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Exploiting Artificial Intelligence to Enhance Human Resource Recruitment

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Patras, Greece, June 2026

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To my beloved son, George

Abstract

This research investigates professionals' perception of Artificial Intelligence (AI) application in recruitment and selection processes, focusing on the effectiveness of AI tools, the quality of decision making, the trust in AI systems, the governance and explainability of algorithms and the role of behavioral profiling, team fit and team-role frameworks in contemporary human resource management. The research technique was quantitative in nature and included a standardized electronic questionnaire that was sent to professionals working in various organizational areas and responsibilities. The total sample consisted of 182 people.

Statistical Package for the Social Sciences (SPSS) was used for data analysis. Tests of reliability and validity, descriptive statistics, exploratory factor analysis, normality tests, Pearson correlations, regression analyses and analyses of variance (ANOVA) were undertaken. The findings demonstrated that the study instrument has good reliability (Cronbach's α = .923) as well as substantial positive connections between perceived efficiency of AI, faith in AI systems, desire to use AI technologies and the relevance of explainability and governance. At the same time, it was revealed that the participants favorably view behavioral profile, team fit and team-role approaches as complimentary aspects in the people selection process. The results show that corporations are more likely to embrace AI technologies when they are seen as transparent, dependable and a complement to human judgment rather than a replacement for it. It also underscores the increasing significance of the combination of technical capabilities and behavioral characteristics in the contemporary recruiting environment. This research adds to the AI-assisted recruiting literature by emphasizing the significance of a balanced strategy that includes technical and human-centric components in HR decision-making.

Keywords

Artificial Intelligence, recruitment, behavioral profiling, team fit, team roles, trust in AI, explainability, human resources.

Μελέτη Αξιοποίησης της Τεχνητής Νοημοσύνης για τη Βελτίωση της Διαδικασίας Πρόσληψης Ανθρώπινου Δυναμικού

Αντώνιος Γ. Μισαργόπουλος

Περίληψη

Η παρούσα έρευνα εξετάζει τις αντιλήψεις επαγγελματιών σχετικά με τη χρήση της Τεχνητής Νοημοσύνης (Artificial Intelligence – AI) στις διαδικασίες προσλήψεων και επιλογής προσωπικού, με ιδιαίτερη έμφαση στην αποδοτικότητα των AI εργαλείων, την ποιότητα λήψης αποφάσεων, την εμπιστοσύνη προς τα συστήματα AI, τη διακυβέρνηση και επεξηγησιμότητα των αλγορίθμων, καθώς και τη σημασία του behavioral profiling, του team fit και των team-role frameworks στη σύγχρονη στελέχωση ανθρώπινου δυναμικού. Η μελέτη βασίστηκε σε ποσοτική ερευνητική προσέγγιση μέσω δομημένου ηλεκτρονικού ερωτηματολογίου, το οποίο διανεμήθηκε σε επαγγελματίες που δραστηριοποιούνται σε διαφορετικούς οργανωσιακούς κλάδους και ρόλους. Το τελικό δείγμα αποτέλεσαν 182 συμμετέχοντες.

Για την ανάλυση των δεδομένων χρησιμοποιήθηκε το στατιστικό πακέτο SPSS. Πραγματοποιήθηκαν έλεγχοι αξιοπιστίας και εγκυρότητας, περιγραφική στατιστική, διερευνητική παραγοντική ανάλυση (Exploratory Factor Analysis), έλεγχοι κανονικότητας, συσχετίσεις Pearson, αναλύσεις παλινδρόμησης και αναλύσεις διακύμανσης (ANOVA). Τα αποτελέσματα έδειξαν υψηλή αξιοπιστία του ερευνητικού εργαλείου (Cronbach's $\alpha = .923$) και ανέδειξαν σημαντικές θετικές συσχετίσεις μεταξύ της αντιλαμβανόμενης αποδοτικότητας της AI, της εμπιστοσύνης προς τα AI συστήματα, της πρόθεσης υιοθέτησης AI τεχνολογιών και της σημασίας του explainability και governance. Παράλληλα, διαπιστώθηκε ότι το behavioral profiling, το team fit και οι team-role προσεγγίσεις αξιολογούνται θετικά από τους συμμετέχοντες ως συμπληρωματικοί παράγοντες στη διαδικασία επιλογής προσωπικού.

Τα ευρήματα υποδεικνύουν ότι οι οργανισμοί εμφανίζονται περισσότερο πρόθυμοι να υιοθετήσουν AI εργαλεία όταν αυτά θεωρούνται διαφανή, αξιόπιστα και υποστηρικτικά της ανθρώπινης κρίσης και όχι υποκατάστατά της. Επιπλέον, αναδεικνύεται η αυξανόμενη σημασία της συνδυαστικής αξιολόγησης τεχνικών δεξιοτήτων και συμπεριφορικών χαρακτηριστικών στο σύγχρονο περιβάλλον στελέχωσης. Η μελέτη συμβάλλει στη βιβλιογραφία της AI-assisted recruitment, αναδεικνύοντας τη σημασία της ισορροπίας μεταξύ τεχνολογικής και ανθρωποκεντρικής προσέγγισης στη λήψη αποφάσεων ανθρώπινου δυναμικού.

Λέξεις-κλειδιά
Τεχνητή Νοημοσύνη, προσλήψεις προσωπικού, behavioral profiling, team fit, team roles, trust in AI, explainability, ανθρώπινο δυναμικό.

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1. Introduction

Recruitment and selection are two of the most strategically important aspects of Human Resource Management (HRM) since they directly impact the quality of the workforce, organizational competence and long-term competitive advantage (Kristof, 1996; Werbel & Gilliland, 1999; Seikiguchi, 2004). Modern recruiting is not only about filling vacancies, it is about identifying the knowledge, skills and behavioural qualities of potential employees that match with corporate goals and contribute to sustainable organisational success (Cable & Judge, 1997; Kristof-Brown et al., 2005; Edwards & Shipp, 2007). This strategic perspective is particularly relevant in organizations in the area of Information and Communication Technology (ICT) where the rapid technological developments and constant shortages of highly skilled professionals and intense labour market competition require organizations to adapt more and more sophisticated recruitment practices (Upadhyay & Khandelwal, 2018; Vrontis et al., 2022). Moreover, the project-based nature of ICT work heavily stresses cooperation, information sharing and good teamwork, which means that recruitment choices extend beyond the assessment of individual credentials and significantly impact total team performance (Marks et al., 2001; Hollenbeck et al., 2012; Banks et al., 2014).

The above issues have made Artificial Intelligence (AI) an increasingly important component of modern recruiting and selection procedures. AI-powered recruiting tools allow firms to analyze massive amounts of application data rapidly, automate repetitive screening operations and empower recruiters to find potentially appropriate individuals (van Esch et al., 2019; Johnson et al., 2020; Thakur et al., 2023). Many firms have thus implemented AI technology to cut recruiting expenses, shorten hiring processes, and increase the consistency of recruitment judgments (Vrontis et al., 2022; Johnson et al., 2020). However, the increased dependence on AI has also resulted in substantial academic and professional debates. Efficiency is certainly a plus for technology, but there is mounting evidence that better automation doesn't equal better quality in recruiting. Rather, questions of algorithmic transparency, fairness, accountability and potential discrimination have become central in the academic literature and in organizational practice, not least because recruitment decisions have major consequences for both individuals and organizations (Floridi et al., 2018; Taeihagh, 2021; Rigotti & Fosch-Villaronga, 2024).

Another constraint found in the current AI enabled recruiting methods is the focus on technical credentials, keyword matching and analysis of curriculum vitae (Faliagka et al., 2012; Upadhyay & Khandelwal, 2018). These methods improve the effectiveness of applicant screening, but often ignore behavioral traits that affect interpersonal cooperation, organizational integration and long-term job retention (Pan et al., 2023; Koechling & Wehner, 2023). Recent research increasingly reveals that effective recruiting cannot be described by a simple matching of technical abilities with job needs. Instead, recruiting results are also influenced by behavioural traits, interpersonal compatibility and the fit of applicants within existing organizational and team contexts (Kristof, 1996; Kristof-Brown et al., 2005; Li et al., 2019). Hence, the behavioural profiling, person–organization fit and team-fit perspectives provide an essential theoretical supplement to AI-assisted recruiting, since they cover elements that traditional AI screening methods typically miss (Edwards & Shipp, 2007; Seong & Kristof-Brown, 2012; Pan et al., 2023). This points to the need of evaluating the efficacy of AI recruitment not just in terms of operational efficiency but also in terms of its potential to facilitate higher-quality recruiting choices contributing to sustained organizational performance (Vrontis et al., 2022; Koechling & Wehner, 2023).

In this context, the current research focuses on the perspectives of HR professionals and ICT recruiting managers in Greece, towards the usage of AI in recruitment and the contribution of behavioural profiling to recruitment decision-making. The research attempts to fill an essential theoretical and practical need in the current literature by the integration of the views of AI-supported recruiting, behavioral profiling, fit theory and team-role approaches into a unified conceptual framework. More specifically, while previous research has extensively investigated AI adoption, recruitment automation, and organizational fit as largely independent streams of research, relatively little attention has been paid to understanding how these perspectives interact in technology-intensive recruitment environments (Pan et al., 2023; Zahedi Nejad et al., 2024). The literature review therefore forms the theoretical foundation for the study by critically reviewing three interconnected areas: (1) AI-based recruitment systems and their opportunities and challenges, (2) behavioural profiling and fit theory as determinants of recruitment effectiveness, and (3) team-fit approaches and team-role frameworks, including the Belbin model, as complementary mechanisms to improve recruitment quality beyond the assessment of technical competencies alone (Belbin, 2010; Vrontis et al., 2022; Rigotti & Fosch-Villaronga, 2024).

2. Literature Review

2.1 Competing on AI in Hiring: Optimization vs Governance Risk

AI has quickly transformed the process of decision-making in companies by automating difficult procedures and enhancing data-driven management in many areas of company. One of the most hit areas is Governance, Risk Management and Compliance (GRC). GRC helps organizations detect risks, maintain effective governance and comply with increasingly severe rules. Governance, risk management and compliance are increasingly seen as interconnected processes that enhance organizational resilience, accountability and economic success.

GRC operations were heavily dependent on manual processes such as interviews, self-assessment questionnaires, compliance checklists, document checks and gap assessments. These approaches provide useful insight into organization, but are labor intensive, time consuming and mistake prone because of human judgment and fragmented information processing. Organizational environments are becoming more complicated and legal requirements are expanding. These boundaries have encouraged organizations to seek more efficient and data-driven governance and compliance management.

AI can revolutionize GRC operations via improved data analytics, pattern recognition, predictive model creation, and automating intelligent processes. AI may be used to analyze large amounts of structured and unstructured data, helping firms see hazards early, see more clearly if they are meeting legal requirements and make quicker management choices based on facts. Operational efficiency, reduction in administrative expenses and organizational response to rapidly changing regulatory environment are advantages associated with the use of AI (Papazafeiropoulou & Spanaki, 2016; Taeihagh, 2021).

However, the use of AI in governance frameworks has ignited an important academic discussion on technical optimization and governance risk. Many studies have highlighted the operational advantages of adopting AI, while others have argued that the rise of automation poses governance challenges, such as algorithmic bias, lack of transparency, diminished explainability, and unclear responsibility for automated decisions. AI-assisted judgments in significant organizational processes like recruiting may effect job opportunities, workforce diversity, and organizational fairness. Therefore, the efficacy of AI should be evaluated in terms of governance principles, ethical responsibility, and compliance pertaining regulatory prerequisites, and not just what involves efficiency issues (Wirtz et al., 2022; Safdar et al., 2020; Xia, 2023).

Current research in AI is concerned with this tension between technical optimization and government accountability. An growing number of experts say that effective AI adoption depends on firms developing governance frameworks that allow for transparency, fairness, human monitoring, and responsible decision-making throughout the AI lifespan. So, AI governance is now considered a strategic competence that enables firms to take use of AI while mitigating its hazards. The theoretical basis for AI-assisted recruitment systems, which have to combine operational efficiency with governance for ethical hiring, is this idea.

2.1.1 Apply Artificial Intelligence to Governance

Effective governance is a vital prerequisite for firms operating in an increasingly complex technological and regulatory environment, especially when relying on Artificial Intelligence systems to support decisions with significant organizational implications. Governance in this sense is far more than just compliance with the law or statutory obligations. It aims, rather, to ensure the use of Artificial Intelligence systems in a manner that is compatible with the strategic objectives of the company and with the ethical principles and obligations that arise from the institutional framework. At the same time it helps to enhancing transparency, accountability and responsible decision-making, decreasing the technical and organisational risks that might arise from the use of these technologies.

The worldwide literature is increasingly focused on the importance of governing Artificial Intelligence. Wirtz et al. (2022) propose the risk-based governance paradigm. It allows organizations to systematically assess dangers of AI systems and allocate available resources according to severity and likelihood. The authors argue that effective governance is not only a matter of formally complying with regulations, but also helps establish organizational resilience via ongoing risk assessment and deployment of proper control mechanisms. Therefore, as Taeihag (2021) states, the rapid development of Artificial Intelligence in autonomous vehicles, robotics and defense requires the development of comprehensive governance frameworks that can address the ethical, legal and social issues that come with the use of these technologies. In general, the methodologies under discussion do not consider AI governance as a problem of regulatory compliance, but as a strategic organizational capability. This facet is especially relevant in AI-assisted recruiting processes, where the availability of effective governance systems will not only influence to assure compliance with the necessary legislative framework but also to foster more fairness, transparency and confidence in staff selection choices.

2.1.2 Use Artificial Intelligence in Risk Management

Risk management is a key part of corporate governance and involves the identification, assessment and mitigation of risks that may adversely influence an organization's operations, strategy and overall performance (Papazafeiropoulou & Spanaki, 2016; Taeihagh, 2021; Wirtz et al., 2022). But the amount and complexity of data that contemporary enterprises have to analyze are increasingly proving difficult for conventional risk management solutions to deal with. The continual rise of information that is accessible and the pace of change of the business environment make required the use of technology able to enable more prompt and evidence-based choices. In this context, Artificial Intelligence has become an important tool to strengthen the risk management, as it allows the processing of large volumes of internal and external data, the identification of new risk patterns and the development of predictive assessments that support the administrative decision-making more effectively (Vinay, 2024; Mujtaba & Yuille, 2024).

The contribution of Artificial Intelligence to risk management is currently seen in a broad variety of organizational applications. In a comparative examination of risk assessment frameworks based on Artificial Intelligence, and implemented in the public, commercial and non-profit sectors, Xia et al. (2023) find that the application of AI may make the risk assessment process more systematic and evidence-based. The offered frameworks include numerous characteristics, such as the parties involved, organizational systems, environment specifics and different evaluation methodologies. The authors also point out that there is still a lot of variation across the various techniques, which shows that risk management using Artificial Intelligence is still in its infancy and needs further theoretical and methodological development.

However, in addition to the application of Artificial Intelligence to address organizational risks, the current research acknowledges that the usage of AI itself generates new issues for the governance of businesses. "Now, risk management strategies need to incorporate critical factors such as cybersecurity, privacy and malicious use of AI technologies," Jeong (2020) said. All the above applications highlight the great potential of Artificial Intelligence in enhancing organizational resilience but at the same time they point out that its successful exploitation requires strong governance mechanisms, which will balance technological innovation with transparency, accountability and effective risk control (Floridi et al., 2018; Hoffmann et al., 2019; Wirtz et al., 2022). This requirement is especially acute in the context of staff recruiting procedures assisted by Artificial Intelligence systems, where algorithmic conclusions need to be not only successful, but also fair, transparent and consistent with the norms of contemporary corporate governance (Shin & Park, 2019; Rigotti & Fosch-Villaronga, 2024).

2.1.3 Artificial Intelligence Application and Adherence

The convergence of AI with Governance, Risk and Compliance (GRC) technologies has revolutionized the companies approach compliance to rules and regulations (Papazafeiropoulou & Spanaki, 2016; Taeihagh, 2021; Wirtz et al., 2022). Traditional approaches relied on periodic and human inspections while AI systems are continuously monitoring and analyzing huge amounts of data in real time. This helps to discover variations or possible violations at an early stage and in this way they assist in decreasing administrative expenses and enhancing control procedures (Vinay, 2024; Mujtaba & Yuille, 2024).

One of the main benefits of AI in regulatory compliance is predictive analytics. AI systems may analyze data from an organization to regulatory criteria and find trends that may signal future non-compliance. This enables firms to avoid infractions and decrease financial fines and reputational damage. AI changes compliance from reactive to proactive and systemic (Vinay, 2024; Wirtz et al., 2022). AI automates reporting, controls, data refreshes, and complete audit trails. This approach may increase the compliance accuracy, consistency, timeliness and organizational transparency and accountability (Vinay, 2024; Papazafeiropoulou & Spanaki, 2016). But such benefits do not remove human monitoring. Far from it. With compliance procedures becoming ever more automated, full governance frameworks will be required to assure the reliability of AI system output, regulatory compliance, and stakeholder confidence (Floridi et al., 2018; Hoffmann et al., 2019; Taeihagh, 2021). AI-powered recruiting procedures are significantly more critical for compliance as it promotes fairness, transparency and ethical decision making throughout the process (Shin & Park, 2019; Rigotti & Fosch-Villaronga, 2024).

2.1.4 Implications for the Present Study

The fragmentation shown in the research to far has significant implications for comprehending the application of Artificial Intelligence in recruiting procedures. Although numerous studies have been published on the adoption of AI, its governance, organizational adaptability and the selection of people, these issues are often considered separate from each other (Vrontis et al., 2022; Pan et al., 2023; Rigotti & Fosch-Villaronga, 2024). Therefore, little is known about the interplay between the operational efficacy of AI systems, governance needs and user perceptions and their impact on the acceptability of Artificial Intelligence in human selection procedures (Koechling & Wehner, 2023; Zahedi Nejad et al., 2024). This gap is especially visible in the Information and Communication Technologies (ICT) industry where the permanent lack of trained workers, the project-based work and the strong engagement between team members make the recruiting choice more complicated and multifaceted (Upadhyay & Khandelwal, 2018; Vrontis et al., 2022).

In this context, the effective usage of AI systems is not just a function of their technological capabilities. Speed of data processing and the possibility of working with large volumes of information are significant advantages, but professionals involved in recruitment processes also seem to assess these systems on the basis of whether they are perceived as reliable, transparent, fair and able to support good decisions on personnel selection (Floridi et al., 2018; Taeihagh, 2021; Rigotti & Fosch-Villaronga, 2024). Operational efficiency is thus not adequate to justify the introduction of Artificial Intelligence in recruiting procedures. The desire to use it is also impacted by factors connected to the governance of AI systems, which determine the amount of trust of users and hence their intention to use these technologies (Davis, 1989; Venkatesh et al., 2003; Nakashima et al., 2024). With the theoretical assumptions presented above, the present study offers a single conceptual framework that consolidates four interdependent dimensions: perceived effectiveness of Artificial Intelligence, perceived risk associated with its use, trust in AI systems and the intention to adopt them in recruitment processes. The choice of these concepts is based on the literature at present, according to which the acceptance of Artificial Intelligence is not only a consequence of its technological capabilities, but it is influenced by the interaction between perceived benefits and concerns about governance, transparency and trustworthiness of the systems (King & He, 2006; von Eschenbach, 2021; Wirtz et al., 2022). Therefore, the current research aims to address a relevant gap in the literature by investigating the above features in the framework of a single interpretative model and providing a more complete picture of the usage of Artificial Intelligence in recruiting processes in the ICT industry (Pan et al., 2023; Koechling & Wehner, 2023; Zahedi Nejad et al., 2024).

2.2 Trust, Explainability and the Limits of Technology Acceptance

Trust is a major element in business AI adoption and acceptance. The only way sophisticated, technical AI systems operate is if humans trust them, are transparent and make good judgments. Trust is therefore not only about technology capabilities, but also about users' conviction that AI systems support corporate objectives, ethics and governance.

Research connects AI trust to transparency, accountability, and user control. Shin and Park (2019) discovered that users trust AI systems better when they understand how decisions are made, have a substantial degree of human oversight, and assign responsibility for automated judgments. These features are usually at odds with the opacity of AI systems. Low consumer knowledge of AI algorithm decision-making limits trust in its reliability and validity (von Eschenbach, 2021).

Less openness greatly influences high-stakes choices. Studies of AI in self-driving vehicles and criminal justice illustrate how confusion about how computers think leads to skepticism, resistance, and lower user acceptability, particularly when AI-assisted judgments touch humans. These results imply that trust is impacted by the accuracy of AI systems and people's capacity to comprehend, analyze, and question automated judgments.

Thus, trust is being conceptualized in terms of ethical frameworks as a governance consequence of justice, accountability and transparency in AI design and deployment. Hoffmann et al. (2019) defines responsible AI as algorithmic systems without prejudice or new discrimination and this needs these three features. Technical ability alone can't build confidence in business AI, study suggests Operational performance, clear governance, ethical responsibility and fairness in the decision-making process are trusted to AI systems. In AI-powered recruiting, recruiters have to trust algorithmic concepts to be effective, fair, transparent and ethical.

2.2.1 Technology Acceptance and Its Functional Assumptions

The use of Artificial Intelligence has drastically changed modern recruitment and selection by allowing organizations to automate repetitive recruitment tasks, speed up the process of sourcing candidates, and enhance the efficiency of screening and matching applicants (Koechling et al., 2023; Pan et al., 2023). More recently the rise of Generative Artificial Intelligence (GenAI), has added to these capabilities by enabling the development of recruitment relevant information, enabling engagement with applicants and helping recruiters at various phases of the recruiting process. But regardless of technology breakthroughs, the effective adoption of AI inside recruiting is still reliant on human acceptability, not just technological capacity. Thus, the question is not so much whether AI can support recruitment, but whether recruiters are willing to trust and embed these technologies into their everyday decision-making processes, which is one of the key challenges confronting contemporary Human Resource Management (Pan et al., 2023; Zahedi Nejad et al., 2024).

The literature continuously provides evidence of significant operational advantages of AI across the recruiting lifecycle. By automating administrative and repetitive jobs using AI, HR professionals may spend more time on strategic initiatives that need human judgment, interpersonal touch and organizational insight. AI-based systems are capable of swiftly searching through vast applicant databases and extracting viable candidates according to certain criteria, as well as doing quick resume screening, thereby decreasing recruitment duration and increasing consistency in the process (Laumer et al., 2016). AI may also be used in making evidence-based recruiting decisions by processing unstructured and structured data, combining resume evaluation, competency assessment and predictive analytics to anticipate candidate suitability and future job performance. These talents might possibly improve the quality of hiring and reduce the influence of subjective human judgement.

In addition to making organizations more efficient, AI has also improved the application experience. Examples of generative AI applications that allow ongoing engagement with applicants include intelligent chatbots and virtual assistants that may respond to routine questions, provide updates on recruiting, and guide candidates through the selection process (Koechling et al., 2023; Pan et al., 2023). But these operational advantages need to be viewed against a number of serious constraints. Previous studies have shown that organizations still struggle with issues such as technological uncertainty, the correct alignment of AI tools to specific recruitment objectives and the risk of algorithmic outputs perpetuating or amplifying existing biases when the training data used is not representative or discriminatory (Zahedi Nejad et al., 2024; Laumer et al., 2016). Thus, the effectiveness of AI depends not only on its technical features, but also on the quality of its implementation and the governance frameworks that limit its use.

Some of the reasons for this include the ongoing opposition by some HR practitioners to AI-assisted recruiting. Previous study indicates that resistance to use AI is often linked to worries about technical dependability, loss of professional autonomy and confusion about the role of human judgment in more automated recruiting procedures. However, recent research consistently emphasize that AI should be seen as a decision-support tool rather than a substitute for human knowledge (Zheng et al., 2024; Beia et al., 2024). AI can free up recruiters to focus on empathy-driven tasks, relationship-building, assessing organizational culture and critical interpersonal judgement by taking over mundane administrative activities, which are fundamentally human aspects of recruitment (Zahedi Nejad et al., 2024; Zheng et al., 2024; Thakur et al., 2023). This view confirms the increasing agreement that the best recruiting results are obtained via a complimentary partnership between humans and AI, rather than through the replacement of technology.

There has been much discussion about the operational advantages of AI in recruitment (Laumer et al., 2016; Koechling et al., 2023; Pan et al., 2023; Zheng et al., 2024), but little research has examined how recruiters view such technologies and what factors impact their willingness to use AI in their everyday recruitment tasks (Zahedi Nejad et al., 2024). This difference is an essential lacuna in the current research since organizational adoption is ultimately a matter of users' perception rather than technology performance alone. Therefore, the Technology Acceptance Model (TAM) offers a particularly relevant theoretical framework for the explanation of the recruiters' behavioral intentions towards the adoption of AI.

TAM, first postulated by Davis (1989), posits that the adoption of technology is mostly driven by two fundamental beliefs: perceived utility and perceived ease of use. In AI-assisted recruitment, perceived usefulness refers to the extent to which recruiters believe that AI may boost the efficacy, productivity and the quality of recruiting choices in recruitment (Davis, 1989; King & He, 2006; Zahedi Nejad et al., 2024). Conversely, perceived ease of use is the level of intuitiveness, user-friendliness, and compatibility of AI systems with current HR practices (Shahzad et al., 2024; Akram et al., 2024). Importantly, the evidence implies that these categories interact with one another, rather than separately. Highly useful AI systems may face opposition if recruiters see the AI system as too sophisticated or difficult to incorporate into their current recruiting processes.

In addition, TAM suggests that the perceptions of recruiters towards AI are mediated by their attitudes, which subsequently influence their desire to use the technology (Davis, 1989; King & He, 2006). Recruiters who see AI as both beneficial and simple to use are more likely to have favorable opinions towards its use, hence boosting their desire to integrate AI into recruiting and selection operations (Azzatillah et al., 2024). However, the current research indicates that technological acceptance is an insufficient explanation of the AI uptake. As the previous sections have revealed, recruiters analyze AI through the lenses of trust, transparency, governance, and perceived risk. Therefore, whereas TAM offers a strong basis for understanding AI adoption, the explanatory value of the model is enhanced when seen through the lens of governance and trust views.

2.3 From Person-Environment Fit to Team Level Complementarity

Companies nowadays are complicated and the teams who hire and manage them are evolving. The world economy, the fast advance of technology and the rise of the knowledge-based economy have generated organizational cultures that depend on interdisciplinary teams and technical capabilities. Hence, companies increasingly see teams as the unit of labor to get things done, rather than individuals. In this case the trick is to hire team players.

It's always been about the people-job fit in recruiting. Those with the right credentials, competence and technical skills would win out. This approach is still used but research shows that the technology abilities alone seldom make a corporation successful. People with outstanding ability may fail if their beliefs, attitude or work style are not compatible with the company's culture or teams. Mismatches may decrease work satisfaction, commitment and turnover, therefore raising recruiting costs and enhancing organisational performance (Lin & Baek, 2019). So corporations have understood that recruiting involves both professional competence and organizational fit.

This wider view is represented in the large body of research on person-environment (P-E) fit, which stresses congruence between human traits and aspects of the work environment. This means that work results are a result of human traits, organizational culture, working environment and organizational ideals and not individuals or organizations alone. The fit between the person and organization is a significant concept in HRM and organizational behavior, notably in the areas of recruiting, selection and career choices (Lin & Baek, 2019; Ashfaq & Hamid, 2020; Dhri & Dutta, 2020; Düşmezkalender & Yılmaz, 2020).

Academics are more informed about how personality influences collaboration. Early study focused on individual personality while more recent research has studied the relationship between team collective personality and performance. Big five personality model study: Conscientiousness and openness to experience enhance team effectiveness and cooperation. The results show that hiring choices should include not just the talents of the applicants but also their possible effects on team dynamics.

Lewin's (1951) interactionist theory maintained that behavior is a function of the continuing interaction between individuals and the environment, which may account for fit. Further study identified person-environment fit features such as person-vocation fit, person-organization fit, person-job fit, person-group fit and person-person fit (Jansen & Kristof-Brown, 2006). Person–organization fit and person–job fit have garnered the greatest empirical attention owing to their well-documented links with organizational outcomes such as work satisfaction, organizational commitment, and job performance.

There has been a lot of study on person-environment fit, but the researchers today feel that it is a dynamic process that changes as people, teams, and organizations grow (Vleugels et al., 2022). This change in perspective has led to an increasing interest in team-environment fit, in particular team-job fit and team-organization fit, expanding individual fit theory to the collective level. The literature on person-environment fit is, by far, more voluminous than team-level fit. Further investigations are required to assess the impact of team-job and team-organization fit on team satisfaction, cooperation and performance. This is especially true for ICT firms where the success of projects relies on good team work and recruitment is more and more about job and team fit.

2.3.1 Fit between the team and the organization

Since corporations have recognized human capital as one of their most precious strategic resources, academics have studied the link between person-organization (P-O) fit and employees' attitudes, behavior and work satisfaction. P-O fit suggests that workers whose values, attitudes and expectations are consistent with the culture and principles of an organization would perform better and be more loyal. Academics believe that P-O fit should be combined with technical skills during recruitment and selection rather than regarding it as a secondary concern (Lin & Baek, 2019; Ashfaq & Hamid, 2020; Dhri & Dutta, 2020; Düşmezkalender & Yılmaz, 2020).

Past study has shown that people are drawn to organizations with similar ideals. Lam et al. (2018) said that individuals choose jobs according to their hobbies and work habits. A highly collaborative person may choose a business that supports cooperation and information sharing. This congruence enhances employees' feeling of belonging and organisational identity, which may result in higher commitment and retention (Afsar & Badir, 2017). P-O fit has been an important element in the process of recruiting new personnel and creating successful teams (Lv & Xu, 2018).

Moving beyond the notion of person-organization fit, academics have expanded the topic to team-organization (T-O) fit, referring to the match between the values, working style and characteristics of a team and those of the larger organization. T-O fit is defined as the extent to which a team's aggregate traits are consistent with organizational culture and goals (Kristof, 1996; Oe and Yung, 2018). Similarly, Sekiguchi (2004) relates T-O fit to the Attraction–Selection–Attrition (ASA) model that states that organizations have a tendency to attract, select and retain individuals—and, eventually, teams—who are comparable in values and traits. From this viewpoint, efficiency of the organization relies on hiring the right people, and on ensuring that the teams are also themselves compatible with the larger organizational environment. A nearly similar notion is team-job (T-J) fit. Caldwell and O'Reilly (1990) first defined person-job (P-J) fit as the degree to which an individual's knowledge, abilities, and personal qualities meet the demands of a certain job. Since then, a considerable body of research has established that person-job fit has implications for crucial organizational outcomes, such as work satisfaction, performance, organizational identity and turnover intentions. More subsequent work has expanded this rationale to the level of the team. For example, Ellis et al. (2017) indicate that T-J fit represents the degree to which a team's collective qualities and skills match the needs of the tasks they are expected to complete. This larger view emphasizes that a team's performance is not simply a function of the capabilities of the individual members of the team, but also of how well the team as a whole is matched to the task that it is asked to do.

2.3.2 The Limits of Individual Level Fit in Team Based Contexts

There has been rising interest in the studies of person-group (P-G) fit, which refers to the fit between an individual and their group, including colleague connections and group needs. As business cooperation expands, experts believe the capacity to articulate how people connect to their groups is key to individual and team success. The construct of P-G fit has been acknowledged as complicated (Li et al., 2019; Seong & Kristof-Brown, 2012), yet there is little research on the effects of the dimensions of P-G fit on organizational performance.

Here is the literary contrast between supplemental and complementary fit: Supplemental fit of people refers to the degree to which they have values, qualities, and attitudes similar to those of other team members (Muchinsky & Monahan, 1987). Complementary fit is when an individual's skills plug a group's gaps or meet its demands. Both forms of fit increase team performance, but in different ways. Previous studies have shown that same mindset and personality are related to healthy interpersonal connections and emotional consequences. Complementary fit—knowledge, skills and talents—appears to be more strongly related to task performance and team success.

Recent study suggests that these qualities should not be studied in isolation. Seong and Choi (2021) discovered that value fit and ability fit had a varied effect on creativity. Complementary values and talents increased employees' creativity; and both forms of fit benefited teams' creativity. The results indicate that person-group fit is complex and may influence organisational outcomes via many mechanisms and additional study is needed (Sung et al., 2020).
Researchers also indicate that P-G fit cannot be described without leaving team setup out. The situational events, human interaction and work environment affect the organizational behavior. Teams are the principal type of work organization in today's firms, hence team relationships are important. Work difficulties are handled by colleagues rather than leaders (Liao et al., 2010; Hollenbeck et al., 2012; Lee, 2020; Seong & Choi, 2021).

One key moderator is team member exchange (TMX) that may enhance or diminish the link between person-group fit and organizational success. TMX measures team support, communication and sharing of resources. TMX quality has been shown to have a positive effect on work performance, organizational commitment, and job satisfaction (Banks et al., 2014; Farh et al., 2017; Seers, 1989). It is also predicted that the moderating variable accounts for the effects of organizational circumstances on employee attitudes and behaviors.

Further study has explored the influence of diverse person-group fit on collective intelligence (CI) from the perspective of team interactions (Seong & Kristof-Brown, 2012; Seong & Choi, 2021; Jørgensen et al., 2007). The idea recognizes that value fit and ability fit affect collective intelligence differently and rely on team-member interaction. This multi-dimensional approach fills a critical research gap and will better understand how team composition, interpersonal relationships and cooperation impact team performance and organizational success.

2.3.3 Behavioral Profiling as a Structured Fit Mechanism

Good planning is a prerequisite to good projects, but the quality of the personnel implementing them is equally key. A well-balanced team can better address the difficulties, adapt to changing conditions and achieve project goals whereas bad team composition may have severe consequences on cooperation, productivity and overall organizational performance (Nikitenko et al., 2017). As firms have become more reliant on interdisciplinary teams, recruiting choices have slowly evolved from finding technically proficient people to finding people that can work well together.

Traditionally, project managers generally choose team members based on personal judgment or experience with past projects. Practical knowledge may have been important, but such judgments were often subjective and there were no clear standards to evaluate them. This resulted in teams being formed with knowledge gaps, duplicated skills or conflicting working styles. These deficiencies may affect the productivity, lead to interpersonal problems and adversely affect the motivation of employees. In addition, unjust recruiting choices may result in workers feeling that their talents are not appreciated, which decreases both commitment and engagement.

To overcome these restrictions, businesses have slowly begun to embrace more systematic recruiting methods based on objective evaluation criteria. Curriculum Vitae (CVs) are still one of the most common tools used by employers to assess applicants' education, work experience and technical skills. CV scanning, when carried out systematically, is a transparent way of evaluating applicants and selecting the ones with the credentials needed for certain projects (Cole et al., 2007; Smart, 2004). But there are substantial drawbacks to depending just on CVs. Technical credentials alone do not provide a whole picture of a person's interpersonal skills, flexibility, motivation or capacity to work with varied teams – all of which are crucial to the effective execution of projects.

The amount of applications is only a reminder of the limits of manual recruiting methods. Because project managers typically have to go through hundreds of CVs in a short space of time, it becomes more difficult to conduct a thorough examination. This has led academics to examine the use of Artificial Intelligence and machine learning to automate applicant screening and increase the efficiency of recruiting. One such strategy is the development of machine learning algorithms that are trained on past assessments of recruiters to evaluate LinkedIn profiles and social media data to predict the relevance scores and personality traits of candidates (Faliagka et al., 2012). Although these methods may greatly decrease screening time and increase consistency, they tend to focus on visible professional information and may ignore behavioural traits such as flexibility, communication skills and interpersonal compatibility.

The constraint has increased interest in behavioral profiling as a supplement to recruiting. AI is good at evaluating technical credentials, while psychology-based evaluation approaches focus on how people are likely to act, communicate and collaborate in teams. Hence, more focus has been paid to profiling strategies that combine technical skill with behavioral features to increase the quality of recruiting rather than the speed of recruitment.

Several research have offered alternative ways for behavior evaluation and profile matching . For instance, Singh et al. (2013) created a multi-agent model that assesses applicants based on factors such as desire to cooperate, trust, reciprocity, and professional ability. They found that consideration of these behavioral factors may make teams more productive by forming teams whose members are complementary to each other. The suggested methodology was nonetheless tested in a particular virtual healthcare setting and doubts remain as to how it may be applicable in diverse organizational situations.

Another well-known behavioral model is the "DISC personality model". It separates people into four primary conduct styles: dominance, influence, stability and compliance. The inclusion of DISC profiles in the recruiting process may give recruiters with more information than only the technical skills of the applicants, and also allow for a better evaluation of behavioral fit (Utami & Luthfi, 2018). However, oversimplifying human conduct into four broad aspects may be an oversimplification of the complexities of human behaviour and the scant empirical data available makes it difficult to generalise results across diverse organisational contexts.

Other academics have tried to increase recruiting using predictive analytics and profile-matching algorithms. Raza and Hasan (2021) used logistic regression to investigate the link between demographic factors and employee engagement, highlighting the importance of statistical models in predicting organizational results. However, demographics alone cannot completely explain engagement, since other factors such as personal beliefs, motivation, career goals and organisational culture all impact employee behavior. Similarly, Tanti et al. (2018) presented a profile matching technique to assess applicants based on many performance-related factors as work discipline, communication, integrity, dependability, and cooperation. This strategy gives a systematic way to find the right people, but pays very little attention to contextual aspects such as company culture and long-term employee development.

Similar limitations have been shown by other profile-based techniques. Educational background, experience, and academic credentials may be used to build a profile matching model for professional placement, according to Soetanto and Budiyanto (2022). Although this paradigm increases the objectivity of placement choices, it does not completely incorporate individual objectives, intrinsic motivation or personal career ambitions, which might impact long-term job satisfaction and organizational commitment. Similarly, Ni et al. (2017) proposed a behavioural profile system based on real-time workplace data acquired via the WeChat Robotic Platform. This method offers continuous and generally objective behavioural data. It largely covers observable work activities and may thus not account for wider psychological traits that impact on cooperation and team effectiveness.

Computational strategies for better team creation have also been investigated by researchers . Paoletti et al. (2016) advocated the use of top-k query strategies for searching the best rated applicants on huge datasets, so that the computational complexity during recruiting may be minimized. However, the success of this approach is strongly dependent on the choice of ranking factors which may be different in various organizational settings. Mulebrock et al. (2019) also used the Gale–Shapley algorithm to match students to projects according to their ranking choices. Whilst this strategy maximised participant happiness, it was based more on individual preferences than behavioral compatibility or team efficiency. Lin et al. (2013) further proposed the Team Formation with Hidden Markov Models (TF-HMM) technique that takes into account both the technical skill and the knowledge-sharing interactions among team members. Although the approach was promising in findings, the computational complexity and the necessity for continual updating would restrict the practical applicability in quickly changing organizational systems.

Together these research reveal that significant advances have been achieved in the development of AI-supported recruiting, behavioural profiling and team building strategies. However, most current techniques still focus on either the technical capabilities or discrete behavioral features, with very little integration of both views. This is a major gap, especially for ICT firms because successful recruitment relies simultaneously on technical competence, behavioral fit and successful cooperation. These restrictions strengthen the need for recruiting techniques that include AI-assisted evaluation and behavioral profiling to provide more balanced, transparent and effective team creation.

2.4 Trait-Based Personality Models versus Role-Based Team Frameworks

For many decades, psychologists have been investigating personality traits in an attempt to understand why people behave differently in professional and social settings. While people's conduct may fluctuate according to the context, personality preferences are largely consistent over time. They influence how individuals communicate, make choices, solve issues and relate to other people (Wilson, 1998). Therefore numerous theoretical models have been established to define personality and to predict individual conduct in organisational contexts.

The Big Five Personality Model is one of the most often recognized and used of these. The model offers a comprehensive framework for analyzing broad personality aspects and has found widespread use in organisational behavior, industrial psychology and Human Resource Management (Meng, 2003). Costa and McCrae (1999) have identified five basic personality traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. Individuals that score high on extraversion are often gregarious, lively, and comfortable taking charge or being a leader. Agreeableness displays a propensity to cooperate and be trustworthy, and to work well with others. Conscientiousness has been linked to responsibility, organization, and tenacity in the pursuit of objectives. Neuroticism is defined as the propensity to feel emotional instability and unpleasant emotional responses, whereas openness to experience is associated with curiosity, creativity and a readiness to explore new ideas and experiences (Costa & McCrae, 1999).

The Big Five model is seeing more application in businesses, since there is a growing awareness that personality impacts many areas of professional conduct. Research has demonstrated that personality characteristics impact communication, team collaboration, leadership style, and individual job performance, making them especially significant in collaborative and project work situations. It is for this reason that, in addition to the standard assessment of technical knowledge and professional experience, many businesses include personality evaluation in the process of recruiting and selection.

Also, competence models were established to give a wider knowledge of employee performance in addition to personality based methods. Competency models, unlike trait based models, integrate technical knowledge with the behavioural, motivational and interpersonal attributes that contribute to effective job performance. Among the most influential are Boyatzis's Onion Competency Model and Spence's Iceberg Model. The Iceberg Model suggests that visible competencies such as knowledge and technical skills, are only a small part of overall performance, instead less visible characteristics such as motivation, values, self-image and personality are much more important in determining long-term behaviour and effectiveness (Wu & Xu, 2006). Similarly, Onion Model argues that deeper personal attributes are harder to see and develop but have a large impact on behavior and professional success (Chen & Lei, 2004).

2.4.1 Personality Traits, Teamwork and Organizational Effectiveness

The study of behavioral qualities that foster efficient cooperation is an important topic of organizational research as firms grow more team dependent. This is especially true in innovation-driven and project-based organizations where individuals are expected to do more than just specific duties, but also to communicate well, share expertise and collaborate closely with colleagues. Researchers have thus paid much attention to investigating the effect of personality factors on communication, cooperation, leadership and performance of the team as a whole.

Among these traits, communication is repeatedly mentioned as one of the most crucial variables affecting effective cooperation. Effective communication minimizes the chances of misunderstandings, simplifies the flow of information and the collaboration of team members, and results in increased team cohesiveness and productivity (TIPPRO Communication in the Workplace Statistics, 2024). Open, straightforward communicators are typically viewed as more dependable, helpful and productive coworkers. Communication is not just verbal contact but also include written communication, presenting abilities and non-verbal behaviors which impact the quality of interpersonal interactions within teams.

Another behavioral attribute crucial to team efficiency is leadership. As Yukl (Portugal & Yukl, 1994) states, leadership is a process in which people influence group goals, encourage others and coordinate activities to achieve goals. Previous research have shown several personality qualities, notably extraversion, self-confidence and social influence to correlate with leadership (Johnstone & Manica, 2011). Leadership is particularly important in complex organizational settings, where good leaders may assist groups to handle diverse perspectives, organize joint efforts and retain attention on shared goals.

Another quality of effective cooperation is **openness to experience. Openness in the Five Factor Model of personality describes intellectual curiosity, creativity, imagination and readiness to embrace new ideas and other views (Batey and Furnham 2006). Those who score high on this dimension are more likely to be open to exploring new ideas and bring new viewpoints to team discussions. Research also indicates openness may favorably impact creative problem solving and invention, especially when accompanied with supportive interpersonal interactions and successful cooperation amongst team members (Hassan & Koning, 2019).

These studies provide a depiction of the impact of personality traits on team and individual success. Classic personality theories, which focus on relatively unchanging individual attributes, only partially explain collaboration. They represent patterns of behaviour but do not convey the dynamic roles people play in cooperation, or how various behavioural profiles complement each other. This limitation considers both individual identity and group performance (team-based behavioral models).

2.4.2 Team frameworks based on roles

Aside methods using personality traits, companies nowadays have turned to team-roled frameworks. According to these frameworks people are looked in terms of their contribution to the team they belong to rather than merely to their personality qualities. Trait-based models describe generally unchanging behavioural characteristics. Team-role models, on the other hand, are primarily concerned with the roles that individuals naturally adopt when working with others, and the way these roles affect team effectiveness.

One of the most famous frameworks in this field was established by Meredith Belbin. He stated that successful teams are not built by bringing together people with similar personalities but by mixing individuals who offer distinct but complementary contributions . The key to effective cooperation, according to Belbin, is not having team members replicate behavioral qualities, but having the right mix of functional duties. In his approach he specifies a variety of informal team responsibilities, for example, the coordinator, implementer, specialist, shaper, monitor evaluator, team worker and resource investigator. Diversity of positions is more beneficial than homogeneity, as different jobs have their own distinct strengths and possible limits.

Research into Belbin's approach tends to support the idea that a combination of team roles may enhance communication, co-operation and overall team efficiency. However, the current data is not fully consistent, partially because many empirical research have been performed with very small samples or in particular organizational settings (Sohmen, 2013). Thus, although the model has been of substantial interest in practice, further study is required to understand the circumstances under which diverse combinations of team responsibilities result in the most beneficial results.

More recently, team-role theory has been related to wider organisational concerns such as leadership development, cooperation and employee development (Whetten & Cameron, 2011). These viewpoints underscore the fact that technical skill is not the only foundation for effective cooperation. Good cooperation also includes communication skills, leadership characteristics, flexibility and the development of strong interpersonal connections. Research has demonstrated that traits such as openness to experience, good communication and leadership orientation may promote collaboration and enhance team performance (Batey & Furnham, 2006; Johnstone & Manica, 2011). Communication is also known as one of the best determinants of successful cooperation and organizational performance (TIPPRO, 2024).

Personality models and team-role frameworks combined provide complimentary lenses for analyzing team performance. Personality models provide the generally stable qualities that people bring to the workplace, while team-role models specify how such attributes are converted into functional contributions in the course of cooperation. This difference is especially crucial in AI-assisted recruiting, as businesses are looking for applicants who are not just technically capable, but whose behavioural profiles are likely to fit in with current teams and contribute to long-term organizational success.

2.4.3 Trait-based vs Role-based approaches

From a variety of standpoints, corporate employee behavior is presented in personality characteristic theories and team-role techniques. Personality based models mostly consist of persistent psychological traits of people that shape the way they think, act and interact throughout time (Costa & McCrae, 1999; Batey & Furnham, 2006). These theories have improved much in understanding how people vary in communication, leadership, and effectiveness at work (Johnstone & Manica, 2011; Meng, 2003). But they only partially capture behaviour in collaborative work situations when people adapt to new jobs, peers, and organisational needs (Muchinsky & Monahan, 1987; Edwards & Shipp, 2007).

Team-role theories, on the other hand, focus on the contributions individuals make to collaboration. These approaches describe how people work together, coordinate and help each other to attain goals (Belbin, 2010; Marks et al., 2001). Thus, they have a more dynamic vision of cooperation, knowing that success relies on individual attributes, roles, connections between people and the interactions of team members (Hollenbeck et al., 2012; Banks et al., 2014).

This difference has a big impact on recruiting. There is increasing evidence that team achievement is not only the result of individual personality qualities. The effectiveness of a team depends on how well its members complement each other, communicate well and have various attributes to promote team performance (Sohmen, 2013; Neuman & Wright, 1999; Halfhill et al., 2005). Behaviour profiling and team-role evaluation therefore provide a more full and accurate picture of employee appropriateness than personality or technical evaluations (Belbin, 2010; Li et al., 2019; Seong & Choi, 2021).

This similar viewpoint is becoming more significant in AI-assisted recruiting. Most AI recruiting systems are meant to find people who meet pre-determined technical standards, based on credentials, experience and keywords (Faliagka et al., 2012; van Esch et al., 2019; Thakur et al., 2023). This may increase the speed of the recruiting process, but it provides little information about behavioral compatibility, cooperation potential and long-term integration in existing teams (Pan et al., 2023; Koechling & Wehner, 2023). The combination of behavioural profiling and team-role techniques therefore offers a chance to supplement AI-based evaluation with information that is typically neglected by traditional recruiting algorithms (Belbin, 2010; Li et al., 2019; Vrontis et al., 2022).

Against this theoretical backdrop, the current research investigates the perceptions of HR professionals and ICT recruiting managers on the importance of behavioural profiling, team fit, team-role integration and AI-supported recruitment. To contribute to a more thorough understanding of recruitment quality in collaborative work settings, this research strives to integrate various viewpoints together into a coherent conceptual framework in which technical skill is just one facet of effective employee selection (Kristof-Brown et al., 2005; Pan et al., 2023; Rigotti & Fosch-Villaronga, 2024).

2.5 The Missing Integrative Model and Theoretical Research Gap

The earlier portions of this literature review have addressed three interconnected domains that are critical to AI-supported recruiting. Firstly, Artificial Intelligence has been suggested as a helpful tool to increase recruiting efficiency by automating administration activities, accelerating applicant screening and boosting decision making (Upadhyay & Khandelwal, 2018; Johnson et al., 2020; Vrontis et al., 2022). Second, an increasing amount of research has pointed out that effective usage of AI relies not only on its technological skills but also governance concerns such as transparency, fairness, accountability and trust (Floridi et al., 2018; Taeihagh, 2021; Wirtz et al., 2022). Finally, research in organizational behaviour have shown that behavioral profile, person-environment fit and team compatibility are significant in quality of recruiting and long-term success of an employee (Kristof, 1996; Kristof-Brown et al., 2005; Edwards & Shipp, 2007).

Each of these fields of inquiry has progressed a lot, although they have grown mostly separately. Most AI recruiting studies concentrate on operational results such as efficiency, automation, predictive accuracy, and recruiter productivity (van Esch et al., 2019; Johnson et al., 2020; Thakur et al., 2023). In contrast, AI governance research is largely concerned with ethical dilemmas, algorithmic bias, explainability and regulatory compliance (Hoffmann et al., 2019; Taeihagh, 2021; Rigotti & Fosch-Villaronga, 2024). At the same time, research on behavioral profile and team fit often examines the organisational outcomes of work satisfaction, collaboration, employee retention and team performance (Kristof-Brown et al., 2005; Hoffman

& Woehr, 2006; Seong & Kristof-Brown, 2012). As a consequence, little attention has been paid to understanding how these varied beliefs interact in the process of recruiting.

This discrepancy is a serious weakness in the literature. Rarely does one thing determine recruitment choices. Recruiters don't only look at how fast AI systems can process applicants or how well they match technical credentials. They also consider whether such methods are reliable, open and fair, and if they can spot the team members who are most likely to fit in (Koechling & Wehner, 2023; Rigotti & Fosch-Villaronga, 2024). These characteristics provide a limited view of how AI helps in organizational recruiting choices.

The same is true with behavioral profiling. In organizational psychology, person-environment fit, personality models, and team-role frameworks have been researched extensively, but they have seldom been used in AI-assisted recruiting research (Kristof, 1996; Kristof-Brown et al., 2005; Belbin, 2010). "Matching, tech skills and expertise are still the main criteria for most AI recruitment algorithms. Considers: Behavioral fit, interpersonal interactions, and candidates' potential to boost team performance (Faliagka et al., 2012; Pan et al., 2023). Despite increasing evidence that these attributes impact long-term recruiting success (Li et al., 2019; Seong & Choi, 2021).

Likewise, models of technology adoption have contributed much to our understanding of why people embrace new technologies. Constructs like perceived usefulness, perceived ease of use and behavioural intention are still of significant relevance when studying AI adoption (Davis, 1989; Venkatesh et al., 2003; King & He, 2006). But recruiting differs from many other procedures in organizations since it has a direct impact on job possibilities and people's careers. As a result, trust, explainability, governance and perceived risk become of special importance and should be examined in connection with conventional technological adoption criteria rather than in isolation (von Eschenbach, 2021; Wirtz et al., 2022; Nakashima et al., 2024).

The extant literature in aggregate points to a significant theoretical gap still existing. Empirical data is scarce on the extent to which perceptions of AI efficacy, confidence in AI systems, governance concerns, perceived AI danger and behavioral profiling together impact recruitment quality and adoption of AI-supported recruiting systems (Pan et al., 2023; Koechling & Wehner, 2023; Zahedi Nejad et al., 2024). Most of the prior research have focused on just a fraction of this larger picture and the links among these dimensions have not been fully investigated.

This dissertation attempts to fill that gap by combining various ideas into a unified conceptual framework. The study explores the interrelationship between AI adoption, governance and behavioral fit in influencing perceptions of recruitment quality and AI-assisted recruitment rather than exploring them as independent streams of research. In so manner, it aspires to offer not just empirical facts from the Greek ICT industry, but also to feed into the wider conversation on the creation of trustworthy, human-centred and behaviourally informed AI recruitment systems (Shneiderman, 2022; Vrontis et al., 2022; Rigotti & Fosch-Villaronga, 2024).

2.6 Conceptual Research Model and Hypotheses Development

This chapter explores three important AI-assisted recruiting issues. The first was the perspectives of stakeholders on the merits and downsides of AI recruitment (Vrontis et al., 2022; Pan et al., 2023). "The second point is trust, explainability and governance for the acceptance and responsible use of AI (Floridi et al., 2018; Taeihagh, 2021; Wirtz et al., 2022). The third looked at the impact of behavioral profile, team fit and team-role methods on recruitment and success of employees (Kristof-Brown et al., 2005; Belbin, 2010; Li et al., 2019). These issues have been explored extensively, although often apart from one other. This has resulted in a lack of empirical research combining multiple viewpoints to portray the complexity of AI-assisted recruiting (Koechling & Wehner, 2023; Zahedi Nejad et al., 2024). While the duties of HR professionals and ICT hiring managers in the recruiting and selection process are distinct, their perceptions have seldom been contrasted (Pan et al., 2023).

The current research provides a theoretical conceptual framework integrating AI adoption, governance and behavioral fit to fill these knowledge gaps. The approach reveals that these attitudes impact the assessment of AI backed recruitment solutions by recruitment professionals (Davis, 1989; Venkatesh et al., 2003; Rigotti & Fosch-Villaronga, 2024).

Two complementary analytical techniques exist inside the framework. The first, the AI Adoption path, investigates the influence of perceptions of AI efficiency and hazards on confidence in AI systems and the choice to use AI in recruiting by stakeholders (King & He, 2006; Nakashima et al., 2024). The second approach, behavioral Fit, investigates how team fit, behavioral profiling and team role integration impact the quality of recruiting (Kristof-Brown et al., 2005; Seong & Kristof-Brown, 2012; Li et al., 2019). Recruitment quality in this research is defined as selecting technically competent personnel, decision quality, fit of the team, and employee potential for long-term contribution to the organization (Werbel & Gilliland, 1999; Edwards & Shipp, 2007).

The suggested technique allows for empirical construct selection. These ideas are the major concerns of the literature study and are tied to the research questionnaire. AI Efficiency, Decision Quality, Risk, Trust, Explainability, Governance Safeguards, Intention to Adopt AI, Team Fit, Behavioural Profiling, Support for Team-Role Integration in AI, Hiring Quality. These ideas explore the key operational, ethical and behavioural issues in the literature on AI-assisted recruiting (Floridi et al., 2018; Vrontis et al., 2022; Rigotti & Fosch-Villaronga, 2024).

In this study, this conceptual framework is used to formulate three research questions and seven hypotheses. The theoretical explanation of this chapter is a preparation for actual investigation (Saunders et al., 2019; Sekaran & Bougie, 2016).

2.6.1 RQ1 - Perceived Value of AI-Based Recruitment

The first research question (RQ1) explores the evaluation of AI-assisted recruiting methods by stakeholders. More precisely, it explores whether recruitment experts think that AI helps the recruiting process, assists in making better decisions and if worries about possible hazards affect their faith in such systems.

In this segment of the research, three important constructs are discussed. Perceived AI efficiency is the degree to which stakeholders feel AI can make recruiting processes better by decreasing manual labour and enhancing operational efficiency. Perceived AI decision quality is the idea that AI aids in more accurate, objective and consistent recruiting choices. Finally, perceived AI risk includes concerns associated with problems such as algorithmic bias, transparency and the likelihood of AI systems relying on incorrect or incomplete data.

The literature reveals that these views are tightly linked. Recruiters are also more inclined to see AI-assisted judgments as better quality if they feel that AI increases the efficiency of recruiting efforts. However, hazards might also cause lack of trust in AI systems and diminish the willingness of stakeholders to use AI in recruiting. Based on these theoretical grounds, we suggest the following hypotheses:

H1: Perceived AI efficiency positively affects perceived AI decision quality.
H2: Perceived AI danger is adversely related to confidence in AI systems.

The first hypothesis investigates whether good impressions of the operational performance of AI are related to more positive assessments of the quality of AI-supported recruiting choices. The second hypothesis is: Do higher worries about AI-related hazards correspond with lower levels of confidence in AI systems?

2.6.2 RQ2 - Trust, Explainability, Governance, and AI Adoption

RQ2: What influences the readiness of stakeholders to use AI technology in recruitment? The conceptual framework described in this paper considers trust as a fundamental motivator for AI adoption. Within the scope of recruitment, trust is understood as the level to which stakeholders consider AI systems to be trustworthy, reliable and able to assist in recruitment decisions in a fair and suitable manner. Recruiters that believe in AI suggestions are more likely to use these technologies in their day-to-day recruiting activities.

The evidence also indicates that trust does not grow in isolation. Two characteristics that are regularly related to better trust in AI systems are explainability and governance protections. Explainability is the capacity of AI systems to provide transparent and intelligible explanations for their recommendations and recruiting choices. Governance precautions include human monitoring, frequent audits, compliance with regulations, and transparent accountability procedures. These are meant to decrease bias, boost transparency, and encourage responsible usage of AI throughout the recruiting process.

Prior work shows that stakeholders tend to trust AI systems better when the decision-making process is transparent and governance measures are properly established. This is especially so in recruiting since employment choices immediately influence job chances and professional advancement. Thus, the issues of justice, accountability and transparency are likely to affect not only confidence in AI but also the willingness of stakeholders to support the further use of AI in recruiting.

Based on these theoretical grounds we advance the following hypotheses:

H3: The goal to improve the use of AI in recruiting is positively linked with trust in AI systems.
H4: Trust in AI systems is positively related to the perceived relevance of governance protections and explainability.

The third hypothesis examined whether greater levels of confidence in AI systems are connected with higher levels of desire to utilize AI technology in recruiting. The fourth hypothesis is to test if stakeholders scoring better on explainability and governance protections also report higher levels of confidence in AI-assisted recruiting systems.

2.6.3 RQ3 - Behavioral Profiling, Team Fit, and Hiring Quality

The third research question (RQ3) focuses on the behavioral and team-related aspects of recruiting. Perceived hiring quality in this research is the overall appraisal by the stakeholders of the efficacy of the recruiting process. In addition to screening technically competent individuals, this assessment assesses the quality of recruiting choices, the fit of candidates with existing teams, and their ability to provide value to the organization in the long run.

The conceptual framework suggests that behavioral profile and team fit are key factors in affecting perceptions of recruiting quality. Behavioural profiling is the measurement of behavioural traits, preferred working methods and interpersonal dispositions that may affect cooperation and job success. By comparison team fit refers to how well the applicant is seen to fit in with the current team and their method of functioning.

Additionally, the framework has support for team-role approaches. The Belbin framework is one example of a model which proposes that teams are more productive when members have complimentary inputs rather than comparable behavioral qualities. Hence, stakeholders that appreciate team-role methods may also view recruiting procedures to be more methodical, balanced and successful.

From these theoretical considerations the following hypothesis are formulated:

H5: Perceived hiring quality is positively related to perceived significance of team fit
H6: Perceived relevance of behavioural profiling is positively related to perceived hiring quality.
H7: Perceived recruiting quality has a favorable association with support for the incorporation of team-role techniques into AI systems.

The first two hypotheses explore the separate effects of team compatibility and behavioral profile on perceptions of recruiting quality. The last hypothesis further extends this idea by investigating whether using team-role concepts inside AI-assisted recruiting systems is likewise related with better recruitment quality assessments. This connection is one of the core assertions of the conceptual framework, linking the technical and behavioral factors described throughout the literature study .

The research hypotheses are experimentally examined with the use of statistical methods appropriate to the operationalisation of the study variables. Correlation analysis explores the correlations between AI-related views and trust, while regression analysis tests the conceptual model's hypothesized predictive associations. Furthermore, an independent-samples t-test is performed to assess the view of HR experts and ICT recruiting managers on important dimensions such as faith in AI, intention to implement AI, behavioural profiling and team fit. These analyses enable the research to investigate whether stakeholders in various recruiting positions perceive AI-assisted recruiting systems differently.

3. Methodology

3.1 Research Philosophy and Overall Design

The research is founded on positivist research philosophy. Positivism maintains that organizational and social phenomena may be investigated by objective observation, measurement and statistical analysis. In this technique, the correlations between the variables are explored based on factual data and focus is on limiting the subjective interpretation throughout the research process.

There were a number of reasons for choosing a positivist framework. The first is the emphasis of the research on quantifiable views and attitudes of AI-assisted recruiting, instead than subjective narratives or individual experiences. Second, data are gathered using a standardized questionnaire that provides quantitative data for statistical analysis. Third, the study questions need the investigation of correlations between well-defined dimensions, including faith in AI, desire to adopt, perceived AI risk, and judgments of team fit and recruiting quality. An alternative philosophical approach may have been pragmatism, which is more methodologically flexible and stresses mainly practical effects. However, the current study used only quantitative data and statistical testing, and the positivist method thus was deemed more congruent with the overall research design and analysis aims.

The study is cross-sectional and quantitative in design. A quantitative approach permits the systematic assessment of perceptions and statistical testing of the correlations between variables. The cross-sectional strategy comprises data collection at a specific moment in time, thereby offering a snapshot of current perspectives on AI-assisted recruiting in the Greek professional setting.

Longitudinal study might provide insight into how perception changes over time, but this would need longer data collecting periods and more research resources. The cross-sectional approach was deemed more acceptable and methodologically possible given the breadth and time constraints of the current MBA dissertation.

3.2 Target Population and Sampling Strategy

The targe sample of the present research includes Greece's recruiting professionals. The research focuses on HR professionals in the areas of recruitment, talent acquisition and human resource management, and on managers, team leaders and heads of departments. The two groups were selected because of their contrasting recruiting viewpoints. HR experts guarantee recruiting is fair, compliant and organized. What hiring managers worry most about is team fit, employee performance and a candidate's long-term impact. Therefore, the inclusion of both groups expands the perspectives of AI-enabled recruiting and behavioral assessment.

The study is based on Greece and the ICT industry is emphasized for its inventiveness, talent shortages and team project dependence . There is no restriction to participation in ICT organizations. The poll may also include professionals in consulting, finance and technology. Different sizes of firms are analyzed, since company size could affect maturity of AI adoption, governance preparedness and recruiting challenges.

The study applies a non-probability sampling method. The research applies convenience sampling, snowball sampling, and professional outreach. The first participants are contacted via the researcher's professional network and they are urged to forward the questionnaire to colleagues in their companies or professional circles. The snowball strategy promotes more widespread involvement and allows access to experts participating in recruiting initiatives. Furthermore, the link for the survey is posted on LinkedIn and related professional groups to enhance the variety of the sample and to avoid over-reliance on a single professional network.

According to Cohen (1988), the needed sample size relies on various criteria, such as the predicted effect size, the level of statistical significance, the desired statistical power, and the number of predictors included in the regression models. In the current work, a parsimonious analytical technique is used to establish consistency between the statistical design and the projected sample size. A significance level of $\alpha = 0.05$, a statistical power of 0.80 and a medium effect size ($f^2 = 0.15$) leads to an estimated sample size of around 80–100 respondents for regression models with one or two variables. Therefore, the suggested sample size is deemed acceptable for the statistical analyses utilized in this investigation.

3.3 Data Collection Procedure

Google Forms is used to create a structured online questionnaire that collects data. This platform was chosen for a number of reasons: (a) it allows for anonymous participation, (b) replies can be readily converted to a spreadsheet, and (c) the survey may be extensively shared online The survey questionnaire is presented in Appendix A.

Participants are told about the study's purpose before they fill out the questionnaire. The scholarly aspect of the investigation is elucidated. Participants are also told that they don't have to take part. Your answers will be kept private. We don't gather any personal information, including names or contact information. Participants may fill out the questionnaire whenever they like. The survey will be available for around three to four weeks. This time frame gives people enough time to respond. After the data collecting time is over, the answers are sent to Excel and set up for statistical analysis.

3.4 Questionnaire Design and Measurement Structure

The questionnaire utilized in this study is based on measuring scales that have been verified and extensively used in prior research. The constructs in the questionnaire are rooted on several study domains such as technological acceptance, trust in AI systems, person-environment fit theory, and behavioral assessment research. Instead of creating a whole new assessment instrument, the current constructs were tailored to the unique situation of AI-assisted recruiting.

In particular, the questions evaluating confidence in AI systems and desire to use AI technologies were constructed based on previous research on technology adoption (Davis, 1989; Venkatesh et al., 2003). Explainability and governance measures were sourced from responsible AI, algorithmic transparency, and ethical AI deployment research. The last parts of team fit, behavioral compatibility and team-role integration were based on person-organization fit theory and research (Kristof-Brown et al., 2005).

There were two reasons for the change of the present arrangements. First, the use of well-established scales enhances theoretical consistency and measurement reliability. These theories have been effectively used in the study of organizations and of behavior. several language modifications were made to several aspects for AI-supported recruiting systems but the original intent was kept.

The questionnaire for the dissertation is based on established constructs from previous research and hence, no pilot study was required. Instead, measuring instrument quality and durability are assessed by statistical testing. Cronbach's alpha (1951) is used to test internal consistency dependability. Exploratory Factor Analysis evaluates the concept validity (Hair et al., 2019). These strategies enable us to understand whether the questions in the questionnaire measure the study constructs.

All questions are measured on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Likert scale is a popular tool used in organizational and management research to measure attitudes and perceptions with enough information yet simple to fill. Multiple items per concept help to increase measurement stability and decrease random measurement error.

Having taken the aforementioned into consideration the questionnaire of the present research is formed into four sections. The first section involves the collection of information pertaining the demographic characteristics of the sample such as their professional role, the years of work experience, the size of the organization they are working for and the industry sector the company they work for belongs to. This information allows the characteristics of the sample to be described. It also enables potential subgroup comparisons.

The second section of the questionnaire involves AI Recruitment Perception for which a number of statements measure perceived efficiency, decision quality, and potential risks.

The third section involves trust, Governance, and Adoption intentions whereby the participants should assess statements like I trust AI-generated candidate recommendations, AI systems are reliable in recruitment contexts and others. These items capture perceptions related to trust, transparency, governance safeguards, and adoption intentions.

Finally, the Behavioral Profiling and Team Fit will also be assessed by the evaluation by the participants. Statements like Behavioral profiling improves hiring decisions, Personality assessment is important in recruitment, Behavioral traits predict long term performance and others measure the perceived importance of behavioral assessment and team role approaches in recruitment processes.

3.5 Statistical Analysis

Statistical analysis of the research was divided into two major sections. First, the reliability and validity of the questionnaire are examined so that the measuring instrument is suitable for the objective of study. Subsequently, statistical analyses are conducted to explore the correlations between the primary research variables and to evaluate the hypotheses provided. For each construct, composite variables are constructed by averaging the questionnaire items pertaining to the construct. For example, the construct "Trust in AI" is operationalized using the mean score of the respective elements. This method is used in survey research, since it helps to make measurements more stable and it decreases random error in measurement.

Cronbach's alpha (Cronbach, 1951) is used to measure the internal consistency dependability of the constructions. Acceptable values are greater than 0.70. In circumstances where lower values are recorded, item-total correlations are analyzed to detect possibly weak items. Construct validity was further assessed by Exploratory Factor Analysis (EFA). Prior to factor extraction, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity are evaluated to assess the data's appropriateness for factor analysis. Acceptable KMO values are >0.60 and Bartlett's test is statistically significant ($p < 0.05$). The factor loadings are then assessed to ensure that questionnaire questions load adequately on the target constructs. All data are acquired by a single self-report questionnaire, hence there is the risk of common method bias. To mitigate this risk, anonymity of the participants is guaranteed and the questions on the questionnaire are counterbalanced when feasible. In addition, Harman's one-factor test is

used. If one component explains less than 50% of the variation, it is unlikely that there is considerable common technique bias (Podsakoff et al., 2003).
After checking reliability and validity, descriptive statistics for all important constructs (mean and standard deviation) are generated. Subsequently, Pearson correlation analysis is undertaken to explore the correlations between the main factors of the research, including perceived AI efficiency, AI risk, faith in AI, adoption intention, team fit, behavioral profile, and perceived recruiting quality.

The suggested hypotheses are tested using regression analysis . For the predicted sample size , basic and parsimonious models are used. Specifically, we analyze confidence in AI in connection to perceived AI risk and governance protections, adoption intention in relation to trust in AI, and perceived hiring quality in relation to behavioral profile and team-fit characteristics.

Major statistical assumptions like normality, linearity, homoscedasticity and multicollinearity are assessed before regression analysis. For this aim, skewness and kurtosis data, residual plots, tolerance statistics and Variance Inflation Factors (VIF) are investigated. Statistical significance is assessed at the 5% level.

Finally, group comparisons are made between HR professionals and hiring managers to investigate if professional function has an effect on views of AI-assisted recruitment and behavioral evaluation. For comparisons of two groups , independent-samples t-tests are performed . If more role categories are present in the final sample , a one-way ANOVA is used.

3.6 Ethical Considerations and Limitations

Participation in the research is on a voluntary and anonymous basis. Participants are told about the academic goal of the study before filling in the questionnaire; no personally identifiable information is gathered. All replies are private and will be used for academic reasons only. The research also adheres to the GDPR criteria of confidentiality, anonymity and data minimisation.
The work is a contribution, however it has numerous limitations that should be noted. First, the use of a non-probability sampling method in the study may restrict the generalizability of the

results. Second, the cross-sectional design of the research indicates that perceptions are studied at a certain moment in time and may therefore be different in various organizational or technical settings. Third, the research depends on self-reported perceptions, not recruitment outcomes or behavioral data. The findings consequently reflect stakeholders' opinions and attitudes toward AI-assisted recruitment rather than objective indicators of organizational performance. However, the research provides key insights into how HR professionals and hiring managers are evaluating AI recruiting platforms, governance controls and behavioral profiling techniques in the context of today's recruitment.

In chapter 3 the methodological approach used for the study was provided. This included the research design, sampling strategy, structure of the questionnaire and the statistical analysis techniques. The empirical results are presented in the next chapter and their implications are discussed with reference to the research questions and the theoretical framework.

4. Results

4.1 Statistical analysis of the quantitative data

Initially, the first descriptive statistics involves the gender of the participants. From the analysis it has been seen that 50.55% of the sample were males, 45.05% were women and a minor fraction of 4.40% decided not to respond. The findings reveal a fairly equal representation of both genders in the study sample.

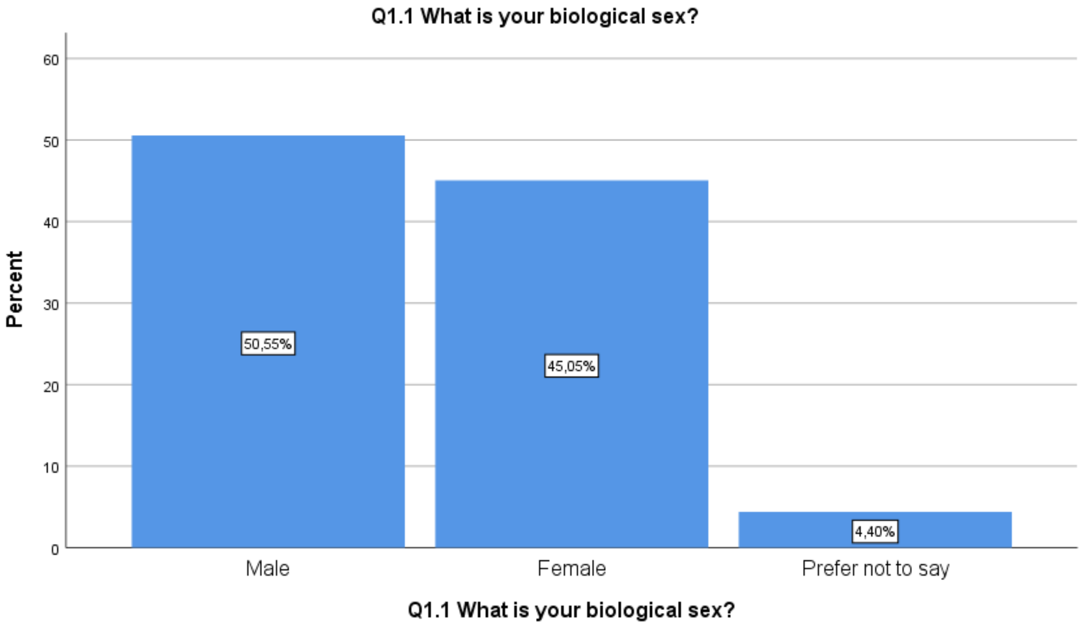

Figure 1: Distribution of participants by biological sex

Regarding the age of the participants, most of the sample belonged to the Millennials or Generation Y (1981-1996) at 62.09%. Following were the Generation X (1965-1980) participants, which were 32.97% of the sample, while only 4.95% belonged to Generation Z (1997-2012). The results indicate that the sample consists primarily of mid-career professionals.

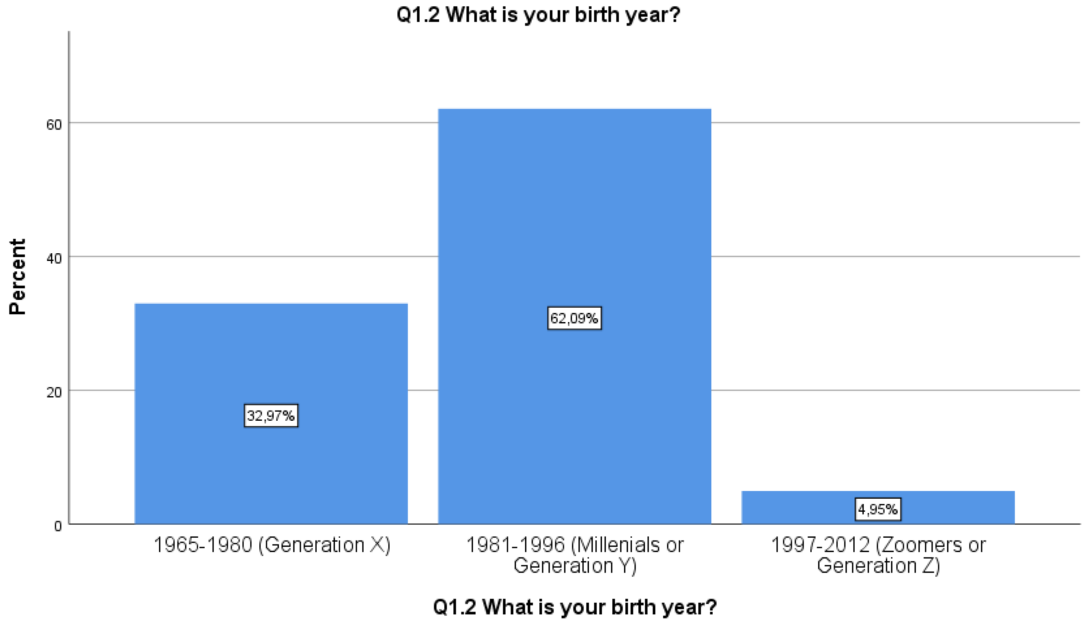

Figure 2: Distribution of participants by generational category

As for the educational level of the participants, most of the sample had a postgraduate degree (68.13%). 26.92% said they had a bachelor's degree and just 4.95% had a professional doctorate or a doctoral degree (PhD). The findings indicate that the sample is characterized by a high level of education, which is deemed especially relevant to the topic of the study and the usage of AI technologies in recruiting procedures.

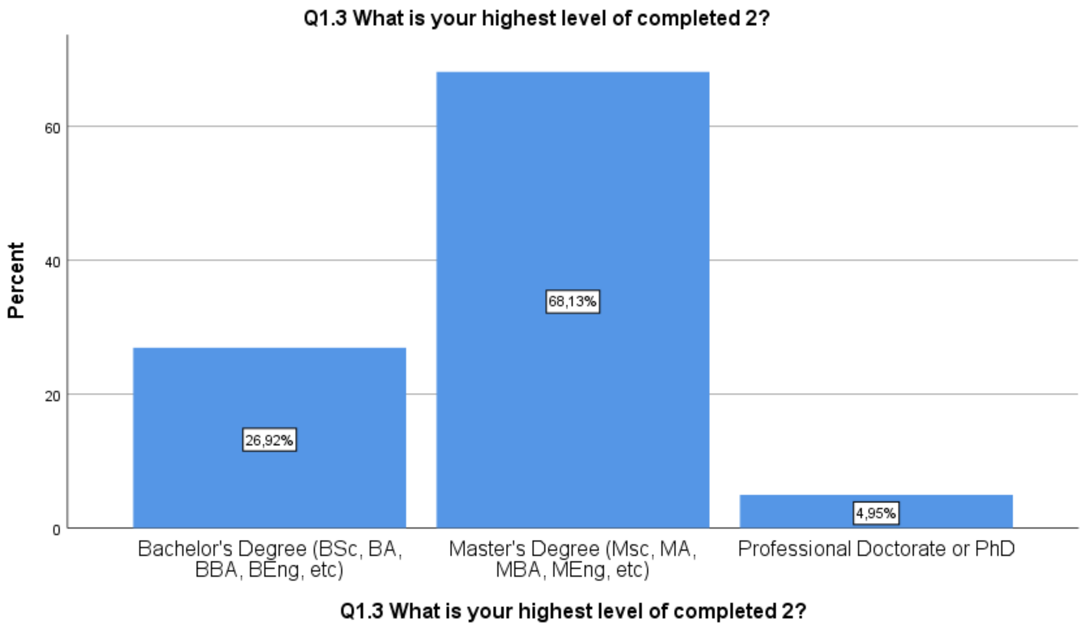

Figure 3: Educational level of the study participants

Concerning the current professional position of the participants, the biggest share of the sample (62.09%) was in the "Other" category, i.e., professionals with varied administrative or organizational tasks. HR / Talent Acquisition Specialists (18.68% of sample), Hiring Managers or Team Leaders (16.48%) A handful (2.75%) of the participants have reported having both HR and recruitment obligations. The results show that the sample comprises of varied professional duties, allowing different points of view on the usage of AI in recruitment processes to be collected.

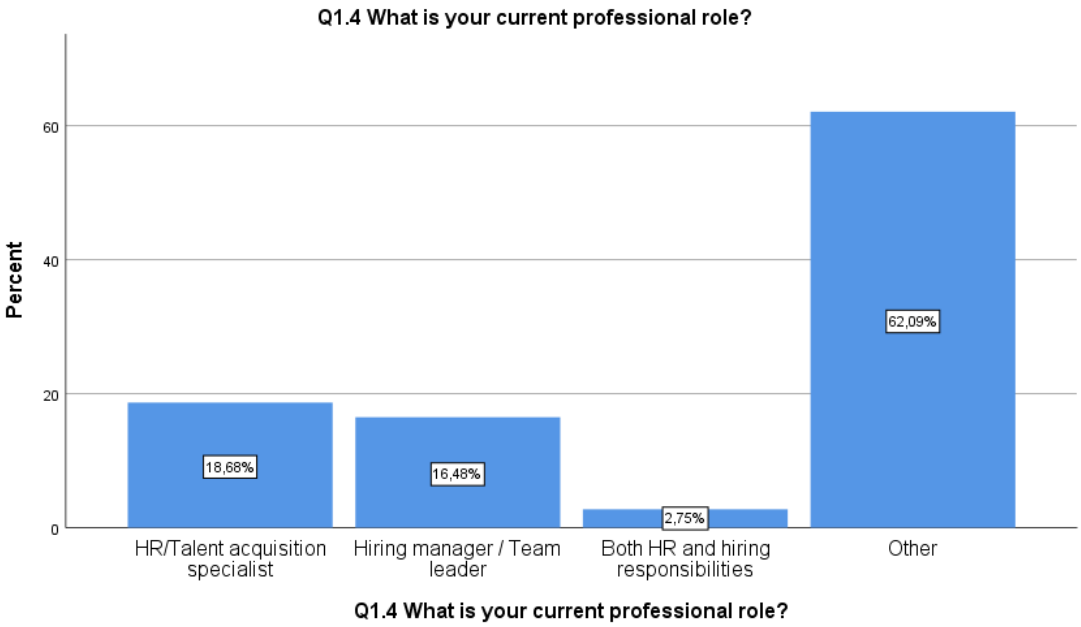

Figure 4: Professional role distribution of the study participants

Regarding the years of professional experience, the highest percentage of the participants (36.26%) had more than 20 years of work experience . After that came those with experience of 6 to 10 years (23.63%). 11.62% had 6-10 years of professional experience. 17.03% had 11-15 years of professional experience. Also, 13.74% had 16-20 years' experience and just 9.34% had up to 5 years. The results suggest that the sample is dominated by professional persons with long work experience which enhances the trustworthiness of recorded remarks on AI-supported recruitment practices.

Figure 5: Professional experience of the study participants

With regard to the sector of activity of the organizations of the participants, the largest share of the sample is that of the education sector (35.16%). The professional services and consulting business followed with 20.33%, and the "Other" category at 18.13%. Moreover, 14.84% of the respondents were engaged in the ICT Technology sector, whereas lower numbers were reported for the energy industry (6.59%), the banking/finance sector (2.75%) and telecommunications (2.20%). The findings point to the sample being made up of participants from diverse areas of activity, which raises the prospect of collecting differing opinions about the employment of AI in recruiting procedures.

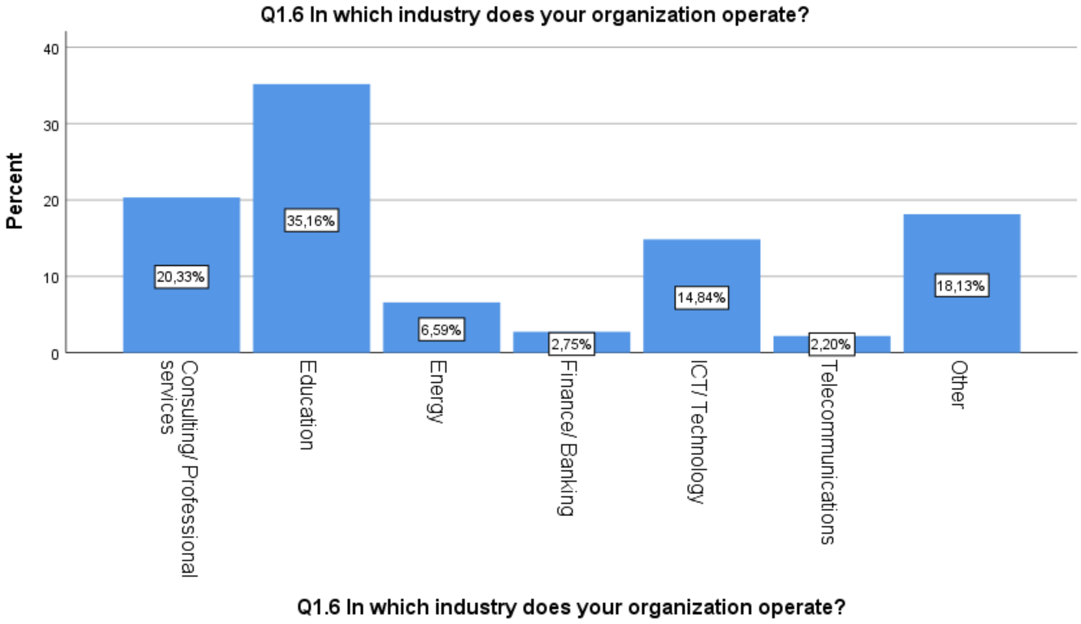

Figure 6: Industry sectors represented in the study sample

Regarding the size of the organizations, the largest percentage of the sample (36.26%) was from organizations with more than 1000 employees. To 26,92 % 18,68% came from small-sized companies employing less than 50 employees. The corresponding figure for organisations with 50-250 employees was 18.13%. The findings indicate that the sample is comprised of professionals working in organizations of different sizes with a higher concentration of large companies and organizations.

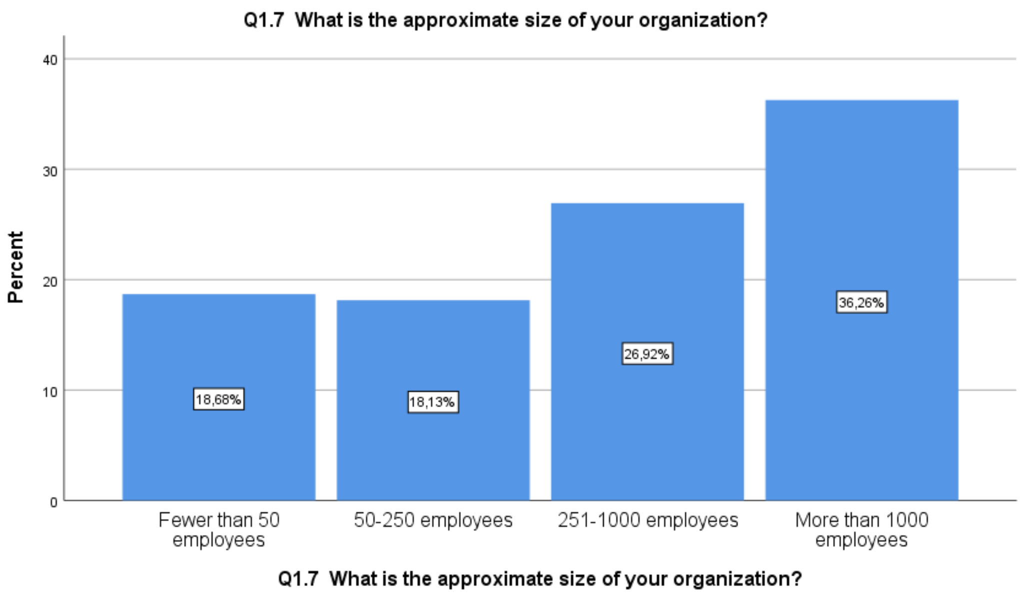

Figure 7: Organizational size distribution of the participating companies

Cronbach's Alpha was used to test the dependability of the research instrument. For the analysis, the internal consistency of the whole questionnaire for the 32 questions was extremely good (Cronbach's α = .923). This result suggests that the research instrument has a high degree of dependability and is appropriate for researching the variables under study.

Table 1: Reliability analysis of the questionnaire constructs

Reliability Statistics

Cronbach's Alpha	N of Items
,923	32

Table 4.2 shows descriptive statistics of the key variables of the survey. The AI Efficiency variable had a reasonably high mean (M = 3.87, SD = 0.84) which suggests that participants saw AI recruiting systems as successful . A similar picture emerged for Behavioral Profiling (M = 3.90, SD = 0.77), suggesting that participants saw behavioral evaluation as important in recruiting procedures.

The highest mean value was found for the Explainability and Governance category (M = 4.29, SD = 0.67), showing that participants judged transparency, accountability and human oversight mechanisms in AI-supported recruiting systems to be very significant. Similarly, the Team Fit variable was also scored very high (M=4.28, SD=0.78) . This shows that the participants value the compatibility of applicants with the team dynamics. The desire to deploy AI recruiting technologies also had a high mean (M = 4.02, SD = 0.84). This means that the attitude towards the future usage of AI in recruitment procedures is generally favorable. On the other hand, the average values of the Trust in AI (M = 3.24, SD = 0.68) and AI Risk Perception (M = 3.38, SD = 0.71) variables were lower, indicating that, despite the positive general attitude towards AI technologies, some reservations about the reliability, transparency and potential risks of AI-assisted recruitment systems are still held.

Table 2: Descriptive statistics of the main research constructs

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AI_efficiency	182	2,33	5,00	3,8700	,84142
AI_DECISION_QUALITY	182	2,00	5,00	3,5073	,73139
AI_RISK_PERCEPTION	182	2,00	4,67	3,3828	,71251
TRUST_IN_AI	182	1,75	5,00	3,2390	,68318
EXPLAINABILITY_AND_GOVERNANCE	182	2,00	5,00	4,2912	,66700
AI_ADOPTION_INTENTION	182	2,00	5,00	4,0201	,84106
BEHAVIORAL_PROFILING	182	2,00	5,00	3,9025	,77096
TEAM_FIT	182	1,00	5,00	4,2802	,78031
TEAM_ROLE	182	1,00	5,00	3,6612	,73789
Valid N (listwise)	182				

Exploratory Factor Analysis (EFA) was carried out to determine the acceptability of the data for factor analysis. Kaiser–Meyer–Olkin (KMO) index was .593, showing a slightly satisfactory sample adequacy for the use of factor analysis. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 6510.411$, df = 496, $p < .001$) at the same time, indicating that the correlations between variables were enough to proceed with the investigation.

The findings indicate that the data were appropriate for the study of the factor structure of the research instrument.

Table 3: Kaiser–Meyer–Olkin (KMO) and Bartlett's Test of Sphericity

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,593
Bartlett's Test of Sphericity	Approx. Chi-Square	6510,411
	df	496
	Sig.	,000

Exploratory Factor Analysis was conducted using Principal Component Analysis with Varimax rotation. The findings indicated the extraction of seven factors with eigenvalues greater than unity, explaining a total of 75.36% of the total variance of the data after rotation.

The first component accounted for 20.07% of the overall variation, while the second and third variables accounted for an additional 15.06% and 13.70%, respectively. The findings reveal that the factor structure of the research tool provides a reasonable degree of explanation of the overall variance, which confirms the structural appropriateness of the constructs utilized in the study.

Table 4: Total variance explained of the extracted components

Total Variance Explained

	Initial Eigenvalues			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10,745	33,578	33,578	6,421	20,066	20,066
2	4,344	13,576	47,154	4,819	15,059	35,125
3	2,991	9,346	56,500	4,383	13,698	48,823
4	1,912	5,976	62,475	2,717	8,490	57,313
5	1,678	5,244	67,720	2,212	6,912	64,225
6	1,336	4,174	71,894	1,958	6,118	70,343
7	1,108	3,463	75,357	1,604	5,014	75,357
8	,995	3,109	78,467			
9	,870	2,720	81,186			
10	,807	2,522	83,709			
11	,727	2,273	85,982			
12	,644	2,012	87,994			
13	,543	1,696	89,690			
14	,510	1,594	91,284			
15	,447	1,398	92,682			

16	,372	1,161	93,843	
17	,330	1,032	94,875	
18	,291	,908	95,783	
19	,224	,700	96,484	
20	,211	,658	97,142	
21	,185	,578	97,720	
22	,149	,464	98,184	
23	,139	,434	98,618	
24	,119	,372	98,991	
25	,085	,267	99,257	
26	,072	,224	99,481	
27	,056	,174	99,655	
28	,034	,107	99,761	
29	,030	,095	99,857	
30	,024	,075	99,931	
31	,012	,037	99,969	
32	,010	,031	100,000	

Extraction Method: Principal Component Analysis.

In Table 4.5 Rotated Component Matrix of Exploratory Factor Analysis is presented and follows Varimax rotation with Kaiser Normalization. The rotation converged after 13 iterations and the findings in general indicate a suitable factor structure of the variables. In particular, most items had substantial loadings on the theoretically predicted variables, which confirms the structural validity of the constructs utilized in the study. The variables of confidence in AI systems, perceived efficiency of AI recruiting tools, explainability and governance protections exhibited robust factor loadings.

At the same time, the elements concerning behavioral profile, team fit and logic of team-role frameworks centered on separate components with rather significant loadings. There were low cross-loadings across factors for several items, which is anticipated in multidimensional organizational and behavioral variables. However, the factor structure was considered generally acceptable and consistent with the theoretical model of the study.

Table 5: Rotated component matrix of the exploratory factor analysis

Rotated Component Matrix[a]

	Component						
	1	2	3	4	5	6	7
Q2.1 AI Efficiency. AI recruitment tools reduce candidate screening time.	,572		,457				
Q2.2 AI Efficiency. AI tools reduce recruiter workload.	,426		,417			,438	
Q2.3 AI Efficiency. AI recruitment systems increase recruitment process efficiency.	,637			,522			
Q2.4 AI Decision Quality. AI systems improve candidate shortlisting accuracy.	,612						
Q2.5 AI Decision Quality. AI systems can support more objective recruitment decisions.	,785						
Q2.6 AI Decision Quality. AI tools help identify suitable candidates more quickly.	,759						
Q2.7 AI Risk Perception. AI recruitment systems may reinforce hidden biases.						,771	
Q2.8 AI Risk Perception. AI systems may rely on incomplete or imperfect data.							,849

Q2.9 AI Risk Perception. AI-generated recruitment decisions may lack transparency.						,432	,501
Q3.1 Trust in AI. I trust AI-generated candidate recommendations.	,796						
Q3.2 Trust in AI. AI systems can be reliable in recruitment contexts.	,766						
Q3.3 Trust in AI. AI outputs are consistent across similar hiring cases.	,622						
Q3.4 Trust in AI. I feel confident using AI-based tools in recruitment decisions.	,833						
Q3.5 Explainability and Governance. AI recruitment systems should provide clear explanations for their decisions.			,696				
Q3.6 Explainability and Governance. Lack of explainability reduces my trust in AI tools.			,715				
Q3.7 Explainability and Governance. Human oversight is essential in AI-supported recruitment.			,750				
Q3.8 Explainability and Governance. Organizations should regularly audit AI recruitment systems.			,797				
Q3.9 Explainability and Governance. Compliance with GDPR is important in AI-supported recruitment.			,778				

Q3.10 Adoption Intention. I would support expanding the use of AI tools in recruitment.	,660		,412		
Q3.11 Adoption Intention. AI will play an important role in future hiring processes.	,443		,555		
Q3.12 Adoption Intention. Organizations should invest more in AI recruitment technologies.	,739				
Q4.1 Behavioral Profiling. Behavioral profiling can improve hiring decisions.				,771	
Q4.2 Behavioral Profiling. Personality assessment is useful in recruitment.				,810	
Q4.3 Behavioral Profiling. Behavioral traits can predict long-term employee performance.					,784
Q4.4 Behavioral Profiling. Behavioral alignment reduces early employee turnover.		,518			,664
Q4.5 Team fit. Team compatibility is important for hiring success.		,853			
Q4.6 Team fit. Hiring for team balance improves team performance.		,858			
Q4.7 Team fit. Technical skills alone are not sufficient for team success.		,498			,442
Q4.8 Team fit. Recruitment decisions should consider team dynamics.		,865			

Q4.9 Team-Role Logic (Belbin concept). Team-role models (e.g., Belbin) can support recruitment decisions.		,625
Q4.10 Team-Role Logic (Belbin concept). Team-role approaches can help identify complementary team contributions.		,714
Q4.11 Team-Role Logic (Belbin concept). AI systems could integrate behavioral profiling and team-fit evaluation.	,424	,475

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 13 iterations.

The Kolmogorov-Smirnov and Shapiro-Wilk tests were used to evaluate the normality of the primary variables of the research. The findings indicated that for all the primary variables of the research there were statistically significant departures from the normal distribution ($p < .05$). However, since the sample size of the research was relatively large (N=182), the variables were derived from composite Likert-scale constructs (composite variables) and parametric techniques are believed to be quite robust to deviations in normality in larger samples, it was deemed appropriate to continue the analysis with parametric statistical techniques such as Pearson correlations, linear regression analysis and ANOVA.

Table 6: Tests of normality for the main research constructs

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AI_efficiency	,147	182	,000	,924	182	,000
AI_DECISION_QUALITY	,130	182	,000	,962	182	,000
AI_RISK_PERCEPTION	,110	182	,000	,952	182	,000

TRUST_IN_AI	,109	182	,000	,973	182	,001
EXPLAINABILITY_AND_GOVERNANCE	,183	182	,000	,833	182	,000
AI_ADOPTION_INTENTION	,147	182	,000	,912	182	,000
BEHAVIORAL_PROFILING	,141	182	,000	,943	182	,000
TEAM_FIT	,178	182	,000	,770	182	,000
TEAM_ROLE	,175	182	,000	,881	182	,000

a. Lilliefors Significance Correction

Pearson correlation analysis was done to analyze the correlations between the key variables of the research. The findings demonstrate that there are multiple statistically significant positive correlations between the variables of the theoretical model. More specifically, AI Efficiency was shown to correlate strongly and positively with AI Adoption Intention ($r = .716$, $p < .001$), and also with Trust in AI ($r = .622$, $p < .001$). Similarly, AI Decision Quality was significantly correlated with Trust in AI ($r =.750$, $p <.001$). This suggests that the more participants perceived that AI systems increased the quality of recruitment decisions, the more they trusted these systems.

The Explainability and Governance variable was also significantly and positively correlated with Trust in AI ($r =.320$, $p <.001$) and intention to adopt AI technologies ($r =.576$, $p <.001$). This suggests that transparency, accountability and governance safeguards are associated with more positive attitudes towards AI supported recruitment systems.

On the other hand, AI Risk Perception was negatively correlated with several variables in the model, such as Behavioral Profiling ($r = -.206$, $p =.005$) and the Team-Role construct ($r = -.171$, $p =.021$), indicating that higher levels of concern about bias, transparency, and reliability are associated with lower evaluations of AI-supported recruitment practices.

Finally extremely large positive correlations were observed between the qualities of conduct and team fit. More precisely, there was a high correlation between Behavioral Profiling and Team Fit ($r = .613$, $p < .001$), and Team Fit was strongly positively associated to the Team-Role construct (r = .665, p < .001). The results show the importance of behavioral and cooperative elements in the current recruitment processes.

Table 7: Pearson correlation analysis between the main research constructs

Correlations

		AI_efficiency	AI_DECISION_QUALITY	AI_RISK_PERCEPTION	TRUST_IN_AI	EXPLAINABILITY_AND_GOVERNANCE	AI_ADOPTION_INTENTION	BEHAVIORAL_PROFILING	TEAM_FIT	TEAM_ROLE
AI_efficiency	Pearson Correlation	1	,625**	,258**	,622**	,556**	,716**	,433**	,465**	,549**
	Sig. (2-tailed)		,000	,000	,000	,000	,000	,000	,000	,000
	N	182	182	182	182	182	182	182	182	182
AI_DECISION_QUALITY	Pearson Correlation	,625**	1	,034	,750**	,287**	,591**	,159*	,035	,309**
	Sig. (2-tailed)	,000		,648	,000	,000	,000	,032	,638	,000
	N	182	182	182	182	182	182	182	182	182
AI_RISK_PERCEPTION	Pearson Correlation	,258**	,034	1	-,030	,176*	-,080	-,206**	-,049	-,171*
	Sig. (2-tailed)	,000	,648		,687	,018	,286	,005	,511	,021
	N	182	182	182	182	182	182	182	182	182
TRUST_IN_AI	Pearson Correlation	,622**	,750**	-,030	1	,320**	,692**	,164*	,217**	,493**
	Sig. (2-tailed)	,000	,000	,687		,000	,000	,027	,003	,000
	N	182	182	182	182	182	182	182	182	182
EXPLAINABILITY_AND_GOVERNANCE	Pearson Correlation	,556**	,287**	,176*	,320**	1	,576**	,245**	,373**	,513**
	Sig. (2-tailed)	,000	,000	,018	,000		,000	,001	,000	,000
	N	182	182	182	182	182	182	182	182	182
AI_ADOPTION_INTENTION	Pearson Correlation	,716**	,591**	-,080	,692**	,576**	1	,293**	,308**	,498**
	Sig. (2-tailed)	,000	,000	,286	,000	,000		,000	,000	,000
	N	182	182	182	182	182	182	182	182	182
BEHAVIORAL_PROFILING	Pearson Correlation	,433**	,159*	-,206**	,164*	,245**	,293**	1	,613**	,552**
	Sig. (2-tailed)	,000	,032	,005	,027	,001	,000		,000	,000
	N	182	182	182	182	182	182	182	182	182
TEAM_FIT	Pearson Correlation	,465**	,035	-,049	,217**	,373**	,308**	,613**	1	,665**
	Sig. (2-tailed)	,000	,638	,511	,003	,000	,000	,000		,000
	N	182	182	182	182	182	182	182	182	182
TEAM_ROLE	Pearson Correlation	,549**	,309**	-,171*	,493**	,513**	,498**	,552**	,665**	1
	Sig. (2-tailed)	,000	,000	,021	,000	,000	,000	,000	,000	
	N	182	182	182	182	182	182	182	182	182

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Using a linear model with Trust in AI as the dependent variable and AI Risk Perception as the independent variable, the influence of perceived risk of AI recruiting systems on Trust in AI was explored. Results revealed that the regression model was not statistically significant (F = 0.163, p = .687) and that the amount of explained variation was very low (R2 = .001). At the same time, the AI Risk Perception variable did not have a statistically significant influence on Trust in AI (β = -.030, t = -0.404, p = .687).

The evidence from this research, however, did not support hypothesis H2, which posited that perceived danger of AI systems would adversely effect confidence in AI systems.

Table 8: Linear regression analysis between AI Risk Perception and Trust in AI

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,030[a]	,001	-,005	,68476

a. Predictors: (Constant), AI_RISK_PERCEPTION

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,076	1	,076	,163	,687[b]
	Residual	84,402	180	,469		
	Total	84,478	181			

a. Dependent Variable: TRUST_IN_AI

b. Predictors: (Constant), AI_RISK_PERCEPTION

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,337	,247		13,513	,000
	AI_RISK_PERCEPTION	-,029	,071	-,030	-,404	,687

a. Dependent Variable: TRUST_IN_AI

Multiple linear regression was done to evaluate the factors affecting the intention to implement AI recruiting technologies. The dependent variable is AI Adoption Intention, while the independent variables are Trust in AI and Explainability and Governance.

The findings indicated that the regression model was statistically significant (F = 145.363, $p < .001$) and explained 61.9% of the total variance of the desire to embrace AI technology ($R^2 = .619$). This result shows that the model has a very high explanatory power.

In instance, trust in AI had a substantial positive influence on the desire to embrace AI technology ($\beta = .565$, $t = 11.603$, $p < .001$). Meanwhile, the variable of Explainability and Governance also had a positive and statistically significant influence on AI Adoption Intention ($\beta = .395$, $t = 8.116$, $p < .001$).

The findings indicate that the more confidence in AI systems and the more significance attached to transparency, accountability and governance structures, the stronger the participants' desire to support the implementation of AI-supported recruiting technology.

Thus, the findings of this investigation supported the hypotheses H3 and H4.

Table 9: Multiple regression analysis predicting AI Adoption Intention

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,787[a]	,619	,615	,52209

a. Predictors: (Constant), EXPLAINABILITY_AND_GOVERNANCE, TRUST_IN_AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79,246	2	39,623	145,363	,000[b]
	Residual	48,792	179	,273		
	Total	128,037	181			

a. Dependent Variable: AI_ADOPTION_INTENTION

b. Predictors: (Constant), EXPLAINABILITY_AND_GOVERNANCE, TRUST_IN_AI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,373	,275		-1,353	,178
	TRUST_IN_AI	,696	,060	,565	11,603	,000
	EXPLAINABILITY_AND_GOVERNANCE	,498	,061	,395	8,116	,000

a. Dependent Variable: AI_ADOPTION_INTENTION

Table 4.10. Descriptive statistics of the major variables of the survey according to the professional function of the participants among the case of majority of the factors linked to the efficacy and acceptance of AI recruiting technology, the mean values were greater among participants with direct HR or hiring responsibilities.

Specifically, Hiring Managers and Team Leaders reported high mean scores on the perceived usefulness of AI systems (M = 4.44), as well as on the relevance of Behavioral Profiling (M = 4.37) and Team Fit (M = 4.46). Similarly, HR/Talent Acquisition Specialists scored well on AI Efficiency (M = 4.14) and AI Adoption Intention (M = 4.30).

The group of respondents who indicated having both HR and recruiting duties had the highest mean values for practically all factors. However, this subgroup contained only a small number of individuals (N = 5), hence caution should be used in interpreting the data.

On the other side the group “Other” showed in general lower values in the means of factors such as Trust in AI, AI Adoption Intention and Behavioral Profiling. This result may suggest a more reserved attitude regarding the usage of AI-supported recruiting tools on the part of professionals not directly engaged in recruitment procedures.

Table 10: Descriptive statistics by professional role

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
TRUST_IN_AI	HR/Talent acquisition specialist	34	3,4632	,90481	,15517	3,1475	3,7789	1,75	5,00
	Hiring manager / Team leader	30	3,3417	,67109	,12252	3,0911	3,5923	2,25	4,25
	Both HR and hiring responsibilities	5	4,2500	,00000	,00000	4,2500	4,2500	4,25	4,25
	Other	113	3,0996	,55956	,05264	2,9953	3,2039	2,00	4,00
	Total	182	3,2390	,68318	,05064	3,1391	3,3389	1,75	5,00
AI_ADOPTION_INTENTION	HR/Talent acquisition specialist	34	4,3039	,91146	,15631	3,9859	4,6219	2,67	5,00
	Hiring manager / Team leader	30	4,2444	,46265	,08447	4,0717	4,4172	3,33	5,00
	Both HR and hiring responsibilities	5	4,6667	,00000	,00000	4,6667	4,6667	4,67	4,67
	Other	113	3,8466	,86950	,08180	3,6845	4,0087	2,00	5,00
	Total	182	4,0201	,84106	,06234	3,8971	4,1432	2,00	5,00
AI_efficiency	HR/Talent acquisition specialist	34	4,1373	,74814	,12831	3,8762	4,3983	3,00	5,00
	Hiring manager / Team leader	30	4,4444	,58939	,10761	4,2244	4,6645	3,33	5,00
	Both HR and hiring responsibilities	5	5,0000	,00000	,00000	5,0000	5,0000	5,00	5,00
	Other	113	3,5870	,80089	,07534	3,4377	3,7363	2,33	5,00
	Total	182	3,8700	,84142	,06237	3,7469	3,9930	2,33	5,00

BEHAVIORAL_PROFILING	HR/Talent acquisition specialist	34	4,0147	,82329	,14119	3,7274	4,3020	3,00	5,00
	Hiring manager / Team leader	30	4,3667	,40860	,07460	4,2141	4,5192	3,75	5,00
	Both HR and hiring responsibilities	5	4,2500	,00000	,00000	4,2500	4,2500	4,25	4,25
	Other	113	3,7301	,78784	,07411	3,5832	3,8769	2,00	5,00
	Total	182	3,9025	,77096	,05715	3,7897	4,0152	2,00	5,00
AI_RISK_PERCEPTION	HR/Talent acquisition specialist	34	3,5588	,61255	,10505	3,3451	3,7726	2,33	4,00
	Hiring manager / Team leader	30	3,3778	,67656	,12352	3,1251	3,6304	2,67	4,67
	Both HR and hiring responsibilities	5	4,6667	,00000	,00000	4,6667	4,6667	4,67	4,67
	Other	113	3,2743	,70462	,06629	3,1430	3,4057	2,00	4,67
	Total	182	3,3828	,71251	,05281	3,2786	3,4870	2,00	4,67
TEAM_FIT	HR/Talent acquisition specialist	34	4,1985	,59918	,10276	3,9895	4,4076	3,00	5,00
	Hiring manager / Team leader	30	4,4583	,45996	,08398	4,2866	4,6301	3,75	5,00
	Both HR and hiring responsibilities	5	5,0000	,00000	,00000	5,0000	5,0000	5,00	5,00
	Other	113	4,2257	,88701	,08344	4,0603	4,3910	1,00	5,00
	Total	182	4,2802	,78031	,05784	4,1661	4,3943	1,00	5,00

Levene’s Test of Homogeneity of variance was conducted before to the analysis of variance (ANOVA). Results revealed statistically significant differences from the assumption of homogeneity of variances for majority of the study variables ($p < .05$).

In particular, statistically significant variations in variances were found for the variables Trust in AI, AI Adoption Intention, AI Efficiency and Behavioral Profiling. On the contrary, the result for the variable Team Fit was found to be marginally non-significant ($p = .053$). For the variable

AI Risk Perception the findings revealed a lower divergence from the assumption of homogeneity.

Despite these variations, analysis proceeded using ANOVA, since these approaches are generally thought to be rather robust to breaches of homogeneity of variances in samples of similar sizes.

Table 11: Levene's test for homogeneity of variances across professional roles

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
TRUST_IN_AI	Based on Mean	6,541	3	178	,000
	Based on Median	5,886	3	178	,001
	Based on Median and with adjusted df	5,886	3	140,111	,001
	Based on trimmed mean	6,419	3	178	,000
AI_ADOPTION_INTENTION	Based on Mean	12,468	3	178	,000
	Based on Median	5,546	3	178	,001
	Based on Median and with adjusted df	5,546	3	111,983	,001
	Based on trimmed mean	11,556	3	178	,000
AI_efficiency	Based on Mean	5,714	3	178	,001
	Based on Median	4,702	3	178	,003
	Based on Median and with adjusted df	4,702	3	166,154	,004
	Based on trimmed mean	5,793	3	178	,001
BEHAVIORAL_PROFILING	Based on Mean	10,088	3	178	,000
	Based on Median	9,487	3	178	,000
	Based on Median and with adjusted df	9,487	3	159,490	,000
	Based on trimmed mean	9,915	3	178	,000
AI_RISK_PERCEPTION	Based on Mean	2,794	3	178	,042
	Based on Median	2,152	3	178	,095

	Based on Median and with adjusted df	2,152	3	162,279	,096
	Based on trimmed mean	2,775	3	178	,043
TEAM_FIT	Based on Mean	2,616	3	178	,053
	Based on Median	2,542	3	178	,058
	Based on Median and with adjusted df	2,542	3	146,121	,059
	Based on trimmed mean	2,879	3	178	,037

A one-way analysis of variance (One-Way ANOVA) was conducted to assess whether the impressions of AI-supported recruiting systems altered based on the participants' professional job.

The findings indicated that there were statistically significant disparities between professional groups in many of the main factors of the research. In particular, significant differences were seen in Trust in AI ($F = 7.370$, $p < .001$), AI Adoption Intention ($F = 4.885$, $p = .003$), AI Efficiency ($F = 16.409$, $p < .001$), Behavioral Profiling ($F = 6.658$, $p < .001$) and AI Risk Perception ($F = 7.758$, $p < .001$).

Conversely, no statistically significant differences were reported across professional groups in the case of the variable Team Fit ($F = 2.296$, $p = .079$), which showed that the value of team compatibility was favorably evaluated regardless of professional function. Overall, the findings of the ANOVA show a substantial impact of the professional job on perceptions of the efficacy, dependability and future use of AI recruiting technologies.

Table 12: One-way ANOVA results across professional roles

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
TRUST_IN_AI	Between Groups	9,334	3	3,111	7,370	,000
	Within Groups	75,144	178	,422		

	Total	84,478	181			
AI_ADOPTION_INTENTION	Between Groups	9,740	3	3,247	4,885	,003
	Within Groups	118,297	178	,665		
	Total	128,037	181			
AI_efficiency	Between Groups	27,761	3	9,254	16,409	,000
	Within Groups	100,383	178	,564		
	Total	128,145	181			
BEHAVIORAL_PROFILING	Between Groups	10,854	3	3,618	6,658	,000
	Within Groups	96,727	178	,543		
	Total	107,581	181			
AI_RISK_PERCEPTION	Between Groups	10,625	3	3,542	7,758	,000
	Within Groups	81,263	178	,457		
	Total	91,888	181			
TEAM_FIT	Between Groups	4,105	3	1,368	2,296	,079
	Within Groups	106,103	178	,596		
	Total	110,209	181			

Post-hoc comparisons using the Tukey HSD technique were used to determine the professional groups in which the significant differences as a consequence of the ANOVA analysis were detected. Results indicated that “Other” category participants had considerably lower levels of Trust in AI than HR/Talent Acquisition Specialists ($p = .024$) and participants that claimed that they had both HR and recruiting duties ($p = .001$). A similar pattern was seen for AI Adoption Intention, with the “Other” group showing a lower intention to use AI technology than HR professionals ($p = .024$).

AI Efficiency: Significant variances were also detected. In particular, Hiring Managers/Team Leaders and HR professionals judged the efficacy of AI recruiting systems much more highly than the group “Other” ($p < .01$). At the same time, the individuals who had HR and recruiting responsibilities rated highest overall.

In Behavioral Profiling, Hiring Managers/Team Leaders scored considerably higher than the "Other" group (p < .001). Likewise, in AI Risk Perception, participants responsible for HR and recruiting were much more concerned about the possible hazards of AI systems than all other categories (p < .01).

Finally, the Team Fit variable was confirmed with the findings of the previous ANOVA study with no statistically significant differences across professional groups.

Table 13: Tukey post-hoc comparisons across professional roles

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) Q1.4 What is your current professional role?	(J) Q1.4 What is your current professional role?	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
TRUST_IN_AI	HR/Talent acquisition specialist	Hiring manager / Team leader	,12157	,16275	,878	-,3005	,5437
		Both HR and hiring responsibilities	-,78676	,31120	,059	-1,5939	,0203
		Other	,36368*	,12709	,024	,0341	,6933
	Hiring manager / Team leader	HR/Talent acquisition specialist	-,12157	,16275	,878	-,5437	,3005
		Both HR and hiring responsibilities	-,90833*	,31385	,022	-1,7223	-,0944
		Other	,24211	,13345	,270	-,1040	,5882
	Both HR and hiring responsibilities	HR/Talent acquisition specialist	,78676	,31120	,059	-,0203	1,5939
		Hiring manager / Team leader	,90833*	,31385	,022	,0944	1,7223
		Other	1,15044*	,29693	,001	,3804	1,9205

	Other	HR/Talent acquisition specialist	-,36368*	,12709	,024	-,6933	-,0341
		Hiring manager / Team leader	-,24211	,13345	,270	-,5882	,1040
		Both HR and hiring responsibilities	-1,15044*	,29693	,001	-1,9205	-,3804
AI_ADOPTION_INTENTION	HR/Talent acquisition specialist	Hiring manager / Team leader	,05948	,20421	,991	-,4701	,5891
		Both HR and hiring responsibilities	-,36275	,39047	,789	-1,3754	,6499
		Other	,45731*	,15946	,024	,0438	,8709
	Hiring manager / Team leader	HR/Talent acquisition specialist	-,05948	,20421	,991	-,5891	,4701
		Both HR and hiring responsibilities	-,42222	,39379	,707	-1,4435	,5991
		Other	,39784	,16743	,085	-,0364	,8321
	Both HR and hiring responsibilities	HR/Talent acquisition specialist	,36275	,39047	,789	-,6499	1,3754
		Hiring manager / Team leader	,42222	,39379	,707	-,5991	1,4435
		Other	,82006	,37256	,127	-,1462	1,7863
	Other	HR/Talent acquisition specialist	-,45731*	,15946	,024	-,8709	-,0438
		Hiring manager / Team leader	-,39784	,16743	,085	-,8321	,0364
		Both HR and hiring responsibilities	-,82006	,37256	,127	-1,7863	,1462
AI_efficiency	HR/Talent acquisition specialist	Hiring manager / Team leader	-,30719	,18811	,363	-,7950	,1807
		Both HR and hiring responsibilities	-,86275	,35969	,081	-1,7956	,0701
		Other	,55023*	,14689	,001	,1693	,9312

	Hiring manager / Team leader	HR/Talent acquisition specialist	,30719	,18811	,363	-,1807	,7950
		Both HR and hiring responsibilities	-,55556	,36275	,421	-1,4963	,3852
		Other	,85742*	,15424	,000	,4574	1,2574
	Both HR and hiring responsibilities	HR/Talent acquisition specialist	,86275	,35969	,081	-,0701	1,7956
		Hiring manager / Team leader	,55556	,36275	,421	-,3852	1,4963
		Other	1,41298*	,34319	,000	,5229	2,3030
	Other	HR/Talent acquisition specialist	-,55023*	,14689	,001	-,9312	-,1693
		Hiring manager / Team leader	-,85742*	,15424	,000	-1,2574	-,4574
		Both HR and hiring responsibilities	-1,41298*	,34319	,000	-2,3030	-,5229
BEHAVIORAL_PROFILING	HR/Talent acquisition specialist	Hiring manager / Team leader	-,35196	,18465	,229	-,8308	,1269
		Both HR and hiring responsibilities	-,23529	,35308	,910	-1,1510	,6804
		Other	,28462	,14419	,202	-,0893	,6586
	Hiring manager / Team leader	HR/Talent acquisition specialist	,35196	,18465	,229	-,1269	,8308
		Both HR and hiring responsibilities	,11667	,35608	,988	-,8068	1,0402
		Other	,63658*	,15140	,000	,2439	1,0292
	Both HR and hiring responsibilities	HR/Talent acquisition specialist	,23529	,35308	,910	-,6804	1,1510
		Hiring manager / Team leader	-,11667	,35608	,988	-1,0402	,8068
		Other	,51991	,33688	,414	-,3538	1,3936

	Other	HR/Talent acquisition specialist	-,28462	,14419	,202	-,6586	,0893
		Hiring manager / Team leader	-,63658*	,15140	,000	-1,0292	-,2439
		Both HR and hiring responsibilities	-,51991	,33688	,414	-1,3936	,3538
AI_RISK_PERCEPTION	HR/Talent acquisition specialist	Hiring manager / Team leader	,18105	,16925	,708	-,2579	,6200
		Both HR and hiring responsibilities	-1,10784*	,32363	,004	-1,9472	-,2685
		Other	,28449	,13217	,141	-,0583	,6273
	Hiring manager / Team leader	HR/Talent acquisition specialist	-,18105	,16925	,708	-,6200	,2579
		Both HR and hiring responsibilities	-1,28889*	,32638	,001	-2,1353	-,4424
		Other	,10344	,13877	,879	-,2565	,4633
	Both HR and hiring responsibilities	HR/Talent acquisition specialist	1,10784*	,32363	,004	,2685	1,9472
		Hiring manager / Team leader	1,28889*	,32638	,001	,4424	2,1353
		Other	1,39233*	,30878	,000	,5915	2,1931
	Other	HR/Talent acquisition specialist	-,28449	,13217	,141	-,6273	,0583
		Hiring manager / Team leader	-,10344	,13877	,879	-,4633	,2565
		Both HR and hiring responsibilities	-1,39233*	,30878	,000	-2,1931	-,5915
TEAM_FIT	HR/Talent acquisition specialist	Hiring manager / Team leader	-,25980	,19339	,537	-,7614	,2418
		Both HR and hiring responsibilities	-,80147	,36980	,136	-1,7605	,1576
		Other	-,02713	,15102	,998	-,4188	,3645

Hiring manager / Team leader	HR/Talent acquisition specialist	,25980	,19339	,537	-,2418	,7614
	Both HR and hiring responsibilities	-,54167	,37294	,469	-1,5089	,4255
	Other	,23267	,15857	,459	-,1786	,6439
Both HR and hiring responsibilities	HR/Talent acquisition specialist	,80147	,36980	,136	-,1576	1,7605
	Hiring manager / Team leader	,54167	,37294	,469	-,4255	1,5089
	Other	,77434	,35283	,129	-,1407	1,6894
Other	HR/Talent acquisition specialist	,02713	,15102	,998	-,3645	,4188
	Hiring manager / Team leader	-,23267	,15857	,459	-,6439	,1786
	Both HR and hiring responsibilities	-,77434	,35283	,129	-1,6894	,1407

*. The mean difference is significant at the 0.05 level.

4.2 Analysis of the qualitative data from the open question of the questionnaire

Together with the closed-ended questions, participants were also given the option to voluntarily record more remarks about the usage of AI enabled recruiting systems and the usefulness of behavioral profiling in recruitment procedures. Qualitative analysis of the answers identified certain repeating themes.

A few participants agreed that AI recruiting systems may considerably increase the speed and efficiency of recruitment procedures, particularly when there are huge numbers of applications and initial screening of applicants. Several comments at the same time highlighted that AI technologies may help recruiters, but do not totally replace human judgement.

Concerns regarding openness, dependability and possible bias hazards in AI-supported recruiting methods was a second major subject. Many participants highlighted the need of human supervision, the explainability of AI-supported decision-making processes and the presence of governance protections.

Additionally, numerous individuals cited behavioral profile, team fit and team-role dynamics as important aspects of recruiting choices. These answers confirmed the perception that a good hiring is not only about the technical abilities of the applicants but also about their capacity to be functionally integrated into the current work teams. Overall, the qualitative comments confirmed the results of the quantitative research and underscored the need to design more human-centered and transparent AI recruiting platforms.

5. Discussion

This study sought to understand the perceptions of professionals regarding the application of Artificial Intelligence systems in recruitment processes, with an emphasis on the efficacy of AI-supported recruitment systems, their trustworthiness, mechanisms for explainability and governance, and the significance of behavioral profiling and team fit in contemporary recruitment procedures. The results of the study indicate that the respondents have a generally positive attitude towards the use of AI technologies in recruitment, but they are not free of reservations about transparency, reliability and potential risks associated with their use (Shin & Park, 2019; Taeihagh, 2021).

One of the main results of the research is a very good evaluation of the efficiency of AI recruiting methods. Participants seemed to agree that AI technologies may help significantly to reduce the time spent screening candidates, reduce administrative burden and generally make recruiting procedures more successful. This discovery is in accordance with prior research that corroborates the fact that AI-supported recruiting systems boost operational efficiency and automate time-consuming staff selection procedures (Upadhyay & Khandelwal, 2018; Vrontis et al., 2022). Meanwhile, substantial connection between AI Efficiency and AI Adoption Intention indicates that perception of operation efficiency is a crucial determinant for the adoption of AI technologies in the recruiting environment.

However, the study's results suggested that operational efficiency does not mean blind trust in AI systems. The Participants rated the skills of AI recruitment technology well, although the degrees of Trust in AI were more moderate. This finding is particularly important from the theoretical point of view, as it suggests that professionals consider AI as a useful supporting tool, rather than a total substitute for human judgment in hiring decisions. This position is consistent with the global literature where the application of AI in decision-making is predicated not only on technical effectiveness but also on some reliability, transparency and accountability (Shin & Park, 2019; von Eschenbach, 2021).

An additional, very significant result of this study is also the influence of explainability and governance protections in the desire to implement AI recruiting systems. The regression analysis indicated that Trust in AI and the significance given to transparency and governance procedures positively and considerably influence the desire to utilize AI technology in recruiting processes. This conclusion confirms the theoretical approach according to which corporations do not assess AI systems just on the basis of their functional performance but also on the capacity to operate in a transparent, auditable and morally acceptable way (Floridi et al., 2018; Hoffmann et al., 2019). Participants seemed to place specific emphasis on the existence of human oversight, explainable decision mechanisms and auditing procedures, an aspect directly linked to the principles of responsible AI and trustworthy AI systems put forward in the current literature (Taeihagh, 2021; Shneiderman, 2022).

Interestingly, in the regression model of the research, the perceived riskiness of AI systems did not have a statistically significant influence on Trust in AI. Participants identified dangers associated with bias, data incompleteness, and transparency but these concerns did not seem to materially erode faith in AI systems. This might suggest that the participants consider the risks manageable if sufficient governance protections and the required human supervision are implemented. At the same time, as businesses get more experienced with AI technology, they are expected to adopt more pragmatic and less scared approaches to using AI in recruiting (Vrontis et al., 2022).

Another significant conclusion of the research is the enormous significance given to behavioral profiling, team fit and team-role techniques . Participants seemed to understand that the success of a recruiting choice is not only based on the technical abilities or formal credentials of a candidate, but also on his ability to integrate functionally into the team and the corporate culture. This research has obvious implications for the theories of person-environment fit and person-group fit, which state that the fit between employee and work environment has a substantial effect on cooperation, job satisfaction and long term performance (Kristof-Brown et al., 2005).

In particular, the notions of Behavioral Profiling, Team Fit and Team-Role showed very significant relationships, which suggests that the participants see the behavioral and collaborative aspects as connected parts of recruiting quality. These findings support the notion that conventional AI recruiting methods, which rely mostly on keyword matching and technical skills, may overlook important aspects of cooperation and teamwork. Therefore, the use of behavioural profile and team-role techniques in AI-assisted recruiting systems may considerably increase the overall quality of recruitment choices (Belbin, 2010).

The ANOVA findings also showed intriguing disparities between the professional groups. The assessment of the efficiency and prospects of using AI recruiting technology was more favorable for HR professionals and Hiring Managers, compared to the members of the “Other” group. This conclusion may be due to the fact that professionals directly engaged in recruiting procedures are more aware of the practical capabilities of AI systems and the operational advantages they may provide. On the other hand, professionals who are not directly engaged in the hiring process may be more hesitant, since they may have less exposure to AI-assisted recruiting procedures.

Finally, the qualitative comments made by the participants were also of significant value, corroborating the results of the quantitative study. Many participants said there was a need to preserve human judgment in recruiting procedures, especially in heavily computerized contexts. At the same time, respondents also reinforced the idea that AI systems should serve in an assisting role to recruiters and not as completely autonomous decision-making systems. This image tends to favor a more humanized approach to the employment of AI technologies in recruiting, where technology is a support tool and not a total substitute for human evaluation (Shneiderman, 2022).

6. Managerial Implications

This study has various practical implications for firms and professionals that are interested in implementing AI in recruitment. While participants acknowledged the operational advantages of AI-enabled recruitment systems, the results indicate that effective implementation needs more than technology competence. AI in recruitment needs trust, explainability, and rigorous governance (Taeihagh, 2021; Vrontis et al., 2022). AI should aid in decision making, not make choices. Participants had more confidence in AI systems when they supported recruiters rather than replacing human judgment. Human-in-the-loop AI highlights the necessity for substantial human oversight when AI is used for critical organizational decisions like hiring (Shneiderman, 2022).

The findings underscore the importance of explainability in AI-assisted recruitment. Recruiters who know how to make suggestions and evaluate prospects may push firms to use AI technology. Explain AI-assisted judgments in a transparent way to increase trust in these technologies, particularly in recruitment, where choices directly influence career outcomes and organizational performance (Shin & Park, 2019; von Eschenbach, 2021).

Explainability is also necessary for successful AI governance. The results show that governance measures should be adopted by corporations to guarantee recruitment transparency, accountability and fairness. Human oversight, routine audits, bias tracking, and adherence to regulations may help decrease risks and build confidence in AI-powered hiring tools. As AI becomes more prevalent, the standards of GDPR and AI governance will have more significance in ethical employment practices (Floridi et al., 2018; Hoffmann et al., 2019).

The study suggests that companies should benefit from a broader view of recruitment quality. When you hire, you should look at behavior profiling, team compatibility and team-role strategies, not just technical talents or key word matches. Participants appreciated such qualities, indicating that the integration of behavioural and collaborative information into recruitment decisions may enhance team cohesion, employee flexibility and organisational effectiveness (Kristof-Brown et al., 2005; Belbin, 2010).

Another practical result is the segmentation of professional groups. HR and recruiting managers were more likely to use AI-supported recruiting than non-hirers. The report suggests firms do AI literacy and customized training to help recruiters, managers and other staff understand AI's promise and limitations. Better understanding of AI systems may minimize uncertainty and support ethical AI recruitment (Upadhyay & Khandelwal, 2018).

The findings suggest that recruitment is likely to not be based entirely on human judgment or AI. The most successful approaches to recruitment will probably be hybrid ones that combine the efficiency of AI with the expertise, governance transparency and behavioural understanding of humans. Thus, the continued success of AI-supported recruitment will depend on technology innovation and organizations' capacity to develop trustworthy, transparent and human-centred recruitment processes.

7. Conclusions

This research explored professionals' perspectives about the use of AI-supported technologies in recruiting. The study focused on the efficacy of AI systems, confidence in AI, explainability and governance mechanisms, and the importance of behavioural profile and team fit in recruitment decision-making. The research shows that professionals usually see AI as a beneficial tool to assist in recruiting procedures, notably by enhancing efficiency, lowering administrative burden and aiding in decision-making. These results support the earlier studies on the practical advantages of AI in Human Resource Management (Upadhyay & Khandelwal, 2018; Vrontis et al., 2022).

The research also shows that technical efficiency alone is not sufficient to assure the effective use of AI in recruiting. Trust, openness, explainability and proper governance protections revealed as relevant variables affecting professionals' readiness to depend on AI-supported recruiting methods. These findings further reinforce the increasing importance of AI that is trustworthy and human-centred, and that for the effective use of AI in organizational decision-making, it is not just about technological capability but also ethical responsibility, accountability and meaningful human oversight (Floridi et al., 2018; Shneiderman, 2022).

The study also points to the relevance of including behavioral elements into recruiting choices. Participants agreed that quality in recruiting was not only about the technical skill of applicants, but also about their capacity to work together, to fit into existing teams and to add to the larger organisational environment. This is in line with previous research into behavioural profiling, person-environment fit and team-role approaches, suggesting that recruitment decisions benefit from combining assessments of technical competence with evaluations of interpersonal and behavioural compatibility (Kristof-Brown et al., 2005; Belbin, 2010).

The differences seen across occupational categories also indicate that experience with AI technology affects judgments of their usefulness and potential. We also find that professionals actively engaged in recruiting seem to have more positive perceptions of AI-supported recruitment systems compared to their counterparts with less practical experience, which highlights the relevance of organizational learning, experience and AI literacy in promoting technology adoption.

In conclusion, the results show that the future of recruiting is unlikely to be dictated by the substitution of human decision-makers with Artificial Intelligence. Instead, the data suggests hybrid recruiting models are emerging in which AI is a tool that complements, not replaces, human skills. The long-term success of AI-assisted recruitment will therefore depend not only on continued technological innovation but also on the ability of organizations to combine efficiency with transparency, responsible governance and a strong understanding of the behavioural factors that contribute to successful recruitment decisions.

8. Limitations

While the current research provides substantially to the existing literature on AI-assisted recruiting, there are a number of constraints to consider when interpreting its results. First, the research used a convenience sample technique, therefore the results are limited in how well they can be generalized to the broader community of professionals participating in recruiting. While participants covered a range of sectors and occupations, the sample is not entirely typical of all businesses or recruiting specialists.

Second, the study design was cross-sectional and data were gathered at one time point. The observed associations are thus not to be regarded as proof of causation. As businesses acquire more experience with AI technology, and as AI tools become more broadly incorporated into recruiting operations, perceptions about AI-assisted recruitment are likely to change.

Another drawback relates to self-reported data. The research focused on participants' views, attitudes and expectations of AI-supported recruiting, rather than objective indices of recruitment performance or real organizational results. This suggests that the results are more indicative of the perception of AI technologies by experts than the actual functioning of the technology.

Furthermore, even though the psychometric features of the measurement model as a whole were deemed good, a limited number of constructs showed only a modest level of reliability and factorial adequacy. Although these problems do not invalidate the conceptual framework as a whole, they should be taken into consideration in the interpretation of certain of the statistical associations found in the research.

Finally, the study was mainly focused on the views of professionals engaged in recruiting. Perceptions of job candidates and workers in AI-supported recruiting procedures were not studied. The inclusion of these stakeholder groups in future studies may give a more holistic view of how AI technologies affect recruiting from many viewpoints.

9. Future Research

The particular section involves recommendation for further research regarding to topic. More specifically, it is proposed further AI recruiting research. More study is required to investigate the use of AI technologies in Human Resource Management, their impact on the recruitment process, corporate decision-making, and the recruitment experience.

In future studies, bigger and more representative samples from various countries, sectors, and organizations may be used. Such comparative and cross-cultural studies would assist to evaluate whether institutional and cultural views of trust, transparency, governance and AI adoption differ. A longitudinal study following experts' perspectives on AI over time would also be helpful. With increasing experience with AI-supported recruiting systems in businesses, trust, explainability, perceived dangers, and acceptability may evolve, giving a more dynamic picture of AI use in recruitment.

Another intriguing direction is to study AI assisted recruiting and objective organizational performance. Future research might explore whether AI-assisted recruiting leads to better recruitment, employee performance, organizational fit, retention and other HR metrics. Assessing AI-assisted recruiting systems could use perceptual data as well as objective organizational metrics.

Future works may combine behavioral profiling and team-role approaches to AI aided recruiting. The integration of behavioural assessments, psychometric tools and team compatibility measures into AI technologies may show their influence on recruitment, team performance and organizational success.

Finally, future research should include the opinions of job searchers. The opinions of candidates on AI aided recruitment, particularly the fairness, transparency, explainability, and acceptability of automated recruiting judgments, will be more essential as AI technologies are reshaping the Human Resource practices (Shin & Park, 2019; van Esch et al., 2019).

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Appenix 1. The Questionnaire

The questionnaire used in this this research has been created in Google Forms as follows.

Section 1 of 6

MBA Dissertation - Hellenic Open University (HOU) Research Questionnaire

Dear Participant.

The following research is conducted in the context of my MBA Dissertation titled "**Exploiting Artificial Intelligence to Enhance Human Resource Recruitment**". The primary purpose of the current thesis is to examine how AI-based recruitment systems can integrate Belbin Team Role Behavioral profiling to enhance interview evaluation, team fit prediction, and overall hiring decision-making.

Target audience: (a) HR professionals responsible for recruitment, talent acquisition, or human resource management, and (b) ICT-related hiring managers, team leaders, and department heads involved in staffing decisions.

Survey format & scoring: The questionnaire consists of first part of **seven (7)** demographic questions. Afterwards the participants will be asked to answer **thirty two (32)** more questions separated into 3 sections, where the answers will be evaluated in a 5-point Likert scale.

Duration: Approximately 7-8 minutes.

Please notice that the participation in the current study is completely anonymous. All responses will be used solely for academic purposes.

For any questions, you may contact me at std165316@ac.eap.gr or via my LinkedIn profile. I would be more than happy to share with anyone the results of the current study, upon its completion.

Thank you in advance for your valuable contribution as part in the current study. Your input is crucial for its successful completion.

Best Regards,

Antonis G. Misargopoulos, MBA Candidate of Hellenic Open University

MSc & BSc in Computer Science, BSc in Mathematics, University of Crete

Email *

Valid email

This form is collecting emails. Change settings

Section 2 of 6

Section 1. Personal & Professional Information

This sections gathers some demographical data for reporting & analytics.

Q1.1 What is your biological sex?

- ○ Male
- ○ Female
- ○ Other
- ○ Prefer not to say

Q1.2 What is your birth year?

- ○ 1946 -1964 (Baby Boomers)
- ○ 1965 - 1980 (Generation X)
- ○ 1981 - 1996 (Millenials or Generation Y)
- ○ 1997 - 2012 (Zoomers or Generation Z)
- ○ Prefer not to say

Q1.3 What is your highest level of completed education?

- ○ High school diploma
- ○ Bachelor's Degree (BSc, BA, BBA, BEng, etc.)
- ○ Master's Degree (MSc, MA, MBA, MEng, etc.)
- ○ Professional Doctorate or PhD
- ○ Other

Q1.4 What is your current professional role?

- ○ HR / Talent acquisition specialist
- ○ Hiring manager / Team leader
- ○ Both HR and hiring responsibilities
- ○ Other

Q1.5 How many years of professional experience do you have?

- ○ 0–5 years
- ○ 6–10 years
- ○ 11–15 years
- ○ 16-20 years
- ○ More than 20 years

Q1.6 In which industry does your organization operate?

- ○ Consulting / Professional services
- ○ Education
- ○ Energy
- ○ Finance / Banking
- ○ ICT / Technology
- ○ Telecommunications
- ○ Other

Q1.7 What is the approximate size of your organization?

- ◯ Fewer than 50 employees
- ◯ 50–250 employees
- ◯ 251–1000 employees
- ◯ More than 1000 employees

After section 2 Continue to next section

Section 3 of 6

Section 2. AI Recruitment Perception

Some answers in the following sections follow a 5-point Likert scale (1-5). I.e.,
1. Strongly disagree - 2. Disagree - 3. Neutral - 4. Agree - 5. Strongly agree

Please select the answer (number) that fits mostly.

Note: In cases where you don't feel sure or competent to answer, please select *3. Neutral.*

Q2.1 AI Efficiency. AI recruitment tools reduce candidate screening time. *

	1	2	3	4	5	
Strongly disagree	◯	◯	◯	◯	◯	Strongly agree

Q2.2 AI Efficiency. AI tools reduce recruiter workload. *

	1	2	3	4	5	
Strongly disagree	◯	◯	◯	◯	◯	Strongly agree

Q2.3 AI Efficiency. AI recruitment systems increase recruitment process efficiency. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.4 AI Decision Quality. AI systems improve candidate shortlisting accuracy. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.5 AI Decision Quality. AI systems can support more objective recruitment decisions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.6 AI Decision Quality. AI tools help identify suitable candidates more quickly. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.7 AI Risk Perception. AI recruitment systems may reinforce hidden biases. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.8 AI Risk Perception. AI systems may rely on incomplete or imperfect data. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q2.9 AI Risk Perception. AI-generated recruitment decisions may lack transparency. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

After section 3 Continue to next section

Section 4 of 6

Section 3. Trust and Governance

Some answers in the following sections follow a 5-point Likert scale (1-5). I.e.,
1. Strongly disagree - 2. Disagree - 3. Neutral - 4. Agree - 5. Strongly agree

Please select the answer (number) that fits mostly.

Note: In cases where you don't feel sure or competent to answer, please select *3. Neutral*.

Q3.1 Trust in AI. I trust AI-generated candidate recommendations. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.2 Trust in AI. AI systems can be reliable in recruitment contexts. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.3 Trust in AI. AI outputs are consistent across similar hiring cases. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.4 Trust in AI. I feel confident using AI-based tools in recruitment decisions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.5 Explainability and Governance. AI recruitment systems should provide clear explanations for their decisions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.6 Explainability and Governance. Lack of explainability reduces my trust in AI tools. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.7 Explainability and Governance. Human oversight is essential in AI-supported recruitment. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.8 Explainability and Governance. Organizations should regularly audit AI recruitment systems. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.9 Explainability and Governance. Compliance with GDPR is important in AI-supported recruitment. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.10 Adoption Intention. I would support expanding the use of AI tools in recruitment. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.11 Adoption Intention. AI will play an important role in future hiring processes. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q3.12 Adoption Intention. Organizations should invest more in AI recruitment technologies. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

After section 4 Continue to next section

Section 5 of 6

Section 4. Behavioral Profiling and Team Fit

Some answers in the following sections follow a 5-point Likert scale (1-5). I.e.,
1. Strongly disagree - 2. Disagree - 3. Neutral - 4. Agree - 5. Strongly agree

Please select the answer (number) that fits mostly.

Note: In cases where you don't feel sure or competent to answer, please select *3. Neutral*.

Q4.1 Behavioral Profiling. Behavioral profiling can improve hiring decisions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.2 Behavioral Profiling. Personality assessment is useful in recruitment. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.3 Behavioral Profiling. Behavioral traits can predict long-term employee performance. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.4 Behavioral Profiling. Behavioral alignment reduces early employee turnover. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.5 Team fit. Team compatibility is important for hiring success. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.6 Team fit. Hiring for team balance improves team performance. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.7 Team fit. Technical skills alone are not sufficient for team success. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.8 Team fit. Recruitment decisions should consider team dynamics. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.9 Team-Role Logic (Belbin concept). Team-role models (e.g., Belbin) can support recruitment decisions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.10 Team-Role Logic (Belbin concept). Team-role approaches can help identify complementary team contributions. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Q4.11 Team-Role Logic (Belbin concept). AI systems could integrate behavioral profiling and team-fit evaluation. *

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

Do you have any other comments on the use of AI in recruitment?

Short answer text

After section 5 Continue to next section

Section 6 of 6

Many thanks for your participation.

Description (optional)