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Innovations in IT Recruitment: How Data Mining Is Redefining the Search for Best Talent (A Case Study of IT Recruitment in Morocco)

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Abstract

The massive volumes of data and the intensification of digital transformation are reshaping recruitment practices within organizations, particularly for specialized information technology (IT) profiles. However, existing studies have often remained conceptual, focused on developed economies, or limited to a narrow set of factors, thereby leaving important gaps in emerging contexts. Moreover, there are few studies that critically assess how Data Mining is impacting the IT recruitment process, and none that assess this in the context of Morocco. This study employs an extensive literature review to explore the role of Data Mining in facilitating the recruitment of top IT candidates, focusing on its ability to improve selection quality, reduce costs, and optimize decision-making procedures. The study provides empirical evidence from the Moroccan aeronautical and digital services sectors, an underexplored context where IT talent scarcity and rapid technological change pose critical challenges. Primary data comes from a survey of 200 IT recruitment professionals operating in these sectors in Morocco, allowing an assessment of the impact of Data Mining on IT talent acquisition initiatives. The findings reveal that a range of capabilities resulting from the application of Data Mining significantly and positively influences the success of IT recruitment processes. The novelty of the article lies in integrating six key determinants of algorithmic recruitment into a unified framework and demonstrating their empirical significance through binary logistic regression. The focus on the Moroccan context adds value to the international discussion and extends the literature on HR analytics beyond its conventional geographical and theoretical boundaries. The article thus contributes to the emerging literature on the role of digital technologies in IT recruitment that will be of interest to industry practitioners and other researchers in this field.

Keywords: data mining; recruitment process; IT profiles; logit model

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1. Introduction

In an era of systemic digitalization across professional environments, the Human Resources (HR) function is undergoing a profound reconfiguration of its conceptual foundations, operational tools, and decision-making logic. Once confined to an administrative role, Human Resource Management (HRM) has now emerged as a strategic function at the heart of innovation and value creation dynamics, driven by the rise in digital technologies, artificial intelligence, and predictive analytics [1,2]. This transformation is fueled by the acceleration of technological cycles, the emergence of interconnected ecosystems, and the explosion of available data volumes all of which are radically reshaping traditional paradigms of talent management [3,4].

In this unstable, fragmented, and highly competitive environment, recruitment has become a critical lever of organizational differentiation, compelled to reinvent itself in response to major structural challenges: talent scarcity, accelerated skills obsolescence, hyper-mobility of career paths, and increasing complexity of the profiles sought [5–8]. These tensions are particularly acute in the information technology (IT) sector, where an organization's ability to rapidly identify, assess, and integrate highly specialized expertise directly determines its competitive survival [9,10].

Traditional recruitment methods, often driven by intuition, heuristics, or rigid evaluation grids, are increasingly revealing their limitations in the face of overwhelming data volumes and the growing need to make critical decisions within shortened timeframes [11,12]. This realization has catalyzed the emergence of new analytical frameworks, foremost among them those related to Data Mining, understood as an algorithmic process of automated or semi-automated exploration of large datasets to extract patterns, regularities, or correlations that are imperceptible to the human eye [13–15].

In the field of recruitment and particularly for IT-related positions, Data Mining is emerging as a decisive lever of process transformation. By cross-referencing heterogeneous sources such as résumés, digital footprints, video interviews, psychometric tests, and online interactions, these tools not only enable the prediction of candidates' future performance but also help rationalize the selection process, optimize associated costs, and enhance transparency and execution speed. Within this perspective, organizations are increasingly shifting toward intelligent recruitment practices grounded in analytical automation and predictive decision-making [11,16,17]. This transition toward algorithmically augmented HRM marks a turning point in how organizations approach recruitment—not as a one-time filtering task, but as a strategic process rooted in data, prediction, and the responsible governance of talent.

In this continuum, Data Mining stands out as a strategic innovation driving the modernization of HR practices [13,14,18]. Far from being a mere filtering function, Data Mining enables the processing of vast amounts of information, the anticipation of candidates' future performance, the reduction in cognitive biases in evaluation, and decision-making guided by enhanced accuracy, speed, and fairness [19–21]. More specifically, when applied to IT recruitment—a domain particularly affected by talent shortages, profile volatility, and rapid technological change—Data Mining deeply redefines selection paradigms [5,22]. Beyond its technical dimension, Data Mining has become a genuine vector of recruitment transformation, especially within the IT sector, where talent scarcity and the accelerated obsolescence of skills demand a profound overhaul of selection logics. The goal is no longer simply to identify candidates who match predefined criteria, but to anticipate dynamic capabilities such as adaptability, creativity, or potential for long-term engagement [10,23]. The integration of machine learning algorithms and artificial intelligence techniques introduces an unprecedented predictive dimension to recruitment, breaking away from the intuitive and standardized approaches that have long dominated HR processes [17,24].

These technologies also make it possible to detect high-potential atypical profiles often overlooked by conventional methods by leveraging heterogeneous data from résumés, social media, psychometric tests, and even video interviews [25,26]. Along similar lines, Hamdane et al. [27] argue that Data Mining has enabled university graduates to connect with potential employers, illustrating a practical application of data exploration in recruitment. Likewise, Kisi [28] examines how blockchain technology can enhance recruitment processes by ensuring transparency and fairness among potential candidates.

Taken together, these reflections highlight the critical role of Data Mining in recruitment processes within organizations. This study specifically aims to assess the impact of Data Mining on the recruitment of IT profiles. More precisely, it seeks to quantify the influence of key Data Mining determinants on the success of IT recruitment processes by investigating the extent to which these determinants contribute to successful IT recruitment initiatives in Morocco.

Using a binary logistic regression model (Logit), this study draws on data collected from a sample of IT recruiters operating in Moroccan firms of varying size and digital maturity. There are two main research objectives (ROs): RO1—to identify which dimensions of Data Mining have the most significant effect on recruitment performance; and RO2—to propose a contextualized analytical framework applicable to other organizational environments with similar characteristics. By offering contextualized insights, this paper aims to inform both academic debates on the use of emerging technologies in HRM and managerial reflections on the digital transformation of recruitment practices.

The article is structured into five sections: Section 2 details the chosen research methodology. In Section 3, relevant literature is reviewed, notably on the relationship between Data Mining and recruitment. Section 4 then presents the empirical results; and Section 5, in conclusion, considers the managerial and scientific implications of the research, discusses limitations, and notes potential future areas of research in the field of study.

2. Research Method

The present study is grounded in a rigorous hypothetico-deductive framework, aligned with the dominant paradigms in empirical research on digital HRM and data-driven decision-making [29,30]. This epistemological posture assumes that scientific knowledge is built through the testing of theoretically grounded hypotheses, formulated on the basis of a critical and systematic review of the literature [31,32]. The choice of this approach is justified by the study's overarching objective: to evaluate the causal effect of data mining determinants on the success of IT recruitment in Moroccan digital-intensive firms. There were two main phases to the research process (Figure 1). In Phase 1, a systematic literature review, designed according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, was undertaken, as recommended by Moher et al. [33]. From the literature analysis, a provisional conceptual framework was developed, which provided the basis for hypotheses generation and the primary research. Phase 2 empirically tested the hypotheses through feedback from 200 IT recruitment professionals. These two phases are discussed in more detail below.

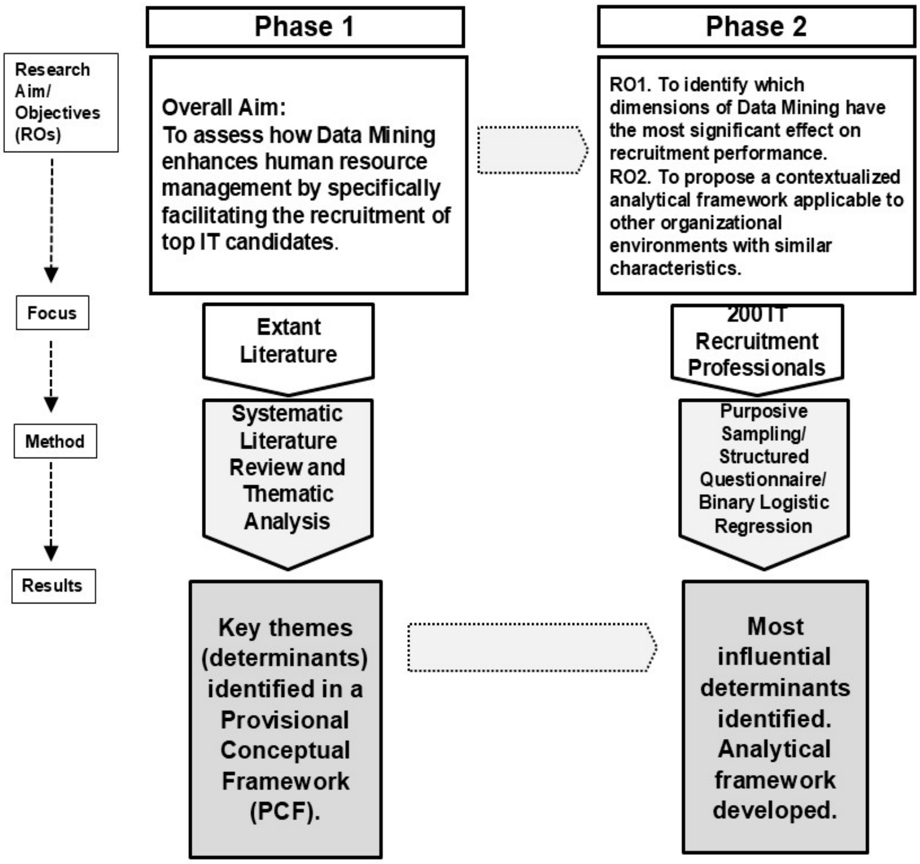


Figure 1. The two-phase research process.

2.1. Phase 1: Literature Review and PCF Development

To ensure methodological transparency and replicability, the literature review was conducted in accordance with the PRISMA guidelines [33], which structure the process of systematic review into four distinct phases: identification, screening, eligibility, and inclusion. During the identification phase, a comprehensive search strategy was implemented across major databases (Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar), using a combination of Boolean operators with keywords such as "data mining", "recruitment analytics", "predictive hiring", and "algorithmic HRM". This initial step yielded a total of n = 2358 publications.

In the screening phase, duplicate entries were removed, and titles/abstracts were examined for relevance, narrowing the sample to n = 1713 articles. The eligibility phase involved full-text screening based on predefined inclusion criteria (peer-reviewed status, publication between 2015 and 2025, empirical grounding, and focus on algorithmic recruitment or data-driven HRM). Studies failing to meet these criteria or lacking methodological transparency were excluded. In the final inclusion phase, n = 267 studies were retained and systematically analyzed (Figure 2).

Following PRISMA, a thematic analysis was conducted using an inductive coding process based on Braun and Clarke [34]. Full-text articles were imported into NVivo 14 for qualitative coding. Initial codes were generated line-by-line, focusing on recurrent patterns related to the strategic use of data mining in recruitment. These codes were then grouped into broader categories through constant comparison techniques and iterative refinement. The last step involved the definition and naming of six dominant themes corresponding to recurrent and theoretically significant determinants of algorithmic recruitment success.

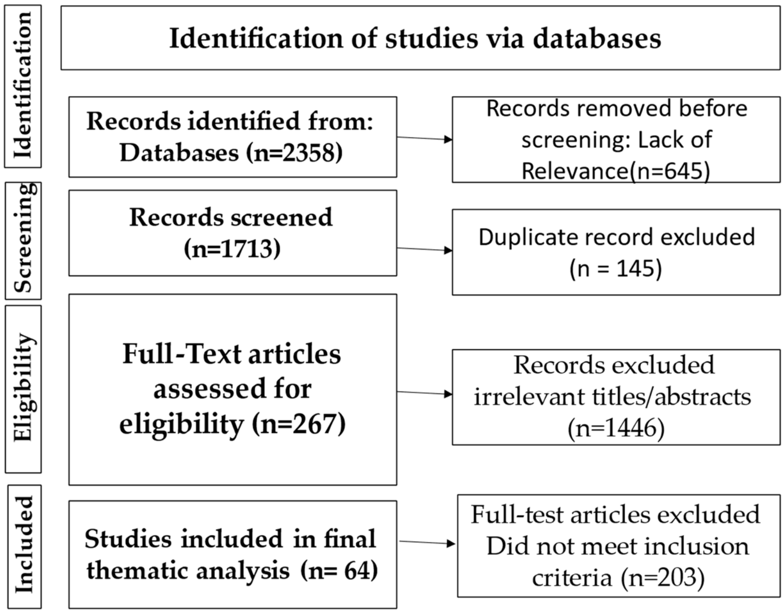


Figure 2. The PRISMA flow diagram for the systematic literature review.

These six determinants—Advanced Data Analytics (ADA), Performance Prediction (PPR), Optimization of the Recruitment Process (ORP), Transparency and Fairness (TF), Adaptability to Specific Needs (ASN), and Detection of Labor Market Trends (DMT)—were selected based on three converging criteria: (1) frequency across the included literature, (2) empirical support in high-impact studies, and (3) alignment with existing theoretical frameworks [10,11,22]. This thematic synthesis allowed us to construct a conceptual framework, later tested through a binary logistic regression model. This thematic synthesis supported the construction of a conceptual framework, later tested through a binary logistic regression model, in which the dependent variable (IT recruitment success) was tested against the six determinants. This is discussed in more detail below.

2.2. *Phase 2: Questionnaire Design and Hypotheses Testing via Binary Regression Analysis*

The empirical phase is based on a structured questionnaire distributed to 200 IT recruitment professionals operating in the Moroccan aeronautical and digital services sectors. The sample was constructed using purposive sampling, targeting experienced HR practitioners with direct exposure to predictive analytics in recruitment. This non-probability sampling method is particularly relevant for studies seeking expert judgments in niche professional fields [35,36]. While purposive in nature, the sample size satisfies methodological criteria for logistic regression, particularly regarding the minimum ratio of observations to predictors (10:1 or higher). This is line with the recommendations of Tabachnick and Fidell [37] and Hair et al. [30], highlighting the suitability of the logit model for binary outcomes, its interpretability, and its widespread use in HR analytics research. The questionnaire included two sections: the first captured demographic and organizational attributes; the second included 30 items measuring the six data mining determinants using five-point Likert scales. These items were adapted from validated instruments in prior studies on predictive recruitment, HR analytics and algorithmic fairness.

In terms of structure, the dataset was organized as a two-dimensional (2D) matrix of size n $\times$ p, where n = 200 observations represent the surveyed IT recruiters and p = 6 predictors correspond to the main determinants of algorithmic recruitment success. Each row in the matrix represented a single respondent, while each column represented one of the independent variables derived from the thematic synthesis. This 2D arrangement is fully consistent with standard procedures for binary logistic regression, ensuring alignment between the dichotomous dependent variable (success/failure of IT recruitment) and the explanatory predictors included in the model.

Some of the main elements of the binary logistic regression are noted here. A set of n independent observations y_i, are considered, where each $y_i \in \{0,1\}$ represents a binary variable indicating the presence (1) or absence (0) of a given characteristic. The vector $y_i = (y_1, y_2, \ldots y_n)$ collects all these observations. The independent variables are contained in a matrix X of dimension $n \times p$ and rank p. The vector β contains the p unknown coefficients to be estimated. It is assumed that each y_i follows a Bernoulli distribution with success probability π. Further detail regarding the logit transformation is included in Appendix A.

The binary logistic regression model was trained on a dataset consisting of the 200 responses and the six independent variables. Each observation corresponded to a response associated with a binary label (success/failure). To evaluate the performance of the deployed model, a ten-fold cross-validation procedure was applied, meaning that the dataset was divided into ten subsets of 20 responses. At each iteration, 180 responses were used to train the model and 20 to validate it. The mean AUC (Area Under the ROC Curve) was employed as the primary performance metric, as it reflects the model's ability to correctly discriminate between the two classes. Prior to the final estimation, the six variables were standardized (mean-centered and scaled to unit variance) in order to ensure a homogeneous scale, which is essential both for stable model convergence and for the correct interpretation of the coefficients.

3. Relevant Literature

3.1. The Transformative Potential of Data Mining in HR Recruitment

The digitalization of HRM has redefined the traditional logic of talent acquisition, giving rise to a new era of algorithmic recruitment. Far from being a mere automation of administrative tasks, this transformation reflects a deeper epistemological shift in how organizations identify, evaluate, and engage talent [38,39]. Particularly in high-tech and IT-intensive sectors, the integration of data science into recruitment strategies is no longer optional—it is a strategic necessity for many such companies.

Data mining, as a subset of advanced analytics, plays a pivotal role in this transformation. It involves discovering patterns, anomalies, and predictive signals in large volumes of structured and unstructured data to support decision-making [40]. In a recruitment context, data mining techniques can be applied to diverse datasets—CVs, psychometric scores, digital footprints, social network activity—to enable predictive modeling of candidate performance, fit, and retention potential [41,42]. These tools facilitate not only the automation of screening and scoring but also the design of more objective, transparent, and data-informed recruitment processes. Sivathanu and Pillai [43] confirm that algorithmic recruitment systems significantly improve process efficiency and candidate–job matching, particularly in environments characterized by talent scarcity and fast-paced innovation. In addition, the use of data-driven tools helps mitigate the cognitive biases that often influence human judgment in candidate selection [17]. Organizations adopting predictive recruitment methods report shorter time-to-hire, lower turnover rates, and improved workforce alignment with strategic goals [44].

In emerging economies, where the IT labor market is both underdeveloped and increasingly exposed to global digital competition, the deployment of data mining in recruitment is of particular value. It can allow organizations to build resilience by proactively identifying high-potential candidates, even in talent-constrained environments [45]. Moreover, algorithmic approaches enable firms to reduce reliance on traditional credentials and explore alternative indicators of competence, such as behavioral data or skill-based assessments [46].

In summary, data mining is central to analytics deployment to support the recruitment process. Organizations can analyze labor market data to improve forecasting of future staffing requirements, thereby enhancing the planning of future staff acquisition and the management of potential skills shortages in the market. By focusing on a data-driven strategy, candidate profile matching to job requirements will be enhanced and the overall recruitment process will be streamlined. A stronger reliance on objective criteria is also likely to minimize bias in recruitment decision-making.

Nevertheless, the rise in algorithmic hiring is not without ethical and managerial implications. Scholars warn against over-reliance on opaque algorithms that may perpetuate or even exacerbate historical discrimination patterns encoded in past recruitment decisions [47,48]. As such, the value of data mining lies not only in its technical accuracy, but in its responsible and transparent deployment within well-governed HR systems.

3.2. Theoretical Foundations: A Multidimensional Framework

Understanding the determinants of algorithmic recruitment success requires a pluralistic theoretical framework, capable of capturing the interplay between technological, individual, organizational, and systemic factors. Originally proposed by Davis [49], the Technology Acceptance Model (TAM) has become one of the most widely used frameworks for understanding the adoption of information systems. In the context of recruitment analytics, TAM provides a lens to explore how recruiters perceive the ease of use and usefulness of data mining tools [50]. More recent adaptations emphasize user trust, perceived transparency, and automation reliability as key antecedents to acceptance. In algorithmic hiring, the perceived legitimacy of recommendations made by AI systems is increasingly considered a critical factor in determining usage behavior [51]. Recent studies have also highlighted that negative perceptions of fairness or opacity may undermine such legitimacy [52], while organizational trust, internal communication strategies, and data-driven HR capabilities significantly influence the effective integration of analytics into recruitment practices [53]. Thus, TAM supports the modeling of psychological enablers and barriers to the adoption of algorithmic tools by HR professionals.

In this respect, Self-Determination Theory (SDT), rooted in motivational psychology, helps explain the individual-level variance in recruiters' engagement with data-driven systems. According to Ryan and Deci [54], the autonomy, competence, and relatedness experienced by users influence their intrinsic motivation to adopt digital innovations. In recruitment contexts, algorithmic systems that restrict discretion or devalue recruiter expertise may hinder motivational alignment [55]. Conversely, when systems enhance perceived control, learning, and efficiency, they strengthen intrinsic motivation to engage with technology [56]. SDT thereby enriches the interpretation of human–AI interaction dynamics in strategic HRM settings.

The TOE framework, initially conceptualized by Tornatzky and Fleischer [57], provides a meso-level perspective on technological adoption. It argues that the diffusion of innovation is conditioned by three categories of factors: technological (e.g., relative advantage, compatibility), organizational (e.g., size, digital maturity), and environmental (e.g., industry pressures, regulation). In algorithmic recruitment, TOE has been extended to include factors such as data governance, ethical compliance, and vendor reputation [58,59].

The Resource-Based View (RBV) posits that sustained competitive advantage stems from the possession and strategic deployment of valuable, rare, inimitable, and non-substitutable (VRIN) resources [60]. In the digital HR context, the ability to harness analytics and data science for talent acquisition can constitute such a resource [61]. However, the pace of technological change calls for more agile frameworks—hence the integration of dynamic capabilities, defined as the firm's ability to sense, seize, and transform its resource base in volatile environments [62]. In algorithmic recruitment, this includes the reconfiguration of HR processes, retraining of personnel, and real-time adjustment of selection criteria [63]. These theories explain how digital competencies in recruitment not only optimize performance but reinforce organizational adaptability.

The Theory of Planned Behavior (TPB) [64] provides additional predictive value by incorporating subjective norms and perceived behavioral control. It helps explain how organizational culture, peer influence, and managerial support affect recruiters' intentions to adopt data mining tools [65]. Organizational culture sets the tone for openness to innovation: recruiters working in data-driven and change-oriented environments are more likely to adopt data mining tools. Peer influence reinforces this process, as observing colleagues successfully using such tools creates social proof that strengthens individual intentions to adopt. Managerial support adds a further layer by providing resources, incentives, and legitimacy, reducing uncertainty and building confidence in the technology. Together, these factors create the cultural and structural conditions that translate positive attitudes into actual adoption behavior. In parallel, Actor–Network Theory (ANT) reconceptualizes technology adoption not as a linear process, but as a negotiation between human and non-human actors [66]. ANT is particularly relevant for studying recruitment platforms that embed algorithmic decisions, as it shifts the focus to the sociotechnical arrangements and power asymmetries involved in digital hiring ecosystems [67]. Finally, the Theory of Complexity [68] is of value in developing an understanding of the nonlinear, emergent nature of recruitment in volatile labor markets. It emphasizes adaptability, feedback loops, and distributed intelligence as features of resilient talent acquisition systems. Complexity theory invites researchers to move beyond deterministic models and embrace uncertainty in the modeling of digital HR transformations.

3.3. Review of Key Determinants in Algorithmic Recruitment

Advanced Data Analytics (ADA) has become a central enabler of evidence-based decision-making in talent acquisition. By leveraging machine learning algorithms, natural language processing, and real-time data integration, ADA enables recruiters to extract actionable insights from vast and heterogeneous datasets [69,70]. In recruitment contexts, this includes parsing resumés, analyzing online behavior, and interpreting interaction data to assess fit, interest, or career potential. Beyond these descriptive functions, ADA transforms fragmented and unstructured inputs into structured profiles that highlight candidates' competencies and risks. By consolidating information from résumés, psychometric assessments, social media activity, and digital interaction patterns, ADA generates multidimensional indicators that recruiters can directly use in decision-making. This integration uncovers latent skills, career trajectories, and behavioral trends often invisible to traditional evaluation methods, thereby turning complex datasets into strategic knowledge that inform precise, evidence-based hiring decisions. According to Bag et al. [71] and Dhamija and Bag [72], analytics-driven hiring improves selection accuracy and reduces reliance on subjective heuristics. Moreover, recent studies confirm that firms adopting advanced analytics in HRM demonstrate higher responsiveness to market fluctuations and outperform peers in talent alignment [43]. In this regard, Fleiß et al. [73] emphasize the importance of explainability in algorithmic systems, which increases recruiter engagement and trust. ADA thus plays a strategic role in transforming recruitment into a data-intelligent function.

Predictive modeling of candidate performance has gained traction as a method to minimize post-hiring failures and optimize human capital investments. By correlating applicant data—skills, psychometrics, digital behavior—with historical success indicators, organizations can forecast the likely contribution of a candidate to specific roles. This is particularly critical in IT sectors, where technical competencies and project adaptability are strong predictors of value creation. As highlighted by Dawson and Agbozo [74], the integration of predictive analytics into recruitment processes enables a shift from reactive staffing to proactive talent planning [75]. Furthermore, performance prediction models foster more equitable hiring by using performance-based rather than background-based criteria. Revillod [76] further identifies technological expertise and competitive pressure as key drivers of AI diffusion in recruitment, reinforcing the value of predictive insights.

Algorithmic tools enable not only better decision-making but also significant process improvements in recruitment operations. Process optimization refers to the automation and enhancement of workflows, including resumé screening, interview scheduling, candidate ranking, and onboarding support [77–79]. These improvements translate into measurable gains in cost, speed, and consistency [80]. Moreover, as Gupta et al. [81] argue, recruitment process optimization contributes to employer branding by reducing candidate frustration and increasing process transparency. Revillod [82] demonstrates that innovative climate and process digitization in Swiss HRM are positively associated with algorithmic adoption, validating the link between digital optimization and organizational readiness. In competitive labor markets, the capacity to deliver an efficient, data-driven, and responsive hiring experience becomes a differentiating factor in attracting top IT talent. Concerns over algorithmic bias and opacity have raised critical questions about the fairness and legitimacy of AI-driven hiring systems. Transparency in algorithmic recruitment refers to the extent to which candidates and recruiters understand how decisions are made, and fairness concerns the absence of discrimination based on irrelevant or protected attributes [83]. According to Binns et al. [47], algorithmic hiring systems that lack interpretability risk undermining user trust and organizational legitimacy. Conversely, transparent machine learning practices such as explainable models, audit trails, and fairness metrics enhance user confidence and compliance with ethical standards [84]. Ochmann et al. [85] demonstrate empirically how transparency and anthropomorphism significantly improve fairness perceptions. Similarly, Hilliard et al. [86] highlight the psychological discomfort users experience when facing opaque systems. TF (Transparency and Fairness) is therefore not only an ethical imperative, but a functional necessity for sustainable algorithmic recruitment.

Equally important is the system's ability to adapt to contextual specificities (sectoral, organizational, or positional) reflecting organizational goals, job characteristics, and sectoral requirements. In recruitment, this includes adjusting models to different job families, firm cultures, or strategic priorities [24]. Adaptive algorithms allow for the customization of evaluation criteria, weighting of competencies, and fine-tuning of candidate scoring to align with local expectations or fast-evolving skill requirements [87]. Particularly in the IT domain, where job roles are fluid and evolving, the adaptability of Data Mining tools determines their practical value. This dimension also aligns with the concept of algorithmic configurability, which enhances both performance and user acceptance [88]. Fumagalli et al. [89] show that workers often prefer human over algorithmic evaluation when personalization and discretion are lacking, underscoring the need for adaptable systems that reflect contextual nuances.

Finally, arguably the most strategic advantage of recruitment analytics lies in its ability to detect and anticipate labor market trends. This includes monitoring demand for specific skills, tracking geographical mobility, identifying emerging job profiles, and analyzing competitor hiring behavior [90,91]. Data mining tools process macro and micro labor data in real time, supporting talent intelligence and workforce planning [92]. Horodyski [93] confirms that AI-driven recruitment allows for nuanced tracking of candidate sentiment and industry movement, enriching the strategic potential of these tools, which can provide a forward-looking view of talent ecosystems.

Based on this analysis of the extant literature, a provisional conceptual framework (PCF) for the primary research was developed (Figure 3).

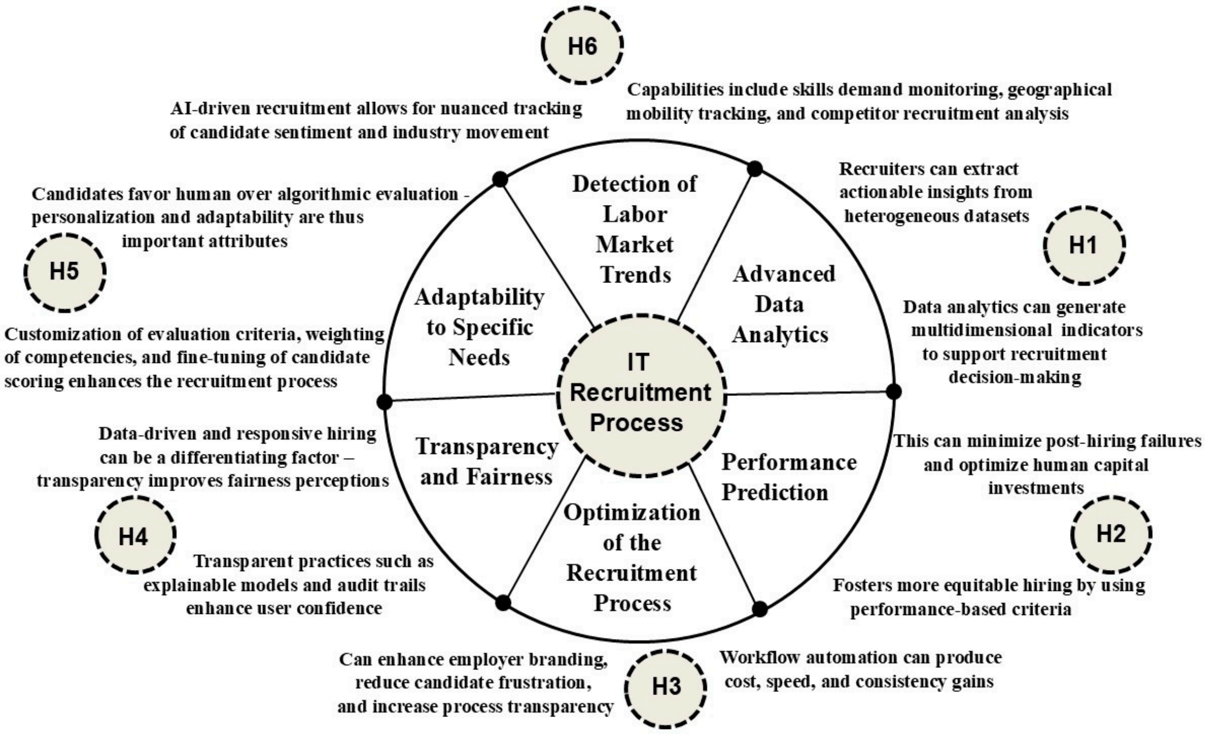


Figure 3. Provisional conceptual framework developed from the literature review, indicating the focus of derived hypotheses (marked with an "H").

The key concepts in the PCF were adopted as the six determinants acting in complementary ways to reshape IT recruitment: ADA strengthens evidence-based selection, PPR reduces mismatches by forecasting performance, ORP improves efficiency, TF ensures ethical legitimacy, ABS aligns models with contextual requirements, and DTM provides strategic foresight. Collectively, they transform recruitment into a more data-driven, transparent, and adaptive process. From here, six hypotheses were postulated, exploring direct relationships between the main constructs (Figure 4). These hypotheses are:

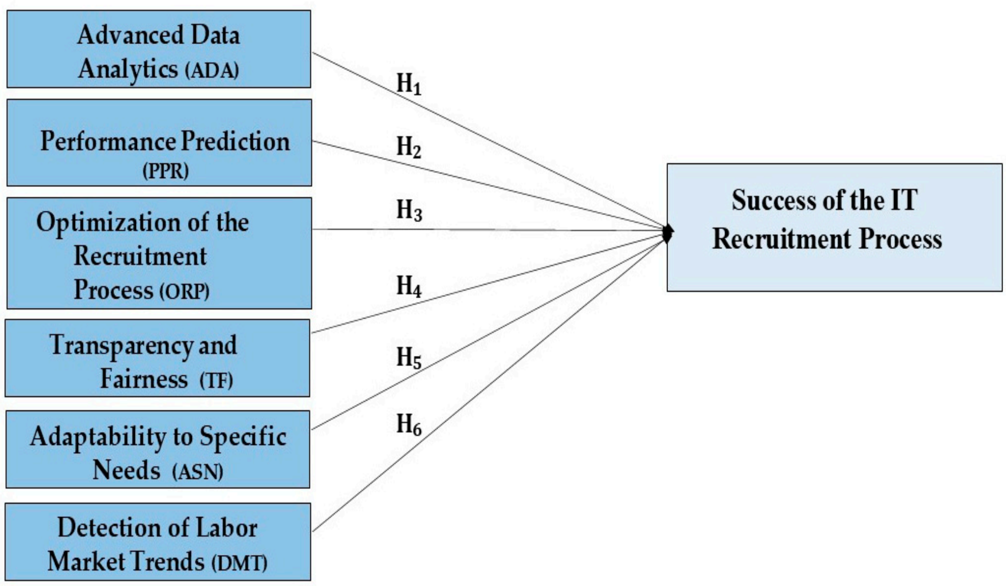


Figure 4. Determinants and hypotheses development.

H_1: *Advanced Data Analytics has a positive effect on the success of the IT recruitment process.*

H_2: *Performance Prediction has a positive effect on the success of the IT recruitment process.*

H_3: *Optimization of the Recruitment Process has a positive effect on the success of the IT recruitment process.*

H_4: *Transparency and Fairness has a positive effect on the success of the IT recruitment process.*

H_5: *Adaptability to Specific Needs has a positive effect on the success of the IT recruitment process.*

H_6: *Detection of Labor Market Trends has a positive effect on the success of the IT recruitment process.*

4. Results

4.1. Study Presentation and Sample Selection

The success of IT profile recruitment processes across various economic units is increasingly being achieved through the use of advanced analytical methods applied to large-scale datasets, leveraging innovative technological tools. This study advances an in-depth econometric analysis to examine the effect of Data Mining on the success of IT recruitment processes in Morocco, with a specific focus on the aerospace industry. A comprehensive review of the literature has been conducted, highlighting numerous studies that address the strong interrelationship between Data Mining and the recruitment process for IT profiles. This theoretical exploration has made it possible to identify a set of independent determinants that contribute to explaining the success of such recruitment initiatives.

To assess the impact of different Data Mining determinants on the IT recruitment process, this study relies on a structured online questionnaire administered to recruitment managers within aerospace industry firms. The goal is to gather insights into the perceived influence of each Data Mining determinant on the success of IT recruitment initiatives. The questionnaire developed for this purpose includes two main sections. The first section collects background information on the recruitment managers themselves, while the second section focuses on the determinants of Data Mining—namely, the factors that drive the success of IT profile recruitment processes. All collected information regarding the surveyed IT recruitment managers remains confidential and will not be disclosed.

A careful sampling strategy was employed to ensure the representativeness of the sample, using a simple random sampling technique. The final sample consists of 200 IT recruitment managers from aerospace firms in the Casablanca–Settat region, accounting for the size of the target population. From the initial pool of 220 questionnaires, a total of 200 valid responses were obtained after filtering.

The introductory part of the questionnaire is dedicated to the demographic and professional characteristics of the respondents. The second part includes multiple-choice questions related to the explanatory determinants of the dependent variable—the success of IT recruitment initiatives—using a Likert scale to measure perceptions of each factor.

To provide a clearer overview of the sample, descriptive statistics of the respondents are presented in Table 1. The table summarizes demographic, professional, and organizational characteristics of the 200 valid responses obtained. The distribution shows that male respondents constituted 62% of the sample, with an average age of 37 years, while 38% were female. Recruitment managers reported an average of 6.9 years of professional experience, with 34% having less than five years and 29% having ten years or more. Regarding firm size, almost half of the respondents (45%) worked in large organizations with more than 500 employees, while 31% were employed in firms with fewer than 250 staff. Sectoral distribution was balanced between aeronautics (54%) and digital services (46%). Educational attainment was also diverse, with 34% of participants holding a bachelor's degree, 47% a master's degree, and 19% a doctorate or other advanced qualifications. These statistics confirm both the representativeness and diversity of the sample, providing a robust basis for the empirical analysis.

Table 1. Descriptive statistics of the survey sample.

Category	Attribute	n	f_i	Arithmetic Mean	Standard Deviation δ
Gender	Male	124	62.0%	-	-
	Female	76	38.0%		
Age (years)	<30	52	26.0%	37	9.3
	30–39	74	37.0%		
	40–49	56	28.0%		
	≥50	18	09.0%		
Recruiter experience (years)	<5	68	34.0%	6.9	3.8
	5–9	74	37.0%		
	≥10	58	29.0%		
Firm size (employees)	<250	62	31.0%	466	206
	250–499	48	24.0%		
	≥500	90	45.0%		
Sector	Aeronautics	108	54.0%	-	-
	Digital services	92	46.0%		
Education	Bachelor's degree	68	34.0%	-	-
	Master's degree	94	47.0%		
	Doctorate/Other	38	19.0%		

4.2. Reliability Test

To assess the internal consistency and reliability among the explanatory determinants of a dependent variable, researchers in the social sciences commonly compare the estimated Cronbach's alpha ($\hat{\alpha}$) to a conventional threshold of 0.70, as recommended by Nunnally [94] and supported by George and Mallery [95]. Thus, $\hat{\alpha} > 0.70$ is generally considered indicative of acceptable reliability.

In this study, we aim to analyze the impact of a set of Data Mining determinants on the success of IT recruitment initiatives (the dependent variable). Before incorporating these independent determinants into the "Logit model" to measure the individual influence of each explanatory dimension on the outcome variable, it is essential to first evaluate their reliability to ensure the coherence and validity of the results.

The values reported in the empirical tables were generated using SPSS v27. In the case of reliability analysis, Cronbach's alpha and standardized alpha were computed for each determinant to assess internal consistency. For subsequent regression models, the binary dependent variable (success or failure of IT recruitment) was specified, while the independent variables continuous, ordinal, or categorical were coded appropriately. Logistic regression was then conducted using the Enter method, with parameters estimated through maximum likelihood, and odds ratios (exp β) calculated to interpret the relative contribution of each predictor. This procedure ensured methodological transparency and statistical rigor in the generation of all reported values. According to the reliability test (Table 2), the estimated Cronbach's alpha value $\hat{\alpha} = 0.856$ significantly exceeds the conventional minimum threshold of $\hat{\alpha} = 0.70$ [94,95]. This result indicates that, for the set of six (06) items analyzed, the internal consistency is satisfactory. However, Cronbach's alpha is an empirical construct derived from a body of psychometric studies that are often more subjective than strictly scientific, due to the absence of a precise distribution that would allow researchers to definitively accept or reject its validity [96]. Nevertheless, various theoretical contributions such as those by Feldt et al. [97], Barnette [98], Van Zyl et al. [99], and Iacobucci and Duhachek [100], have proposed statistical approaches for estimating the distribution and confidence intervals of this coefficient. The construction of a confidence interval for Cronbach's alpha requires statistical rigor and provides additional insight for the research community. In this regard, the work of Feldt et al. [100], as well as that of Iacobucci and Duhachek [100], offers methodological procedures to calculate such intervals. However, for the purposes of this study, the approach proposed by Feldt et al. [97] is adopted, this demonstrating that the distribution of $\hat{\alpha}$ follows a Fisher F-distribution, with degrees of freedom $ddl_1 = (n-1)$, et $ddl_2 = (n-1)(k-1)$, where n denotes the sample size and k the number of items included in the scale. Applying Feldt's procedure to the present dataset (n = 200, k = 6) allowed the construction of confidence intervals around the observed Cronbach's alpha ($\hat{\alpha} = 0.856$) based on Fisher's F-distribution. The results confirmed that the reliability coefficient was statistically significant, thereby validating the internal consistency of the scale and justifying its integration into subsequent regression analysis. Accordingly, given a sample of size n, a scale comprising k items, an observed Cronbach's alpha value ($\hat{\alpha}$), and a significance level (γ), the bounds of the confidence interval for Cronbach's alpha following Feldt's method can be computed as follows:

$$IC_{inf} = 1 - \left[(1 - \hat{\alpha}) \times F_{(1-\gamma)/2},\ ddl_1,\ ddl_2\right]$$

$$IC_{sup} = 1 - \left[(1 - \hat{\alpha}) \times F_{(\frac{\gamma}{2})},\ ddl_1,\ ddl_2\right]$$

where F represents the Fisher statistic corresponding to the $\gamma/2$ and $(1-\gamma)/2$ percentiles, respectively, with degrees of freedom $ddl_1 = (n-1)$, and $ddl_2 = (n-1)(k-1)$ (Figure 5).

Table 2. Reliability test.

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Elements	Number of Elements
0.856	0.846	6

Figure 5. Cronbach's alpha value compared to the recommended threshold.

Based on the results presented above, it can be seen that the estimated Cronbach's alpha coefficient $\hat{\alpha} = 0.822 \in IC^{5\%} = [0.838, 0.804]$ falls within the 95% confidence interval, calculated with a sample size of n = 200, and k = 6 independent variables forming the measurement scale. The corresponding degrees of freedom are $ddl_1 = (n-1) = 199$ and $ddl_2 = (n-1)(k-1) = 995$. It is also noted that the values obtained are highly significant, with a p-value = 0.000, which is well below the conventional significance threshold of 0.05. $p = 0.000 < 0.05$ (Table 3).

Table 3. Intra-class correlation coefficient (ICC).

Intra-Class Correlation		95% Confidence Interval		Fisher Test			
		Lower Bound	Upper Bound	Value	ddl_1	ddl_2	Sig.
Single Measures	0.397	0.370	0.425	5.611	199	995	0.000
Average Measures	0.852	0.834	0.868	5.611	199	995	0.000

4.3. Chi-Square Test

The chi-square (χ^2) test (Table 4) is applied exclusively to qualitative variables whether nominal, ordinal, grouped into classes, or binary. Its primary objective is to compare distributions between such variables. There are three main types of chi-square tests (χ^2) the test $\left(\chi^2\right)$ of homogeneity, the goodness-of-fit test (χ^2), and the test (χ^2) of independence. The latter is used in this study to assess whether there is a statistically significant association between the independent variables and the response variable, using a single sample of size n [101]. In other words, the chi-square test of independence allows the determination of whether or not there is a statistical relationship between two qualitative variables X (presumed explanatory) and Y (dependent). As a hypothesis test, the following definition is used: The null hypothesis H_0 is generally rejected when the p-value is less than 0.05, indicating a significant association. In H_0, the two variables X and Y are thus seen to be independent.

Table 4. Chi-square test results.

Explanatory Variables	Pearson Chi-Square	Likelihood Ratio	Linear-by-Linear Association	ddl	Asymptotic Significance (2-sided)
X_1 (ADA)	61.341	59.291	47.001	05	0.001
X_2 (PPR)	58,209	55.376	50.501	05	0.030
X_3 (ORP)	47.129	40.673	38.242	05	0.000
X_4 (TF)	63.304	58.479	51.112	05	0.007
X_5 (ASN)	39.199	31.200	29.470	05	0.013
X_6 (DMT)	51.783	47.490	41.190	05	0.000

Based on the chi-square results, the relationship between the independent variables —Advanced Data Analytics (ADA) (X_1), Performance Prediction (PPR) (X_2), Optimization of the Recruitment Process (ORP) (X_3), Transparency and Fairness (TF) (X_4), Adaptability to Specific Needs (ASN) (X_5), and Detection of Labor Market Trends (DMT) (X_6)—and the dependent variable "Success of the IT Recruitment Initiative" is highly significant, with asymptotic significance values $p < 0.05$, and most often $p = 0.000$.

These results indicate that the null hypothesis H_0 can be rejected, thereby confirming that the selected independent variables are statistically associated with the response variable. In other words, these factors have a significant and influential effect on the success of the IT recruitment process.

4.4. Cramer's V Test

Beyond the chi-square test, which is used to determine whether a relationship exists between variables, Cramer's V test measures the strength and intensity of such a relationship. Cramer's V test was performed using the Pearson chi-square value to clarify the strength of the relationship between the two dependent and independent qualitative variables. For the two qualitative variables X and Y, with k_1 and k_2 categories, respectively, and a valid sample size *n*, Cramer's V is calculated using the following formula:

$$V = \sqrt{\frac{\chi^2}{n \times \min(k_1 - 1, k_2 - 1)}}$$

The absolute value of V ranges between 0 and 1. In our case, the results indicate that all independent variables demonstrate Cramér's V values above 0.30, suggesting a significant relationship with the dependent variable: the success of IT recruitment processes. According to Cramér's test, the determinants Advanced Data Analysis (X_1), Performance Prediction (X_2), Optimization of the Recruitment Process (X_3), Transparency and Fairness (X_4), Adaptability to Specific Needs (X_5), and Detection of Labor Market Trends (X_6) all exhibit a relatively strong association with the recruitment success of IT profiles in the aerospace industry (Tables 5 and 6).

Table 5. Cramer's V test results.

		Cramer's V	Approximate Significance
Explanatory Variable	X_1 (ADA)	0.490	0.001
	X_2 (PPR)	0.449	0.000
	X_3 (ORP)	0.420	0.020
	X_4 (TF)	0.435	0.017
	X_5 (ASN)	0.422	0.000
	X_6 (DMT)	0.389	0.000

Table 6. Interpretation of Cramer's V coefficient.

Absolute Value of Cramer's V	Strength of Association
Between 0 and 0.10	Negligible association
Between 0.10 and 0.20	Very weak association
Between 0.20 and 0.40	Moderate association
Between 0.40 and 0.60	Relatively strong association
Between 0.60 and 0.80	Strong association
Between 0.80 and 1.00	Very strong association

4.5. Adjusted R^2 Test

The model summary provides the values of the −2 Log Likelihood (−2LL), Cox and Snell R^2, and Nagelkerke R^2 for the full model. The −2LL value is 396.009. This value was compared to that of the baseline (null) model using the chi-square test, revealing a highly significant decrease between the two ($p = 0.000 < 0.05$). This result indicates that the full model is significantly better fitted than the null model (Table 7).

Table 7. Adjusted R^2 test.

−2 Log Likelihood	Cox and Snell R^2	Nagelkerke R^2	Total Sum of Squares R^2	Adjusted (R^2)
396.009	0.339	0.611	0.848	0.886

Cox and Snell's R^2 indicates the approximate proportion of the variance in the dependent variable that is explained by the model. In this case, Cox and Snell's $R^2 = 0.339$, suggesting that 33.9% of the variation in the probability of successful IT recruitment is explained by the independent variables.

Nagelkerke's R^2, an adjusted version of Cox and Snell's R^2 and closer to the true coefficient of determination, reaches 0.611. Thus, the independent variables account for approximately 61.1% of the variation in the likelihood of successful IT recruitment.

Furthermore, a high value of the Adjusted R^2—also known as the Adjusted Coefficient of Determination—indicates a better fit of the binary logistic regression model to the observed data. Here, Adjusted R^2 = 0.886, meaning that 88.6% of the variance in the dependent variable is explained by the model. The adjusted R^2 is calculated as follows:

$$R^2\text{Adjusted} = R^2 - \frac{K\left(1 - R^2\right)}{N - K - 1}$$

where

N: Sample size

K: Number of independent variables

R^2: Coefficient of determination

4.6. Estimation of the Coefficients $\hat{\beta}$

A sample of n = 200 was considered, divided into two groups, G_1 and G_2, identifiable by a set of independent variables: Advanced Data Analysis ADA (X_1), Performance Prediction PPR (X_2), Optimization of the Recruitment Process ORP (X_3), Transparency and Fairness TF (X_4), Adaptability to Specific Needs ASN (X_5), Detection of Labor Market Trends DMT (X_6). Let Y be the dichotomous qualitative variable to be predicted (dependent variable), representing the success of the IT recruitment process. Y takes the value (1) if the IT recruiters belong to group G_1, and (0) if they belong to group G_2. These elements are summarized in Table 8.

Table 8. Variables included in the study.

Dependent Variable	Y = 1: Success of the IT recruitment process Y = 0: Failure of the IT recruitment process
Independent variables	X_1: Advanced Data Analytics (ADA) X_2: Performance Prediction (PPR) X_3: Optimization of the Recruitment Process (ORP) X_4: Transparency and Fairness (TF) X_5: Adaptability to Specific Needs (ASN) X_6: Detection of Labor Market Trends (DMT)

The prediction of the success of the IT recruitment process in the aerospace industry based on Data Mining leads to the use of generalized linear models, specifically binary logistic regression under the extension of the logit model. The results obtained are outputs from IBM SPSS Statistics, version 27.

Table 9 provides the regression coefficients $\hat{\beta}$, the Wald statistic for testing statistical significance, the odds ratio ($Exp(\hat{\beta})$) for each explanatory variable, and finally, the confidence interval for each odds ratio (OR). By first examining the results, a highly significant effect of all predictive variables on the dependent variable "success of the IT recruitment process" is observed. However, the two-tailed asymptotic significance (p-value) of the independent variables is as follows: Advanced Data Analysis ADA (X_1): $p = 0.008 < 0.05$, Performance Prediction PPR (X_2): $p = 0.001 < 0.05$, Optimization of the Recruitment Process ORP (X_3): $p = 0.000 < 0.05$, Transparency and Fairness TF (X_4): $p = 0.005 < 0.05$, Adaptability to Specific Needs ASN (X_5): $p = 0.000 < 0.05$, and Detection of Labor Market Trends DMT (X_6): $p = 0.000 < 0.05$.

$X_1 X_2 X_3 X_4 X_5 X_6$ Although it is easy to interpret the *p*-values, the question arises at this stage as to how to interpret the regression coefficients $\hat{\beta}$. This coefficient can only indicate the direction of variation between the explanatory variable and the dependent variable. That is, a positive sign of the coefficient $\hat{\beta}$ indicates a variation in the same direction between the explanatory variable (X) and the response variable (Y), whereas a negative sign implies variation in opposite directions between the two variables. However, the $\hat{\beta}$ coefficient is not directly interpretable. In contrast, the exponential of $\hat{\beta}$, Exp($\hat{\beta}$), is easily interpretable by statisticians.

Table 9. Variables in the equation.

	$\hat{\beta}$	E.S	Wald	ddl	Sig.	Exp ($\hat{\beta}$)	95% Confidence Interval for Exp ($\hat{\beta}$)	
							Inf.	Sup.
X_1 (ADA)	2.110	0.207	28.661	1	0.008	8.248	8.017	8.437
X_2 (PPR)	0.877	0.101	43.495	1	0.001	2.403	2.225	2.611
X_3(ORP)	1.501	0.214	39.023	1	0.000	4.486	4.283	4.627
X_4(TF)	2.201	0.092	25.723	1	0.005	9.034	8.820	9.283
X_5(ASN)	1.980	0.121	35.311	1	0.000	7.242	6.948	7.492
X_6(DMT)	1.328	0.118	41.567	1	0.006	3.773	3.539	3.918
Constant	−10.298	0.771	71.097	1	0.030	0.000	-	-

Exp($\hat{\beta}$), also called the odds ratio (OR), the odds quotient, or the relative risk approximation, expresses the degree of dependence and the effect of an explanatory determinant on the response variable.

The column Exp($\hat{\beta}$) (Odds Ratio) shows that each of the independent variables influences the dependent variable in a distinct manner. According to our study, we can state that the determinant Advanced Data Analysis ADA (X_1) results in eight times greater odds (OR(X_1) = 8.248; 95% CI = [8.017, 8.437]) that recruiters in the aerospace sector are likely to succeed in IT recruitment rather than fail. Similarly, Performance Prediction PPR (X_2) also offers twice the odds (OR(X_2) = 2.403; 95% CI = [2.225, 2.611]) that recruitment managers will succeed rather than fail. Likewise, Optimization of the Recruitment Process ORP (X_3) presents four times greater odds (OR(X_3) = 4.486; 95% CI = [4.283, 4.627]) of achieving a successful IT hire than failure.

Similarly, the determinant Transparency and Fairness TF (X_4) has a strong impact on recruitment success, offering nine times greater odds (OR(X_4) = 9.034; 95% CI = [8.820, 9.283]) of success. Meanwhile, Adaptability to Specific Needs ASN (X_5) provides seven times greater odds (OR(X_5) = 7.242; 95% CI = [6.948, 7.492]) that these industries are capable of promoting the success of the recruitment initiative. Finally, Detection of Labor Market Trends DMT (X_6) results in three times greater odds (OR(X_6) = 3.773; 95% CI = [3.539, 3.918]) that these aerospace firms achieve success in their recruitment efforts rather than fall short of their objectives (Figure 6).

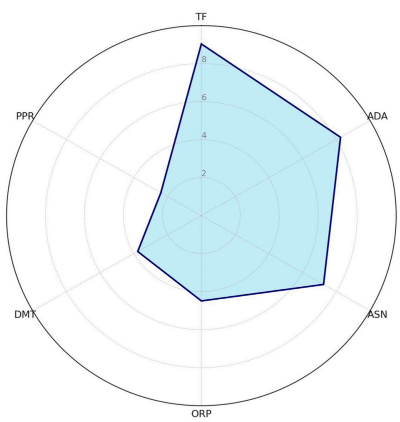
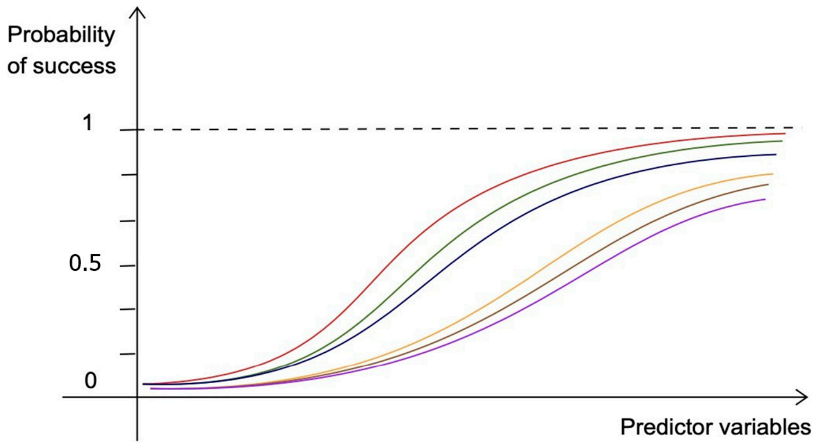


Figure 6. Radar chart of determinants impact (odds ratio).

4.7. Sigmoïd Functions

The probability of success in the IT recruitment process within the aeronautical and digital services industries, when supported by Data Mining, cannot take the form of a straight line, as it is bounded between two values, 0 and 1 (Figure 7). Indeed, the probability of an outcome cannot be represented by a straight line due to its bounded nature. However, it can take the form of a sigmoid function, also known as an S-shaped function, which also represents the cumulative distribution function of the logistic law. This is a mathematical function that can accept any real value from $\mathbb{R}$ and transform it into a value between 0 and 1, thereby generating an S-shaped curve.



Key:

	TF : Transparency and Fairness
	ADA : Advanced Data Analytics
	ASN : Adaptability to Specific Needs
	ORP : Optimization of the Recruitment Process
	DMT : Detection of Labor Market Trends
	PPR : Performance Prediction

Figure 7. Logistic functions (sigmoids).

The logistic function has two asymptotes, Y = 1 and Y = 0, and is thus defined as:

$$Y = \pi = \left(\frac{\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}{1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)} \right) = \left(\frac{1}{1 + \exp\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)} \right)$$

Moreover, if the value of x tends toward positive infinity ($x \rightarrow +\infty$), then Y approaches 1 ($Y \rightarrow 1$), which represents a scenario reflecting the possibility of success in recruiting IT profiles in the aerospace industry through the technological advances of Data Mining. Conversely, if x tends toward negative infinity ($x \rightarrow -\infty$), then Y approaches 0 ($Y \rightarrow 0$), indicating a potential failure in the recruitment process. Success probabilities greater than the 0.5 threshold are classified in class 1, and those below 0.5 in class 0.

Based on the logistic curves presented in the figure above, "Transparency and Fairness" emerges as a powerful determinant of Data Mining, having a highly significant influence on the success of the IT recruitment process in the aerospace sector. The sigmoid curve corresponding to this determinant is the first to change direction in its variation and to cross the probability threshold π = 0.5, thus moving from π = 0, indicating failure of the process, to class 1, that is π = 1, indicating success ($OR(X_4) = 9.034$; $IC^{5\%}$= [8.820, 9.283]).

The second curve is associated with the determinant "Advanced Data Analysis", which surpasses the threshold π = 0.5 immediately after "Transparency and Fairness", placing it in the second rank ($OR(X_1) = 8.248$; $IC^{5\%}$= [8.017, 8.437]).

The third and fourth positions are held, respectively, by the determinants "Adaptability to Specific Needs" and "Optimization of the Recruitment Process". These two Data Mining determinants are characterized by odds ratios of ($OR(X_5) = 7.242$; $IC^{5\%}$= [6.948, 7.492]) and ($OR(X_3) = 4.486$; $IC^{5\%}$= [4.283, 4.627]), surpassing the π = 0.5 threshold shortly after "Advanced Data Analysis".

In contrast, the Data Mining determinants "Detection of Labor Market Trends" and "Performance Prediction" appear in the final positions, represented by sigmoid curves that cross the π = 0.5 threshold more gradually, with odds ratios of ($OR(X_6) = 3.773$; $IC^{5\%}$= [3.539, 3.918]) and ($OR(X_2) = 2.403$; $IC^{5\%}$= [2.225, 2.611]), respectively.

Nonetheless, the representation of sigmoid curves enables a precise ranking of Data Mining determinants based on their degree of impact on the probability of success in the IT recruitment process within the aerospace industry.

4.8. Area Under Curve (AUC) Test

The AUC (Area Under the Curve) represents the probability of ranking a positive instance before a negative one (Table 10). The AUC values were obtained in two complementary steps. First, each explanatory determinant was entered individually into a univariate logistic regression, with the resulting AUC reflecting its standalone discriminant capacity in predicting recruitment success. These AUCs are therefore independent measures of predictive performance and should not be interpreted as additive contributions, which explains why their summation does not equal 100%. Second, a multivariate logistic regression including all six determinants was also estimated, from which the global regression coefficients ($\hat{\beta}$) and the overall AUC of the full model were derived. This combined approach allows both the assessment of each determinant's individual predictive capacity and the evaluation of their joint explanatory power. This technique proposes a reference value of AUC = 0.5, which the classifier must exceed to demonstrate predictive utility. At first glance, all results are highly significant, with $p = 0.000 \leq 0.05$. Moreover, the table below also displays AUC values that exceed the reference threshold (AUC = 0.5), indicating that the Data Mining determinants involved in this study have a pronounced impact on the probability of successful IT recruitment in the aerospace sector.

Table 10. Area under curve test.

Independents Variables	AUC	Standard Error	Asymptotic Sig.	Asymptotic Confidence Interval for 95%	
				Inferior	Superior
X_1 (ADA)	0.723	0.021	0.010	0.760	0.802
X_2 (PPR)	0.223	0.017	0.007	0.206	0.240
X_3(ORP)	0.461	0.022	0.027	0.439	0.483
X_4(TF)	0.827	0.020	0.000	0.807	0.847
X_5(ASN)	0.623	0.012	0.009	0.611	0.635
X_6(DMT)	0.389	0.028	0.000	0.361	0.417

Furthermore, “Transparency and Fairness” is likely to contribute to the success of the IT recruitment process in the aerospace industry at a rate of 82.7% ($IC^{5\%}$ = [0.807–0.847]). Similarly, “Advanced Data Analysis” contributes 72.3% ($IC^{5\%}$ = [0.601–0.802]) to the probability of success in this operation. Additionally, Data Mining determinants such as “Adaptability to Specific Needs” and “Optimization of the Recruitment Process” influence success with frequencies of 62.3% ($IC^{5\%}$ = [0.611–0.635]) and 46.1% ($IC^{5\%}$ = [0.439–0.483]), respectively, in achieving successful IT recruitment in the aerospace sector.

However, in the lowest ranks, the determinants “Detection of Labor Market Trends” and “Performance Prediction”, respectively, offer 38.9% ($IC^{5\%}$ = [0.361–0.417]) and 22.3%. ($IC^{5\%}$ = [0.206–0.240]) likelihood for recruitment managers in various aerospace branches to achieve their recruitment objectives in the IT field (Figure 8).

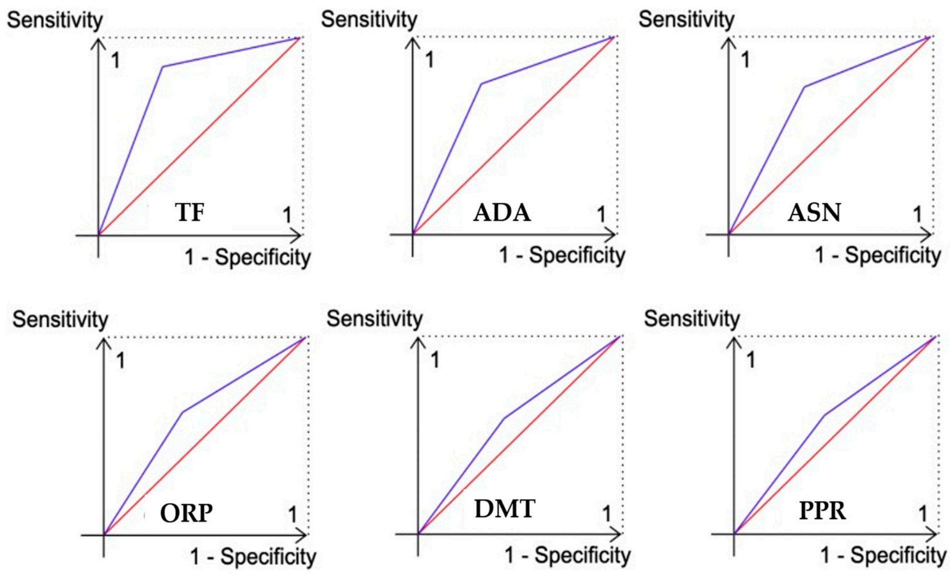


Figure 8. Area under the curve.

4.9. Summary Responses to the Research Objectives

This subsection provides a synthesis of the findings in relation to the two main research objectives outlined above. It aims to clarify how the empirical results support each objective and highlight the broader relevance of the proposed model.

RO1: *To identify which dimensions of Data Mining have the most significant effect on recruitment performance.*

The empirical analysis confirms that all six dimensions of Data Mining significantly influence the success of IT recruitment processes. Among them, Transparency and Fairness (TF) emerges as the most influential determinant (OR = 9.034), followed closely by Advanced Data Analytics (ADA) (OR = 8.248) and Adaptability to Specific Needs (ASN) (OR = 7.242). These results demonstrate that beyond predictive power, ethical governance and contextual alignment are critical levers for performance. The logit model, the sigmoid functions, and the AUC values consistently indicate that these dimensions substantially enhance the likelihood of successful hiring outcomes in digitally intensive firms.

In addition, the findings provide clear managerial implications for reducing recruitment time and costs. Specifically, Optimization of the Recruitment Process (ORP) contributes to cycle-time compression and administrative cost reduction through the automation of repetitive tasks, while Advanced Data Analytics (ADA) decreases search time and costly interview rounds by generating more accurate shortlists. Similarly, Adaptability to Specific Needs (ASN) curbs waste by tailoring recruitment models to organizational requirements, ensuring that resources are allocated efficiently. These insights align with prior research showing that e-recruitment and e-HRM decrease transaction times, lower per-hire costs, and generate measurable efficiency gains [102–104]. More recent evidence confirms that AI-enabled selection shortens time-to-hire and produces cost savings by expediting candidate–vacancy matching [105].

RO2: *To propose a contextualized analytical framework applicable to other organizational environments with similar characteristics.*

Building upon the thematic synthesis and the empirical findings, this study proposes a six-dimensional analytical framework tailored to recruitment contexts characterized by high digital maturity, talent scarcity, and strategic use of data (Figure 9).

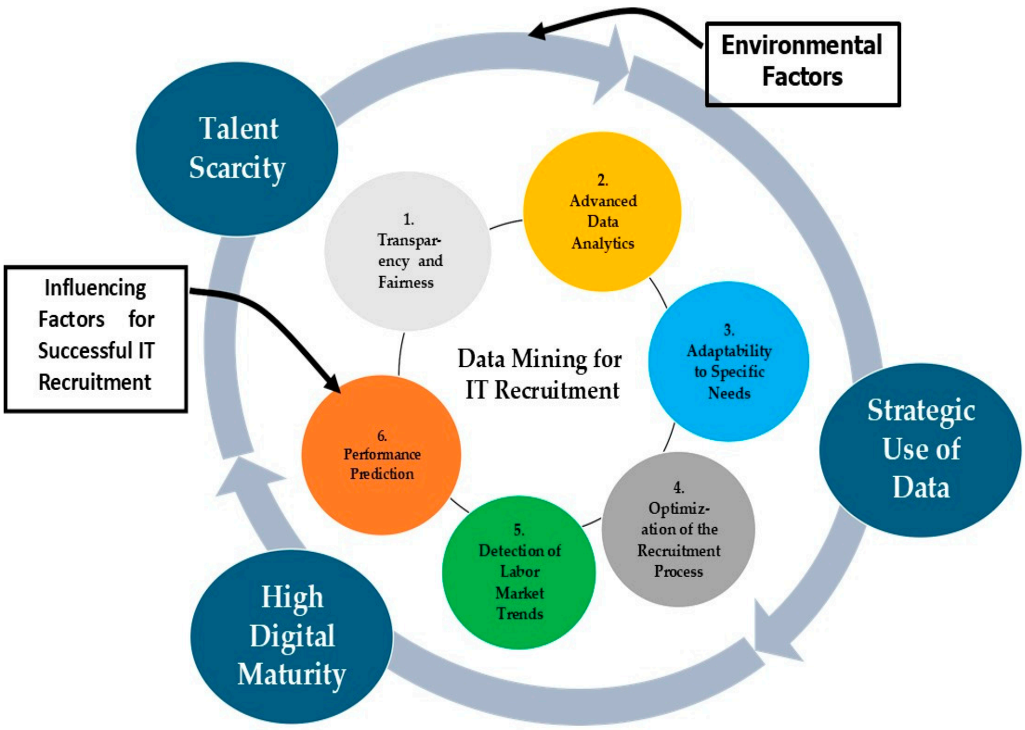


Figure 9. Analytical framework: the key determinants for Data Mining in IT recruitment.

The model integrates both technological and ethical dimensions, making it adaptable to other sectors facing similar recruitment pressures—such as fintech, aerospace, or smart manufacturing. It also aligns with broader theoretical traditions (TAM, TOE, RBV, TPB), reinforcing its conceptual transferability. Thus, the framework offers not only explanatory power but also practical guidance for organizations seeking to operationalize algorithmic recruitment in a responsible and effective manner.

5. Conclusions

This article set out to establish and investigate the Data Mining determinants influencing the success of IT profile recruitment. These determinants, conceptualized as independent variables, were: Transparency and Fairness (TF), achieved through algorithmic decision-making that avoids human bias, ensuring objective evaluation of candidates' skills and qualifications regardless of their background or identity; Advanced Data Analytics (ADA), which relies on machine learning techniques and statistical algorithms to extract high-value insights from large datasets (Big Data), thereby facilitating and optimizing the recruitment process; Adaptability to Specific Needs (ASN), which allows for tailored identification of required competencies and attributes for each position, thereby improving the alignment between candidates and organizational needs; Optimization of the Recruitment Process (ORP), which identifies inefficiencies and automates repetitive tasks to reduce the time and costs associated with recruitment; and Detection of Labor Market Trends (DMT), which enables anticipation of future recruitment needs and supports the adjustment of sourcing and hiring strategies to remain competitive in any market; and Performance Prediction (PPR), which draws on historical data and predictive statistical models to better assess a candidate's suitability for a specific role and to reduce subjective biases.

The results highlight the crucial importance of integrating advanced technologies and strategic Big Data analysis into intelligent and modern recruitment practices. By adopting these approaches, companies can not only improve the quality of their IT hires but also reduce recruitment costs and timelines, while ensuring a fairer and more objective assessment of candidates. These benefits clearly position Data Mining and its related technologies as fundamental tools for the sustained success of recruitment strategies in a competitive environment marked by continuous change.

When positioned within the international literature, the results of this study both confirm and nuance existing findings. Similarly to studies conducted in advanced economies, the evidence presented here shows that advanced analytics, predictive modeling, and process optimization significantly improve recruitment outcomes [17,106]. However, in contrast to research from the U.S. and Europe where automation and efficiency dominate the debate [44,83], the Moroccan context underscores the critical importance of transparency, fairness, and adaptability. This suggests that in emerging economies, algorithmic legitimacy and contextual alignment weigh more heavily in shaping adoption. Methodologically, the reliance on a binary logit model provided robust inferential power and interpretability, yet it limits predictive accuracy compared to machine learning approaches.

From a theoretical perspective, this research advances the literature on HR analytics by synthesizing insights from diverse conceptual traditions. It demonstrates that algorithmic recruitment is not a purely technical shift but a complex socio-organizational transformation that requires alignment between data capabilities, ethical safeguards, and contextual adaptability. Moreover, it provides empirical support for the argument that the adoption of Data Mining in recruitment is mediated by organizational readiness, candidate perception, and sectoral dynamics.

On the managerial side, the findings offer concrete recommendations for recruiters, HR strategists, and digital transformation leaders. First, investing in advanced analytics infrastructure must be accompanied by training programs to enhance digital literacy among HR professionals. Second, algorithmic tools should be designed to be transparent, auditable, and responsive to feedback, ensuring fairness and accountability. Third, organizations should adopt a modular and adaptive approach to talent acquisition systems, allowing for customization according to job categories, business models, and evolving market needs.

Whilst the strength of the approach adopted in this research lies in testing theory-driven determinants and providing transferable insights for similar contexts, its main limitations include the cross-sectional design, the national focus, and the exclusion of temporal dynamics: the analysis being based on cross-sectional data collected within a single national context limits the generalizability of the findings to other regions or industries. Moreover, while the binary logistic regression provides a solid inferential framework, it does not capture the temporal dynamics or potential nonlinearities in algorithmic adoption and its outcomes. This article identified and assessed only a limited number of Data Mining determinants explaining the success of IT recruitment processes. It may also be beneficial to employ more powerful predictive models than the Logit model and to conduct comparative analyses of the results obtained. Similarly, a larger sample size may yield more robust estimations. In addition, future research in this field could profitably consider the contribution of additional Data Mining techniques, such as Natural Language Processing (NLP), Candidate Lifetime Value (CLV) analysis, and others, to the success of recruitment processes across various sectors and industries. Future studies could build on the findings presented here by employing longitudinal or comparative international studies, as well as hybrid models that combine econometrics with machine learning. Taken together, the present research contributes to bridging a geographic and methodological gap in HR analytics, while situating the Moroccan experience within a broader global conversation on the digital transformation of recruitment.

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Appendix A. Logit Transformation Detail

Logistic regression, introduced by Nelder and Wedderburn [107], is one of the extensions of Generalized Linear Models (GLMs). It is commonly used to model binary response variables (presence/absence), as discussed in the work of Bordeaux and Couto [108]. The dependent variable y_i follows a Bernoulli distribution, i.e., $y_i \sim \mathcal{B}(1, \pi)$. The conditional probability of success is given by $P\ (y_i = 1 \mid X) = \pi$, and the probability of failure by $P\ (y_i = 0 \mid X) = 1 - \pi$, where XX denotes the matrix of independent variables. The "logit" model is expressed through the following logit function:

$$\text{logit}(\pi) \ = \ \ln\left(\frac{\pi}{1-\pi}\right) = \sum_{k=0}^{p} \beta_k x_{ik},\ \text{with } i = 1, \ldots, n \quad \text{(A1)}$$

By applying the logit transformation to Equation (A1), Equation (A2) is obtained:

$$\left(\frac{\pi}{1-\pi}\right) = \ \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right) \quad \text{(A2)}$$

Equation (A2) is solved to express π and $1 - \pi$ as follows:

$$\pi = \left(\frac{1}{1+\exp\left(-\sum_{k=0}^{p}\beta_k x_{ik}\right)}\right) \tag{A3}$$

$$1 - \pi = \frac{\exp\left(-\sum_{k=0}^{p}\beta_k x_{ik}\right)}{1+\exp\left(-\sum_{k=0}^{p}\beta_k x_{ik}\right)} \tag{A4}$$

The estimation of the parameters β of the nonlinear Bernoulli equations by maximum likelihood estimation (MLE) assigns a contribution of π when y_i = 1, and $1 - \pi$ when y_i = 0. The expression of this contribution to the likelihood function is therefore written as follows:

$$\mathrm{L}\ (y_1, y_2, \ldots y_n, \pi)\ =\ \prod_{i=1}^{n}\pi^{y_i}(1-\pi)^{1-y_i} = \prod_{i=1}^{n}\left(\frac{\pi}{1-\pi}\right)^{y_i}(1-\pi) \tag{A5}$$

$$\mathrm{L}\left(y_1, y_2, \ldots y_n, \beta_1, \beta_2, \ldots \beta_p\right) = \prod_{i=1}^{n}\left(\exp\left(y_i\sum_{k=0}^{p}\beta_k x_{ik},\right)\right)\left(1\exp\left(\sum_{k=0}^{p}\beta_k x_{ik},\right)\right)^{-1} \tag{A6}$$

For computational simplicity, the natural logarithm is introduced. Being a monotonic function, the maximum of the likelihood corresponds to the maximum of the log-likelihood. Thus, the log-likelihood function ℓ is expressed as follows:

$$\ln(\mathrm{L}(y_{\ 1}, y_2, \ldots y_n, \beta_1, \beta_2, \ldots \beta_p)) = \ln\left(\prod_{i=1}^{n}\left(\exp\left(y_I\sum_{k=0}^{p}\beta_k x_{ik}\right)\right)\left(1+\exp\left(\sum_{k=0}^{p}\beta_k x_{ik}\right)\right)^{-1}\right) \tag{A7}$$

$$\ell\ \left(y_1, y_2, \ldots y_n, \beta_1, \beta_2, \ldots \beta_p\right) = \sum_{i=1}^{n} y_i\left(\sum_{k=0}^{p}\beta_k x_{ik}\right) - \ln\ \left(1+\exp\left(\sum_{k=0}^{p}\beta_k x_{ik}\right)\right) \tag{A8}$$

The estimation of the parameters $\hat{\beta} = (\hat{\beta_0}, \hat{\beta_1}, \ldots, \hat{\beta_p})$ that maximize the log-likelihood function can be obtained by differentiating the score function ℓ' (the gradient of ℓ), and then verifying that the Hessian matrix ℓ'' is negative definite, meaning that each diagonal element of this matrix is less than zero.

$$\frac{\partial\ell(\beta)}{\partial\beta_k} = \ell'_{\beta_k} = \sum_{i=1}^{n} y_i x_{ik} - \pi.x_{ik} \tag{A9}$$

To solve the nonlinear equations in ββ, the iterative Newton–Raphson optimization method is used. This method starts by choosing a starting point β0β0 or βoldβold. Then, the method proceeds as follows:

$$\beta^{new} = \ \beta^{old} + \left[-\ell''\left(\beta^{old}\right)\right]^{-1} \times \ell'\left(\beta^{old}\right) \tag{A10}$$

Appendix B. Extract of the Survey Questionnaire

Explanatory Variables

(Please indicate your level of agreement with each statement. Scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree).

1. Advanced Data Analytics (ADA): Advanced data analytics contributes positively to the success of the IT recruitment process.
2. Performance Prediction (PPR): The prediction of candidate performance has a positive effect on the success of IT recruitment.
3. Optimization of the Recruitment Process (ORP): The optimization of the recruitment process improves the success of IT hiring.
4. Transparency and Fairness (TF): Transparency and fairness promote the success of the IT recruitment process.

5. Adaptability to Specific Needs (ASN): Adaptability to specific job requirements has a positive effect on IT recruitment success.
6. Detection of Labor Market Trends (DMT): The detection of labor market trends contributes to the success of IT recruitment.

Dependent Variable

7. Success of IT Recruitment (Binary):

Does data mining support the success of IT recruitment in the aerospace sector?
☐ No (0) ☐ Yes (1)

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