complementary rather than substitutive tool in recruitment processes.

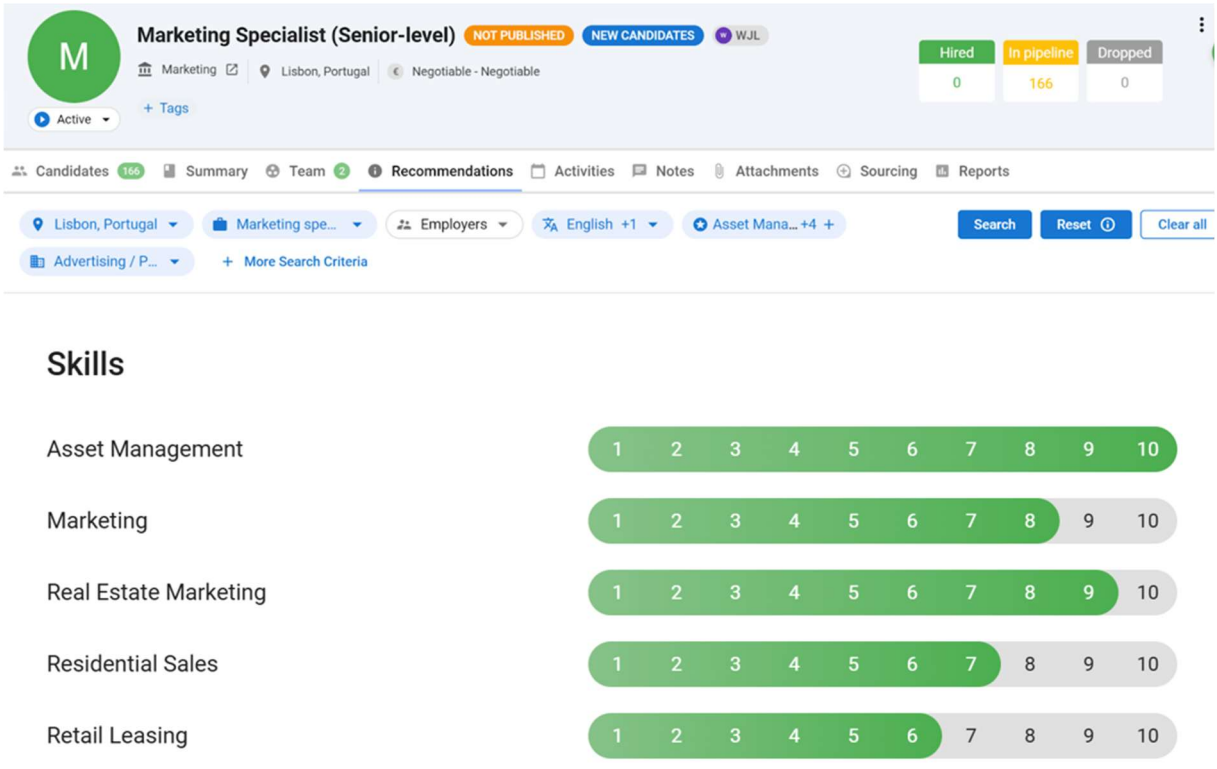
5.2 Marketing

The Marketing Specialist position requires a minimum of five years of professional experience in the residential sales sector, with a proven track record of successfully managing residential projects and delivering measurable value creation. Candidates are expected to demonstrate a strong understanding of retail market dynamics, particularly within the context of urban development projects, as well as solid communication and negotiation skills. Proficiency in both Portuguese and English is essential for this role, given the need to manage diverse stakeholders and operate effectively in high-pressure environments. While a degree in Business, Real Estate, or a related field is preferred, substantial professional experience in marketing and sales is considered equally valuable. The detailed selection criteria applied to this position are illustrated in Figure 5.2 which illustrates how the Manatal system translates the job requirements of the Senior-level Marketing Specialist role into weighted capability categories. These skill weightings reflect the expectations outlined in the job description, where responsibilities focus primarily on residential and commercial project marketing, value creation for property assets, and coordination across development and commercial teams. Accordingly, skills such as Real Estate Marketing, Marketing, and Residential Sales receive the highest relevance levels (8–10), indicating their direct contribution to role performance.

From an HR perspective, senior-level recruitment prioritises candidates with sector-specific expertise and a proven record of driving business outcomes. Because this role operates within property development rather than general marketing, candidates must demonstrate strong commercial understanding of the residential market and the ability to influence sales and occupancy performance. These competencies therefore act as primary screening criteria and are weighted more heavily in the system's evaluation.

Although Retail Leasing is not the primary responsibility of this role—typically being led by a dedicated retail leasing department—the position involves frequent cross-departmental collaboration in urban development projects. Consequently, familiarity with retail leasing processes and related market dynamics remains valuable for facilitating internal coordination and ensuring integrated marketing execution. This practical requirement explains why Retail Leasing retains a moderate, but not dominant, weighting within the model.

Figure 5.2 Skills assessment for Marketing Specialist position.



Note. Screenshot from the Manatal recruitment platform, captured by the author (2025).

5.2.1 Coefficient Analysis Between AI and Human Decisions

To assess the similarity or divergence between AI and human recruitment decisions, a Phi coefficient analysis was performed. The cross-tabulation of selection outcomes is shown in table 5.2:

Table 5.2 Cross-tabulation of AI and HR recruitment decisions for Marketing Specialist position analysis.

	HR selected	HR not selected	Total
AI selected	16	31	47
AI not selected	31	88	119
Total	47	119	166

Note. Created by the author using recruitment selection data (2025).

Based on the calculated Phi coefficient value (ϕ=0.080) by applying the formular 4.1, according to the table 4.1, the correlation between AI-driven and human recruitment decisions for the Marketing Specialist position is interpreted as negligible or very weak, highlighting substantial differences between the two decision-making processes.

In addition to effect size estimation, a chi-square test of independence was performed to assess the statistical significance of the observed relationship. The hypotheses were formulated as follows:

H_0 : AI and HR recruitment decisions are independent (no association).

H_1 :AI and HR recruitment decisions are not independent (there is an association).

The Chi-square test of independence was applied using the recruitment data, yielding P-value = 0.402. As the p-value exceeded the conventional threshold of 0.05, the null hypothesis could not be rejected, indicating no statistically significant association between AI and HR recruitment decisions.

Taken together with the negligible Phi coefficient (ϕ = 0.080), these results suggest that AI and HR recruitment outcomes for the marketing specialist position are largely independent.

This indicates minimal consistency between the two decision-making processes, highlighting a substantial divergence in their recruitment patterns.

5.2.2 Cases of Selection

For the Marketing Specialist position, a manual codebook was developed to ensure consistent evaluation of candidates. The primary dimensions (must-have) included: (1) a Bachelor's or Master's degree in Marketing, Communication, Business, or a related field; (2) a minimum of five years of relevant professional experience, preferably within the commercial real estate, hospitality, or retail sectors; (3) demonstrated strategic marketing skills, including the ability to design and implement commercial strategies, brand positioning, and go-to-market plans; and (4) full professional proficiency in both Portuguese and English, as required for reporting and stakeholder communication.

The secondary dimensions (nice-to-have) consisted of stakeholder communication (experience collaborating with cross-functional teams, consultants, or government entities) and presentation and reporting skills (the ability to present strategic ideas and project updates to senior leadership or external stakeholders).

Each CV was manually coded using a binary system: 1 if the qualification was clearly demonstrated, and 0 if absent or unclear. Candidates were then classified into three groups: *Recommend* (all four primary dimensions present, plus at least two secondary), *Borderline* (three primary plus at least one secondary), and *Not Recommend* (any primary missing). Strategic marketing skills were elevated to a primary dimension because the job description explicitly tied them to sales performance and market positioning, making them non-negotiable. In contrast, stakeholder communication and presentation were considered secondary, as these tasks are typically handled by senior executives or directors, while this role emphasizes internal coordination and written reporting.

An illustrative case of divergence is CV3, who was Recommended by the AI system but Rejected by the human recruiter.

From the HR perspective, the candidate did not meet the essential requirements. Although he held an Executive MBA and a degree in Industrial Engineering, his professional background consisted primarily of over 15 years of experience in energy, engineering, and industrial operations, without clear evidence of senior marketing or real estate leadership experience.

Furthermore, language proficiency was self-reported at “Negotiation” level in both Portuguese and English, which was not considered sufficient to demonstrate full professional working proficiency. As a result, the candidate failed to satisfy two of the four primary dimensions (experience and language proficiency) and was therefore classified as *Not Recommend*, despite strong evidence in the secondary dimensions such as project leadership, stakeholder coordination, and commercial strategy.

From the AI perspective, however, Manatal parsed the CV3 differently. The system recognized the Executive MBA as fulfilling the education requirement and classified the candidate’s 15 years of executive experience in energy and asset management as relevant professional experience. Language proficiency, although labeled only as “Negotiation” level, was likely accepted by the parser as meeting the job’s bilingual requirement. In addition, the AI identified several strong keyword matches, including “real estate and energy director,” “strategic development plans,” “profitability improvement,” “M&A processes,” and “board of directors.” These matches fulfilled the required skill overlap and reinforced the candidate’s suitability. As a result, the AI assigned a high matching score and recommended the candidate.

5.2.3 Summary of Comparative Analysis

The analysis of the marketing specialist position provides main findings. First, the Phi coefficient ($\phi = 0.080$) indicates that there is negligible correlation between AI and HR recruitment decisions, with no statistically significant association. This demonstrates that AI and HR recruiters applied distinct decision-making criteria and operated largely independently, resulting in minimal overlap in candidate selection outcomes.

This case demonstrates a situation where AI and HR diverged due to differences in interpretive logic. HR evaluators emphasized sector-specific experience (marketing and real estate) and professional-level language proficiency as non-negotiable requirements, whereas the AI algorithm weighted general executive experience, broad strategic skills, and keyword overlaps as sufficient evidence of suitability. Discrepancy highlights the potential risk of over-recommendation by AI systems when structured fields and keywords are present but do not fully align with the nuanced requirements of the role.

5.3 Head of Project Management

5.3.1 Coefficient Analysis Between AI and Human Decisions

The Head of Project Management position requires a bachelor's or advanced degree in Real Estate Development, Construction Management, or a related field, as well as a minimum of fifteen years of professional experience in real estate development or construction, particularly in large-scale or mixed-use projects. Candidates are expected to demonstrate a comprehensive understanding of real estate fundamentals and the full development life cycle, alongside a proven ability to prepare high-quality reports and presentation materials such as memos and slide decks. The role further demands exceptional analytical, communication, and negotiation skills, combined with strong organizational capabilities, flexibility, and an open-minded approach to problem-solving. Full professional proficiency in both English and Portuguese is mandatory for effective performance in this senior leadership role.

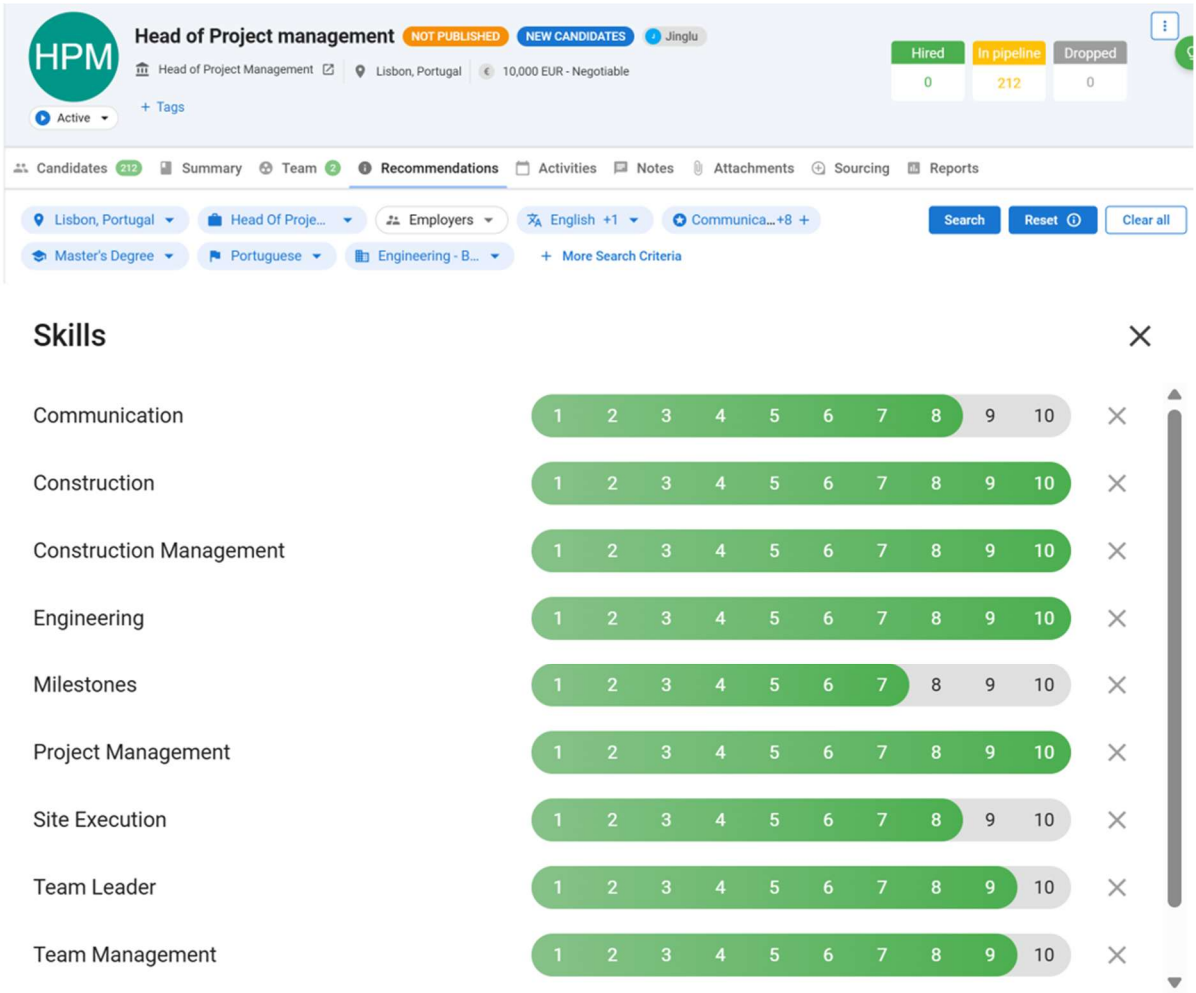
The selection criteria are shown in Figure 5.3 shows how the Manatal system translates the competency requirements of the Head of Project Management role into weighted skill attributes. This senior leadership position involves oversight across the full development lifecycle, including coordinating construction delivery, monitoring regulatory compliance, negotiating with multiple stakeholders, and managing project risks. Therefore, core capabilities such as Construction, Construction Management, Engineering, and Project Management receive the highest weightings (9–10), as they directly determine the successful execution of large-scale or mixed-use development projects.

A defining requirement of this position is the ability to assume full accountability for project outcomes. The Head of Project Management represents the entire project team when reporting to senior executives and external stakeholders and must therefore demonstrate strong upward management skills. This includes communicating critical risks, strategic needs, and milestone progress clearly and responsibly at the organizational level. Consequently, leadership-related competencies—such as Communication, Team Leadership, and Team Management—also carry substantial weight, reflecting their central role in driving collective performance and influencing senior decision-making.

In contrast, skills such as Milestone management and Site Execution, while still important, receive moderately high rather than maximal weightings. In large development organizations, these functions are typically led by specialized construction teams on-site, whereas the Head of

Project Management is responsible for ensuring alignment, validating performance, and making strategic interventions when necessary. Thus, these skills are considered supportive rather than primary drivers of senior-level performance, explaining their slightly lower relative weighting in the AI evaluation model.

Figure 5.3 Skills assessment for Head of Project management position.



Note. Screenshot from the Manatal recruitment platform, captured by the author (2025).6.3.1 Phi Coefficient Analysis (Correlation Between AI and Human Decisions)

To assess the similarity or divergence between AI and human recruitment decisions, a Phi coefficient analysis was performed. The cross-tabulation of selection outcomes is shown in table 5.3:

Based on the calculated Phi coefficient value by formular 4.1 (ϕ =0.298), the correlation between AI-driven and human recruitment decisions for this position is interpreted as weak to

moderate, indicating that while there are notable differences, there is also a certain degree of consistency in the decision-making patterns of AI and human recruiters.

Table 5.3 Cross-tabulation of AI and HR recruitment selections for head of project management position

	HR selected	HR not selected	Total
AI selected	7	12	19
AI not selected	12	159	171
Total	19	171	190

Note. Created by the author using recruitment selection data (2025).

In addition to effect size estimation, a chi-square test of independence was performed to determine whether the association between AI and HR recruitment outcomes was statistically significant. The hypotheses were specified as follows:

H_0 : AI and HR recruitment decisions are independent (no association).

H_1 : AI and HR recruitment decisions are not independent (there is an association).

Resulting in p-value < 0.001, given that the p-value falls well below the conventional threshold of 0.05, the null hypothesis was rejected, indicating a statistically significant association between AI and HR recruitment decisions.

Taken together, the Phi coefficient ($\phi = 0.298$) and the significant chi-square result provide evidence of a weak-to-moderate but meaningful consistency between AI and HR decision-making in the selection process for the head of project management position. While differences remain, the overlap in recruitment outcomes suggests that AI and human recruiters exhibit partially aligned decision patterns in this case.

5.3.2 Cases Selection

For the Head of Project Management role, a manual codebook was developed to evaluate candidates consistently. The primary dimensions (must-have) included: (1) a Bachelor's or advanced degree in Real Estate Development, Construction Management, or a related field; (2) at least 15 years of professional experience in real estate development or construction, preferably with large-scale or mixed-use projects; (3) full professional proficiency in both English and Portuguese; and (4) analytical and communication skills, reflecting the ability to interpret complex project data, negotiate, and engage with stakeholders in critical decision-making.

The secondary dimensions (nice-to-have) included stakeholder communication, reporting and presentation skills, and team leadership/mentoring. Each CV was coded using a binary scale (1 = present, 0 = absent or unclear). Candidates were classified as *Recommend* (all four primary dimensions plus at least two secondary), *Borderline* (three primary plus at least one secondary), or *Not Recommend* (any primary missing). Analytical and communication skills were elevated to a primary dimension given the leadership nature of the position, while stakeholder communication, reporting, and mentoring were considered supportive but non-essential due to the organizational structure, where external liaison and formal presentations are handled mainly by directors or executives.

An illustrative case of convergence is CV4, who was rejected by both the AI system and the human recruiter.

From the HR perspective, CV4 did not meet the essential requirements. She held a BSc in Industrial Engineering and had around eight years of experience in operations, logistics, and property support, without evidence of large-scale real estate or construction leadership. Language proficiency was also insufficiently demonstrated, as the CV4 was in English but did not specify standardized levels or Portuguese proficiency. As a result, she failed to satisfy all three primary requirements and was classified as *Not Recommend*. While her CV showed secondary strengths, including project reporting (SOPs, KPIs, templates), planning and analytical skills (five-year pipeline planning, KPI monitoring), and small team leadership, these were not sufficient to compensate for the lack of core qualifications.

From the AI perspective, Manatal similarly rejected the candidate. The system detected mismatches across all structured fields: her education (Industrial Engineering) did not align

with Real Estate or Construction, her professional experience did not reach the required 15 years in project leadership, and language proficiency was not formally specified. As none of the primary dimensions were matched, the AI also classified the candidate as not suitable.

This case illustrates a scenario where both HR and AI converged, rejecting the candidate based on the absence of fundamental qualifications. CV5 Recommended by AI but Rejected by Human Recruiter.

From the HR perspective, CV5 was not recommended. Although he held an MBA in Business Management and a bachelor's in computer network management, his professional trajectory was rooted in digital marketing, product management, and media, with no background in real estate or construction. He satisfied only one primary requirement (language proficiency, with English C1 and native Portuguese) but failed on education and industry-specific experience. Despite strong secondary evidence—such as leading teams of 35+, developing strategies, and producing project reports—HR concluded that his profile was fundamentally misaligned with the technical and industry requirements of the position, and therefore rejected him.

From the AI perspective, however, Manatal classified him as recommended. The system parsed his MBA as fulfilling the educational requirement, accepted his 15+ years of project and managerial roles as sufficient professional experience, and confirmed bilingual proficiency. Furthermore, NLP keyword detection identified multiple relevant terms: "Project and Product Manager," "Operations Director," "reported to CEO," "roadmap development," "prepared dashboards," and "managed team of 35+." These keywords aligned with project management, stakeholder coordination, reporting, and leadership. As he matched all structured fields and exceeded the skill overlap threshold, the AI produced a strong recommendation.

This case demonstrates a clear divergence: HR emphasized sector-specific expertise and industry relevance as non-negotiable, whereas the AI system weighted general project management and leadership terminology as sufficient. The discrepancy underscores the risk of false positives in AI recommendations, where managerial experience in unrelated sectors is overvalued due to keyword matches, while domain-specific expertise is overlooked.

5.3.3 Summary of Comparative Analysis

The analysis of the head of project management position yielded two key findings. First, the Phi coefficient ($\phi = 0.298$) and the chi-square test of independence ($\chi^2(1, N = 190) = 13.75$, $p < 0.001$) indicated a weak-to-moderate but statistically significant association between AI and HR recruitment decisions. This result contrasts with the findings for the financial analyst and marketing specialist positions, suggesting that in this higher-level managerial role, AI and HR recruiters demonstrated a measurable degree of alignment in their candidate selections, despite notable differences remaining.

Taken together, the two cases illustrate both convergence and divergence between human and AI decision-making in the Head of Project Management position. In CV4, both HR and AI rejected the application because the candidate failed to meet fundamental requirements such as education, industry-specific experience, and language proficiency, showing alignment in their evaluation logic. In contrast, CV5 revealed a clear divergence: HR rejected the candidate due to the absence of sector-specific qualifications, while AI recommended him on the basis of general managerial experience and keyword matches. These findings emphasize that although AI can replicate human judgments when candidates lack core criteria, it may also generate false positives when relying on surface-level textual features, highlighting the importance of human oversight in senior leadership recruitment.

5.4 Discussion

The results of this study corroborate prior research indicating that AI and HR recruiters often reach divergent conclusions when screening the same candidate pool. This divergence has been widely discussed in the literature, particularly in relation to how algorithms interpret data versus how humans apply contextual judgment. Köchling and Wehner (2020) observed that AI recruitment tools, although designed to enhance objectivity, frequently diverge from human decisions because they depend primarily on quantifiable and structured information. Similarly, Köchling and Claus Wehner (2020) found that algorithmic decision-making tends to overweight explicit features such as keyword frequency or job title matches, while underestimating qualitative cues that human recruiters intuitively recognize.

Consistent with these observations, the present findings show negligible correlations between AI and HR decisions for junior and mid-level positions, implying that AI lacks the capacity to fully capture the implicit reasoning processes humans employ when evaluating candidates'

trajectories, motivation, and contextual fit. Raghavan et al. (2020) and Drage and Mackereth (2022) have argued that this limitation arises because AI models are trained on historical datasets that reflect simplified decision patterns, rather than the nuanced interpretations humans apply in real-world contexts. Consequently, AI systems reproduce surface-level correlations instead of deep evaluative understanding.

On the other hand, the partial convergence observed for senior positions in this study—such as the Head of Project Management role—supports findings by Upadhyay and Khandelwal (2018), who reported that AI achieves higher alignment with human recruiters when tasks involve structured, standardized qualifications. In such cases, the decision criteria (e.g., years of experience, education level, managerial responsibilities) are explicitly defined, allowing algorithms to mimic human judgment more closely. However, even under these favorable conditions, the observed correlation remains moderate, suggesting that AI still cannot replace human expertise in interpreting complex leadership competencies or contextual indicators of performance potential.

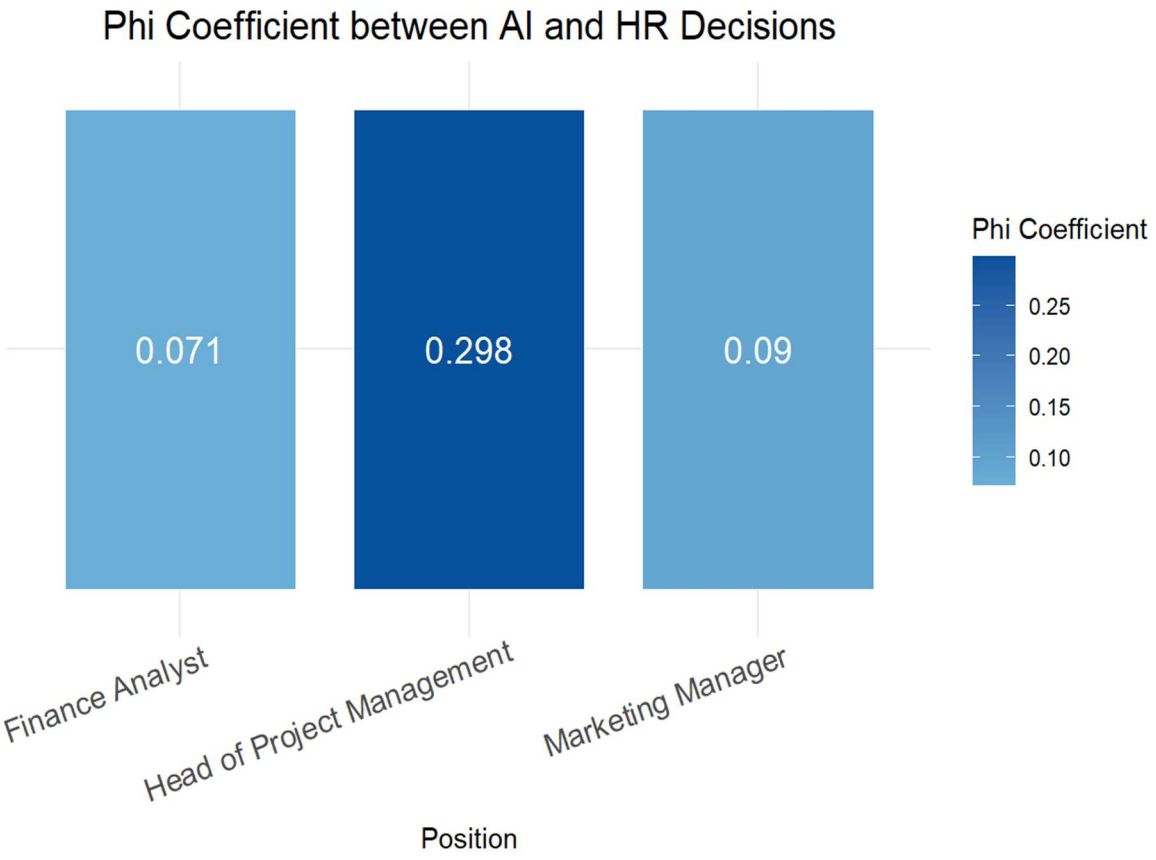
Overall, these comparisons reinforce the growing consensus that AI recruitment systems should be positioned as complementary decision-support tools rather than full substitutes for human recruiters. As noted by Hunkenschroer and Luetge (2022), integrating AI insights with human contextual reasoning offers the most balanced approach—enhancing efficiency while maintaining interpretive depth and ethical oversight.

The empirical analysis was facilitated through Phi Coefficient correlation assessments, depicted clearly via visual analytical tools (Figures 5.4), enabling nuanced insights into recruitment biases and decision-making consistency.

First, in terms of alignment between AI and HR decision-making, the results indicate negligible and non-significant correlations for the financial analyst ($\phi = 0.071$, $p = 0.646$) and marketing specialist ($\phi = 0.080$, $p = 0.402$) positions. These findings demonstrate that AI and HR recruiters applied substantially different selection criteria at junior and specialist levels, resulting in largely independent outcomes. By contrast, for the head of project management role, a weak-to-moderate but statistically significant association was observed ($\phi = 0.298$, $p < 0.001$). This suggests that AI and HR recruiters demonstrate a greater degree of alignment in higher-responsibility managerial positions, where candidate qualifications may be evaluated in a more convergent manner.

One possible explanation for the divergence between AI- and HR-based decisions lies in the fundamental difference between algorithmic and human reasoning processes. AI recruitment systems rely primarily on structured data and keyword matching, emphasizing explicit information such as education level, job title, or specific technical skills that appear in standardized formats. This approach enables speed and objectivity but limits the system's ability to capture implicit or contextual elements of a candidate's profile, such as career progression, professional stability, or qualitative competencies. In contrast, human recruiters interpret contextual cues—including the coherence of a candidate's career trajectory, the transferability of skills across roles, and subtle linguistic indicators of motivation or adaptability.

Figure 5.4 Phi Coefficient between AI and HR recruitment decisions for different positions.



Note. Created by the author using recruitment selection data (2025) and R Studio.

In relation to the study's research questions, the empirical findings partially confirm the initial expectations. The analysis revealed that recruitment decisions made by AI and human recruiters show significant differences in candidate selection outcomes. Across both junior and senior positions, the correlation between AI- and HR-based decisions remained weak or

negligible, indicating that the two systems operated largely independently. These findings suggest that AI and human recruiters apply fundamentally different evaluation frameworks when interpreting candidate information, leading to divergent selection patterns.

Moreover, the observed differences appear to stem from AI's reliance on structured data and keyword-based pattern recognition, in contrast to HR's contextual reasoning and interpretation of implicit cues such as career progression, stability, and qualitative skill descriptions. The qualitative case comparisons in this study further support this explanation. For instance, AI tended to overvalue explicit technical terms while overlooking unstructured expressions of competence, whereas HR recruiters were able to recognize contextual signals that indicated adaptability, initiative, or leadership potential. These results reinforce the conceptual framework proposed for this study, confirming that divergence between AI and HR decision-making is primarily rooted in their distinct informational and cognitive processing mechanisms.

Chapter 6 Conclusion

6.1 Contribution

This study sought to examine the degree of consistency between AI- and HR-based recruitment decisions and to understand the factors underlying their divergences.

Regarding **Research question 1** – "Do AI and HR recruiters differ significantly in their candidate selection outcomes?"

The empirical results clearly indicate that AI and HR recruiters differ substantially in their selection outcomes. Across all three job categories—Financial Analyst, Marketing Specialist, and Head of Project Management—the Phi coefficient analyses revealed weak or negligible correlations for the first two positions and only a weak-to-moderate correlation for the senior managerial role. These results confirm that AI and HR recruitment systems operate largely independently, relying on distinct evaluative logics. AI's decisions are grounded in algorithmic pattern recognition and structured data fields, whereas HR recruiters employ interpretive judgment based on contextual understanding and professional experience. Consequently, the overall evidence supports the view that AI and HR decision-making processes remain fundamentally different in nature and output.

Regarding **Research question 2** – "What factors explain the divergences between AI and HR based recruitment decision?"

The observed divergences can be attributed primarily to differences in data processing and interpretive reasoning. AI systems rely heavily on explicit and structured indicators—such as education level, job titles, and keywords—to rank candidates. This narrow reliance on standardized information limits AI's capacity to identify implicit competencies and non-technical attributes such as teamwork, problem-solving, or leadership potential. In contrast, HR recruiters interpret broader contextual signals, including the coherence of career trajectories, professional adaptability, and qualitative indicators of motivation and interpersonal skills. Furthermore, the findings suggest that AI tends to undervalue candidates with non-traditional or less standardized CVs, while HR professionals can recognize their underlying potential. These differences highlight the complementary, rather than substitutive, relationship between AI and human decision-making in recruitment.

Taken together, the results address the main research question by demonstrating that AI and HR recruiters produce inconsistent candidate selection outcomes in real-world recruitment processes. The divergences stem from their fundamentally different approaches to information interpretation and evaluation, confirming that AI enhances efficiency but still lacks the contextual intelligence and qualitative discernment inherent in human decision-making.

In summary, the comparative findings highlight a pattern: AI and HR recruiters tend to operate independently at lower-level roles but demonstrate measurable convergence in decision-making at senior managerial levels. The Phi coefficients reveal generally weak consistency between AI and HR recruitment decisions across all three positions, with the highest value observed for Head of Project Management (0.298). This suggests that while AI and HR show slightly more convergence in positions with clearer formal requirements, their overall selection logics remain largely divergent, highlighting the limitations of AI as a substitute for human recruiters.

The five selection results (CV1–CV5) provide valuable insights into the similarities and differences between AI-based and HR-based decision-making across three job categories. Several key patterns emerge from the analysis.

First, alignment occurs when candidate profiles explicitly satisfy both structured job requirements and human evaluative criteria. In CV1 and CV4, both AI and HR reached the same conclusion, albeit for different reasons: in the former, the candidate clearly fulfilled all requirements, leading both systems to recommend him; in the latter, the absence of essential qualifications resulted in rejection by both. These cases demonstrate that when CVs are either strongly aligned or strongly misaligned with job requirements, AI and HR decisions tend to converge.

Second, divergence arises when implicit signals, contextual interpretation, or industry-specific nuances play a decisive role. CV2 and CV5 highlight this phenomenon. CV2 was recommended by HR but overlooked by AI because his in-progress role and unstandardized language proficiency were insufficiently recognized by the algorithm, despite being acceptable to human recruiters. Conversely, CV5 was recommended by AI but rejected by HR: the system overvalued general project management experience and keyword matches, while HR prioritized sector-specific expertise in real estate and construction. These examples show that AI may

underestimate candidates when implicit information is present or overestimate them when general managerial terms substitute for domain-specific qualifications.

Third, AI exhibits a strong reliance on explicit structured fields and keyword overlaps, whereas HR recruiters incorporate broader contextual reasoning, including career progression, implicit signals, and the transferability of competencies. This explains why CV3 was recommended by AI but rejected by HR: the algorithm treated executive experience and strategic phrasing as sufficient, while HR emphasized the absence of marketing-sector expertise and professional-level language proficiency.

Taken together, the findings demonstrate that AI and HR recruitment decisions are not interchangeable, and their level of alignment varies depending on role complexity and the nature of required competencies. While AI and HR recruiters occasionally converge in clear-cut cases where explicit job requirements are fully met or entirely missing, significant divergences emerge when implicit professional attributes or industry-specific expertise become critical to suitability.

A key implication of these findings is that neither HR judgment nor AI judgment can be considered universally superior. Instead, the results highlight two distinct forms of bias that shape decision-making in different ways. AI introduces structural bias by relying heavily on explicit and standardized information such as job titles, keywords, and degree labels, which makes it prone to discounting non-linear career paths, implicit competencies, and less conventional skill expressions. In contrast, HR decision-making is informed by interpretive and experience-based reasoning, which enables the recognition of contextual strengths—such as communication ability, team collaboration, and sector alignment, but also creates vulnerability to subjective heuristics and inconsistent assessments across recruiters.

This study provides empirical clarity on this distinction. AI performs relatively well in junior roles with well-defined and measurable technical requirements—such as the Financial Analyst position—where performance potential is more closely tied to explicit credentials. However, as job complexity increases, as in the Head of Project Management role, success depends more on contextual leadership, stakeholder influence, and accountability for strategic outcomes. These qualities remain difficult for AI to infer from structured text alone, making HR the more accurate decision-maker in such contexts.

Overall, the results confirm that AI functions most appropriately as a complementary rather than substitutive mechanism in recruitment. AI can effectively streamline early-stage screening and improve efficiency by filtering large applicant pools based on standardized criteria, while HR recruiters provide the necessary qualitative intelligence and contextual discernment to ensure fairness, relevance, and long-term talent fit. Organizations should therefore adopt a hybrid decision model that integrates both AI-driven efficiency and human expertise to optimize recruiting outcomes.

6.2 Limitation and future recommendation

The current study underscores essential methodological and practical contributions by validating a rigorous empirical approach to assessing recruitment fairness and offering tangible insights for organizations committed to enhancing equity and inclusion in their hiring processes. However, several limitations inherent to this study provide pathways for future scholarly exploration and methodological refinement.

First, the analysis was based on a relatively small dataset of CVs (117 for Finance Analyst, 166 for Marketing Specialist, and 228 for Head of Project Management). While sufficient for case-based comparison, the sample size limits the generalizability of the findings to broader recruitment contexts. Future studies could expand the dataset to include a larger number of job functions and industries, thereby improving the robustness and external validity of the results.

Second, the study focused exclusively on three positions within a single company in Portugal. Organizational context, industry requirements, and cultural factors may influence both HR and AI decisions. Future studies should therefore replicate the analysis across multiple organizations, sectors, and geographical regions to assess the consistency of findings and capture cross-cultural variations in recruitment practices.

Third, the methodology was limited to a binary coding system and Phi coefficient analysis. While effective in capturing patterns of agreement and divergence between HR and AI, this approach does not fully capture the qualitative nuances of decision-making. Incorporating additional methods such as interviews with recruiters, think-aloud protocols, or advanced natural language processing audits could provide deeper insights into the reasoning processes behind both human and AI selections.

Fourth, the AI system used in this study (Manatal) operates on a rules-based matching algorithm. Different recruitment platforms may apply alternative algorithms (e.g., machine-learning-based models with contextual embeddings), potentially yielding different patterns of decision-making. Future study should therefore conduct cross-platform comparisons to evaluate how different AI architectures influence candidate assessment outcomes.

Finally, this study examined decision outcomes (recommend vs. not recommend) without testing the actual job performance of selected candidates. As a result, the findings provide insights into selection processes but not into predictive validity. Future study should explore longitudinal outcomes by tracking the on-the-job performance of candidates recommended by AI versus HR, thereby assessing whether differences in selection logic translate into meaningful differences in employee success.

In sum, while this study highlights important divergences between AI and HR in recruitment decision-making, future studies should broaden the empirical scope, incorporate richer methodological approaches, and explore multiple AI platforms to build a more comprehensive understanding of the role of AI in candidate selection. By systematically highlighting disparities and alignment with theoretical fairness benchmarks, the study offers valuable insights for practitioners, policymakers, and scholars alike. Future study, addressing the noted limitations and extending analytical scope, holds substantial promise for further enhancing fairness, transparency, and equity within global recruitment practices.

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