

## Beyond algorithms: Artificial intelligence driven talent identification with human insight

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### ABSTRACT

The rapid evolution of Artificial Intelligence (AI) is reshaping Human Resource Management (HRM), with growing interest in its role in talent identification. While AI has demonstrated effectiveness in analysing structured data, its limitations in assessing qualitative attributes such as creativity, adaptability, and emotional intelligence remain underexplored. This study addresses these gaps through an exploratory mixed-methods design, combining a global survey ( $n = 240$ ) with semi-structured interviews of HR professionals. Quantitative analysis highlights patterns of association between key competencies, while qualitative findings provide contextual insights into perceptions of fairness, bias, and cultural resistance. The results suggest that AI can complement, but not replace, human judgement, supporting a Hybrid Evaluative Model that integrates algorithmic efficiency with human interpretation. The study contributes rare empirical evidence to a nascent field, highlights the ethical imperatives of bias mitigation and transparency, and underscores the importance of cultural context (collectivist versus individualist orientations) in shaping the acceptance and effectiveness of AI-enabled HR practices. These findings offer practical guidance for organisations and advance theory-building at the intersection of AI and HRM.

### 1. Introduction

The rapid evolution of Artificial Intelligence (AI) has reshaped industries worldwide, with Human Resource Management (HRM) representing a key area of application. In HRM, AI systems can automate routine administrative tasks and forecast employee potential through data-driven analytics. These capabilities have the potential to transform talent identification and assessment, enabling organisations to make faster, more accurate, and less biased decisions. Within the context of the Fourth Industrial Revolution, AI has become a critical resource for organisations seeking to sustain competitiveness (Agrawal et al., 2022; Manyika et al., 2017).

Nevertheless, these advancements come with challenges. While AI demonstrates strong capacity to evaluate structured data with high efficiency—creating new opportunities for technical competency assessments (Stone et al., 2024; Wandhe, 2023) its application to qualitative attributes such as emotional intelligence, adaptability, and

cultural fit remains limited. Mittelstadt et al. (Mittelstadt et al., 2016) emphasise the difficulty of capturing such complex traits algorithmically, as subjective qualities are inherently resistant to quantification. This limitation underscores the importance of a hybrid evaluation model that combine human judgement with AI-driven analytics.

Existing research primarily emphasises theoretical frameworks or case-based examples, with limited empirical evidence on AI's efficacy in HR contexts (Chamorro-Premuzic et al., 2017; Vivek, 2023). This study addresses these gaps by formulating research questions that examine how AI can be used to evaluate employee potential, how reliable it is in talent identification, and how it influences bias in evaluative processes.

Through a mixed-methods approach, this study combines a global survey of professionals with qualitative insights from expert interviews. The findings indicate that although AI enhances efficiency and objectivity in analysing structured data, its limitations and ethical challenges highlight the importance of hybrid models that incorporate human judgement and oversight.

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This research contributes to the growing body of literature by providing empirical evidence on AI's role in HRM. It underscores the importance of adopting transparent, ethical frameworks, such as the EU AI Act (European Union, 2021), to ensure that AI systems are practical yet also fair and inclusive. The study offers insights for HR professionals, researchers, and policymakers on how AI can be leveraged responsibly to enhance talent management practices. In doing so, it advances the argument that AI and human judgement should be integrated to promote workplaces that are both high-performing and equitable, balancing innovation with responsibility.

The literature on AI in HRM highlights both its potential and its limitations. Although AI tools are widely used in recruitment and assessment, they still struggle to evaluate qualitative traits and mitigate bias, such as creativity, adaptability, and cultural fit (Bujold et al., 2024; França et al., 2023). Current research tends to focus on theoretical models or isolated case studies, lacking comprehensive empirical evidence on AI's performance in holistic talent evaluation.

Ethical concerns further complicate this picture. Algorithmic transparency, accountability, and fairness are widely discussed (Bankins, 2021; Mittelstadt et al., 2016), yet operational frameworks remain underdeveloped. The EU AI Act (European Union, 2021) provides a macro-level foundation, but micro-level mechanisms for bias mitigation in day-to-day HR processes are still poorly understood (Barletta et al., 2023). Moreover, although hybrid evaluative models combining AI and human oversight are increasingly discussed conceptually (Tambe et al., 2019; Vivek, 2023), few empirical studies test how such models can balance efficiency with fairness.

This study addresses these gaps through a theory-informed, exploratory mixed-methods design, integrating survey data and interviews with HR professionals. It examines how AI interacts with measurable and qualitative aspects of talent, while assessing how ethical principles are enacted in practice. These gaps directly inform the research questions presented in Section 1.3.

In today's technology-driven world, organisations face increasing pressure to maximise the utilisation of their human capital (Dries, 2013a). Traditional HR practices struggle to keep pace with workforce complexity, data quality challenges, and decision-making biases (França et al., 2023). AI provides a potential means to streamline processes and improve talent identification (Jia et al., 2018; Tambe et al., 2019). Yet translating this promise into practice is fraught with operational, ethical, and contextual challenges.

Notable failures, such as Amazon's biased recruitment tool (Zappulla, 2024), illustrate how reliance on historical data can unintentionally perpetuate discrimination (Drage & Mackereth, 2022). While AI tools efficiently source and screen candidates, they often fail to address broader organisational imperatives such as diversity and inclusion (Burton, 2019; Chamorro-Premuzic et al., 2017). These limitations highlight the need for approaches that extend beyond operational efficiency to foster inclusivity and strategic alignment.

Recent studies emphasise the potential of hybrid AI models, where algorithmic precision complements human judgement (Aleessawi & Djaghrouri, 2025; Kuzmanko & Vrbová, 2024). Although efficiency gains are clear (Roppelt et al., 2025), risks such as bias, privacy concerns, and reduced decision quality persist. Organisational interventions, such as recruiter upskilling, workflow redesign, and structured oversight, are therefore essential to mitigate harmful outcomes.

This study responds to these challenges by empirically examining the viability of a hybrid evaluative model in HRM, seeking to balance efficiency with fairness and align AI applications with ethical and organisational values.

In sum, these challenges underline the need for theory-informed, empirical research into hybrid evaluative models that integrate algorithmic efficiency with human judgement. This forms the central focus of the present study.

This urgency is reinforced by recent market analyses. Gartner's Hype

Cycle for Human Capital Management (HCM) Technology highlights that AI-driven solutions, such as internal talent marketplaces and predictive workforce analytics, are transitioning from experimental pilots to mainstream adoption, with projections indicating dedicated investment by 35 % of large enterprises by 2025 (Kostoulas & Chiba, 2022). This trend is consistent with Gartner's "Top Strategic Technology Trends" (Gartner Inc., 2023), which emphasises the transformative role of AI in workforce planning and skill development. Similarly, an IBM study (IBM Study, 2024) reports that 89 % of organisations intend to maintain or increase AI-related investments despite economic uncertainty.

The Priority Matrix further identifies technologies poised to redefine HRM. Machine learning in HCM streamlines processes while enabling more personalised, data-driven decisions. Internal talent marketplaces are enhancing organisational agility by optimising talent utilisation, while AI-driven recruitment and analytics are projected to reach mainstream adoption within two years (Kostoulas & Chiba, 2022).

Amid this technological momentum, HR professionals must navigate the balance between innovation and responsibility. Empirical studies confirm AI's strengths in analysing structured data and predicting technical competencies (Abiodun et al., 2018; Bersin & Chamorro-Premuzic, 2019). However, its limitations in assessing qualitative traits, such as cultural fit or emotional intelligence, underscore the necessity of a hybrid evaluation model, where algorithmic precision is complemented by human judgement.

At the same time, ethical safeguards are indispensable. Regulatory frameworks such as the EU AI Act (European Union, 2021) highlight the need for accountability, transparency, and fairness in high-risk applications like HRM. Beyond compliance, effective integration demands collaboration between policymakers, technologists, and HR practitioners to ensure that AI adoption enhances both organisational performance and workplace equity.

França et al.'s (França et al., 2023) identifies persistent gaps in the application of AI to talent and potential assessment, particularly regarding bias mitigation, transparency of evaluative criteria, and the integration of automated systems with human judgement. Addressing these gaps requires examining how AI systems can be made more trustworthy, accepted by human stakeholders, and aligned with regulatory and ethical standards. They directly inform the research questions of this study, which investigate how evaluative models can incorporate subjective criteria, ensure fairness, and be operationalised ethically within talent identification processes. Accordingly, this study is guided by three research questions:

**RQ1.** How can AI models be used to evaluate employee potential in HRM contexts?

**RQ2.** How reliable are AI models in identifying high-potential talent?

**RQ3.** How do AI models influence bias and fairness in talent identification processes?

These questions reflect persistent limitations in the existing literature and the practical challenges faced by organisations. To address them, the study pursues the following objectives: (a) to provide empirical evidence on AI's effectiveness and limitations in talent evaluation, (b) to examine how human and AI perspectives can be combined in hybrid evaluative models, and (c) to analyse the ethical implications of such integration for HR practice.

By articulating these questions and objectives together, the study ensures conceptual coherence and highlights its contribution to both academic research and HR practice.

For conceptual clarity, the following key terms are used consistently throughout the manuscript:

- **Hybrid Evaluative Model** - The central concept of this study, referring to the integration of AI-driven analytics with human judgement in talent identification and development.

- **AI-human collaboration** - The operational dimension of shared decision-making between algorithmic outputs and human evaluators, informing but not substituting the hybrid evaluative model.
- **Sociotechnical systems** - A theoretical perspective emphasising the interdependence of technological and social subsystems, which provides the foundation for balancing AI capabilities with human oversight.
- **Human capital** - The skills, attributes, and potential of individuals, conceptualised as a core organisational resource that AI may help to identify and develop when applied responsibly.

The paper proceeds as follows: [Section 2](#) reviews background concepts, [Section 3](#) presents the methodology, [Section 4](#) reports the findings, [Section 5](#) discusses implications, and [Section 6](#) concludes.

## 2. Background research

To analyse the transformative role of AI in talent identification within HRM, it is necessary to outline the foundational concepts that underpin this field. This section examines the essential ideas of talent, potential, and performance alongside the key personal and professional attributes influencing effective talent identification. These concepts establish the link between theory and the empirical findings presented later, providing the groundwork for understanding how AI can enhance HRM practices.

**Talent** can be defined as a combination of inherent abilities, developed skills, and an individual's alignment with organisational goals. It represents the unique qualities that enable individuals to thrive in specific roles. Closely related is the evolving notion of **potential**. Traditionally seen as a fixed trait, potential is now understood as dynamic and capable of being nurtured and developed through opportunities, training, and experience. This reconceptualisation has significant implications for how organisations evaluate and support their workforce. The relationship between **performance** and potential is central to how organisations measure success and identify future leaders. Although performance data are critical, they provide only a partial picture. Personal and professional attributes, such as adaptability, emotional intelligence, and leadership ability, add nuance to these assessments and offer deeper insight into an individual's capacity to grow and succeed.

This section integrates theoretical insights into the broader body of knowledge, highlighting the gaps that AI may help address. Whereas traditional HR methods emphasise static metrics like prior experience, AI has the capacity to analyse dynamic factors such as adaptability and cultural fit, thereby providing a more holistic view of talent. Linking these concepts to contemporary research establishes the basis for examining how AI can respond to these gaps and transform HRM practices.

The study synthesises these foundational ideas by identifying the attributes most critical for identifying talent and potential. This synthesis informs the study's theoretical foundation and connects these insights to practical applications in HRM, supporting a more data-driven and inclusive approach to managing human capital.

The integration of AI into HRM represents an evolving paradigm characterised by significant potential and inherent complexity. In this context, AI is increasingly regarded not only as a tool for streamlining recruitment processes but as a strategic asset capable of forecasting workforce trends, evaluating employee performance, and mitigating human biases. This transformative capacity has increasingly become the subject of substantial scholarly attention and empirical investigation. Tambe et al. (Tambe et al., 2019) demonstrate that AI excels at analysing structured data, such as performance metrics and recruitment patterns, uncovering valuable insights into employee-related outcomes. However, their findings also highlight challenges related to fairness, data quality, and ethical dilemmas.

The ethical dimension of AI in HR has been widely debated. Mittelstadt et al. (Mittelstadt et al., 2016) examined the societal implications

of algorithmic decision-making, raising critical concerns about bias, transparency, and accountability. Their work underscores the tension organisations face when adopting AI technologies, leveraging efficiency while addressing the risks of algorithmic inequity. However, much of this literature remains grounded in theoretical frameworks and isolated case studies, leaving much to be understood about how AI performs in real-world HR contexts.

This study contributes to the literature by adopting a mixed-methods approach, merging quantitative surveys with qualitative insights from HR professionals. Unlike the predictive analytics focus of Tambe et al. (Tambe et al., 2019), it examines diverse organisational contexts, uncovering how AI operates across industries and geographies. The qualitative findings complement quantitative results by contextualising algorithmic outcomes with human experiences. For instance, while AI excels in analysing structured data, it remains limited in evaluating qualitative attributes such as emotional intelligence or cultural fit, where human judgement continues to be essential.

HR analytics has progressed from descriptive dashboards to increasingly sophisticated applications of artificial intelligence, including predictive modelling for recruitment, attrition, and performance management (Tambe et al., 2019). While these developments enhance efficiency and scalability, recent studies have critically interrogated the ethical and operational trade-offs associated with algorithmic decision-making. Scholars point to a fundamental tension between the efficiency gains offered by data-driven systems and the imperative for equity, transparency, and human-centred judgement in HR practice (Vivek, 2023). This tension is particularly evident in designing and deploying AI tools for talent identification, where technical accuracy may conflict with normative values such as fairness or inclusivity.

This study addresses these concerns by examining hybrid evaluative models that combine AI-generated insights with human oversight. Rather than treating automation and human judgement as opposing forces, it considers how these elements can be configured to complement one another, mitigating bias, contextualising outcomes, and preserving interpretive flexibility. In doing so, it responds to calls in the HR analytics literature for more practitioner-informed research that not only assesses what AI can do but also interrogates what it should do in the context of people management.

By situating empirical findings within this broader analytical landscape, the study advances a more critical, reflective, and ultimately actionable perspective on responsible innovation in HRM.

**AI effectiveness and limitations.** Prior research highlights AI's growing role in HRM, particularly in recruitment and assessment tasks. Studies show strong performance in automating routine processes and analysing structured data, including test scores, *résumés*, and behavioural indicators (Chamorro-Premuzic et al., 2017; França et al., 2023).

AI-driven assessments, such as personality and logic tests, are increasingly used by firms and have been shown to provide valuable indicators of candidates' future capabilities, particularly in relation to cognitive ability and structured behavioural traits (Stanek & Ones, 2023; Stankov, 2023). These assessments can capture relevant predictors of performance and life outcomes, complementing traditional intelligence and personality measures (Furnham et al., 2009). However, growing evidence suggests that such tools remain limited in evaluating complex, non-cognitive attributes such as creativity, adaptability, and emotional intelligence (Bujold et al., 2024). Research shows that creativity and innovative potential, for instance, are only partially explained by cognitive ability measures, leaving significant variance unaccounted for (Corgnet et al., 2016; Karwowski et al., 2021). Similarly, AI-based personality prediction systems employed in hiring contexts have been found to suffer from instability and questionable validity, raising concerns about their effectiveness in capturing nuanced traits (Rhea et al., 2022). Thus, while AI-driven assessments hold promise for structured domains, their current scope is insufficient to robustly evaluate higher-order, non-cognitive attributes critical for success in dynamic

work environments.

Such traits are context-dependent and central to predicting long-term performance, yet remain largely beyond the scope of current AI tools. This gap underscores the need for empirical investigations into how AI systems can be integrated with human evaluation in more holistic talent assessments.

**Ethical considerations.** Alongside technical performance, concerns about ethics and fairness are central to the literature. Research has documented risks of algorithmic bias, lack of transparency, and accountability challenges (Bankins, 2021; Mittelstadt et al., 2016). Notable cases, such as Amazon’s recruitment tool, illustrate how biased training data can unintentionally reproduce discrimination (Drage & Mackereth, 2022). To address such risks, regulatory frameworks have emerged, most prominently the EU AI Act (European Union, 2021), which classifies employment-related AI as “high-risk”, as summarised in Table 1, and mandates strict documentation and oversight. While these instruments set important macro-level standards, operationalising fairness and accountability in day-to-day HR practice remains insufficiently studied (Barletta et al., 2023). Table 1 summarises the core obligations set out in the EU Artificial Intelligence Act (European Union, 2021) that directly apply to high-risk AI systems deployed in Human Resource Management (HRM).

**Adoption challenges and hybrid models.** Beyond ethics, organisational adoption of AI tools faces practical barriers, including data quality issues, limited recruiter skills, and resistance to change (Roppelt et al., 2025). Studies highlight the growing discussion of hybrid models, in which AI systems provide analytical precision while humans supply contextual interpretation and ethical oversight (Tambe et al., 2019; Vivek, 2023). Although these models are conceptually promising, empirical applications are still scarce. As a result, there is limited understanding of how organisations can operationalise such models to balance efficiency with fairness and inclusivity in talent management. Table 2 compares existing literature on AI applications in HRM with the current study, highlighting gaps addressed and novel contributions across key focus areas such as recruitment, workforce analytics, ethics, and hybrid evaluation models.

**Table 1**  
Summary of EU AI Act requirements for HRM applications.

AI Act Provision	Implication for HRM	Purpose
High-Risk Classification (Annex III)	AI systems used in recruitment, selection, promotion, or performance evaluation are classified as high-risk.	Ensures stricter regulatory oversight for systems affecting fundamental rights.
Transparency Obligations (Art. 13)	Employers must inform individuals when AI is used in decision-making affecting them.	Promotes informed consent and reduces opacity.
Human Oversight (Art. 14)	High-risk AI systems must include mechanisms for adequate human supervision.	Prevents overreliance on automation and reinforces accountability.
Data and Data Governance (Art. 10)	Training data must be relevant, representative, and free from bias.	Reduces risk of discriminatory outcomes and unfair treatment.
Technical Documentation (Art. 11)	Developers and users must maintain detailed records of the system’s functionality and use.	Enables auditing and regulatory traceability.
Post-Market Monitoring (Art. 61)	Organisations must monitor AI performance after deployment and report incidents.	Encourages ongoing accountability and correction of unintended harms.

Table 1 notes: This table summarises the core obligations set out in the EU Artificial Intelligence Act (COM/2021/206 final) that directly apply to high-risk AI systems deployed in Human Resource Management (HRM).

## 2.1. Talent

The concept of talent remains contested, yet its definition remains as varied and dynamic as the individuals it seeks to describe. At its core, talent refers to the unique combination of skills, abilities, and characteristics that enable individuals to excel in their roles. However, as Gallardo-Gallardo et al. (Gallardo-Gallardo et al., 2013) note, interpretations of talent in the workplace differ widely, ranging from inherent abilities and skill mastery to an alignment with organisational culture and goals. These varied perspectives reflect the complexity of talent as both an individual and organisational phenomenon.

Dries (Dries, 2013b) distinguishes two critical dimensions of human capital: **value** and **uniqueness**. Value refers to how an employee’s contributions enhance the organisation’s core competencies and competitive advantage. Uniqueness measures how difficult it is to replace that employee’s skills or knowledge. Together, these dimensions define talent as the organisation’s most valuable and irreplaceable human capital, those individuals who elevate the organisation’s performance beyond what is easily replicated by competitors.

Talent is often described as a combination of natural abilities, acquired skills, knowledge, experience, and personal attributes such as motivation and judgement (Boudreau & Ramstad, 2007; Michaels et al., 2001). Ulrich (Ulrich, 2008) expands on this, framing talent as a dynamic interplay of skills, dedication, and impact. Skills capture an employee’s expertise and capabilities, while dedication reflects their commitment to applying these qualities at work. Impact, in turn, measures the results of their efforts and their contributions to the organisation’s success. This multifaceted view underscores that talent is not merely about what employees possess but also how they use these qualities to drive meaningful outcomes.

Talent is a contested concept, often shaped by cultural and organisational contexts. For example, in European languages, talent is usually seen as an innate characteristic, while in Japanese, it is understood as a learned skill (Ansar, 2018). This cultural variation highlights that talent is not a fixed attribute but a context-dependent quality shaped by societal values and organisational needs. In practice, talent is also linked to how well individuals align with a company’s culture and strategic objectives (Lewis & Heckman, 2006). Organisations often face challenges in defining the scope of talent management, viewing it alternately as a philosophy, a strategy, or even as a reflection of individuals who embody the company’s values.

Talent management involves more than recognising individual excellence. It is about forecasting human capital needs and addressing them proactively. While much of the focus has been on leadership roles, talent management applies to all positions critical to an organisation’s operation and difficult to replace (Ansar, 2018). From identifying the high-potential employees who will drive future growth to supporting the essential contributors whose work keeps the organisation running, talent management is an ongoing, strategic endeavour.

Talent should be understood not only in terms of individual attributes but also as the collective potential that benefits the organisation. It is a resource to be nurtured, a capacity to be developed, and a driving force for organisational success.

According to Ulrich (Ulrich, 2011), talent can imply everything a business manager chooses to mean because each understands what the concept includes and excludes. Table 3 shows several definitions of talent and associated terms in academic HRM literature.

## 2.2. Potential

The concept of potential has evolved significantly over time. Historically, potential was seen as a fixed and largely inherited trait, something an individual possessed or did not (Dai, 2020). It was distinct from achievement, viewed as an immutable quality determining a person’s capabilities. However, as the understanding of human development evolved, so did the perception of potential. Today, it is recognised

**Table 2**  
Summary of related work on AI in HRM and current study contributions.

Key Focus Area	Insights from Related Work	Limitations/Gaps	Current Study Contributions
AI in Recruitment and HR Tasks	AI automates repetitive tasks like resume screening and interview scheduling, improving efficiency and engagement (Stone et al., 2024; Tambe et al., 2019).	Limited application to qualitative assessments, such as emotional intelligence and cultural fit (Chamorro-Premuzic et al., 2017).	It bridges this gap by advocating hybrid evaluation models that combine AI analytics with human oversight.
AI in Workforce Analytics	Predictive analytics identify skill gaps and guide tailored training programs (Tambe et al., 2019).	Insufficient exploration of AI's role in long-term workforce planning and organisational strategy.	Demonstrates how AI-driven models align with strategic workforce development goals.
Ethical Considerations in AI	The highlighted risks include algorithmic bias, lack of transparency, and concerns about accountability (Mittelstadt et al., 2016; Raji & Buolamwini, 2019).	Existing research remains theoretical, with limited real-world frameworks for bias mitigation (Barletta et al., 2023; Prem, 2023).	Provides empirical insights and actionable strategies, such as audits, diverse datasets, and adherence to ethical AI frameworks.
Bias in Talent Identification	AI systems can perpetuate systemic inequities, such as gender bias, due to historical data flaws (Dragé & Mackereth, 2022; Mittelstadt et al., 2016; Raji & Buolamwini, 2019).	Few frameworks explore real-world bias in talent identification processes (Bujold et al., 2024; Dima et al., 2024; Rao & Zhao, 2025; Tuffaha, 2023).	Investigates bias across ethical, operational, and technical dimensions while offering strategies for fairness and inclusivity.
Challenges in AI Adoption	High costs, resistance to change, and the need for reskilling HR teams hinder AI adoption (J. Boudreau & Cascio, 2017; Davenport & Ronanki, 2018).	Smaller organisations often lack resources and infrastructure, leading to additional barriers (Stone et al., 2024).	Proposes solutions for SMEs, including leadership engagement and structured training programmes.
Hybrid Evaluation Models	Combining AI analytics with human intuition is proposed to address AI's inability to evaluate qualitative traits (Tambe et al., 2019).	Lack of empirical validation for hybrid models in practical HRM settings.	Validates hybrid models with empirical evidence, highlighting their potential to improve holistic talent assessments.
Training and Reskilling HR Teams	Effective AI adoption requires HR professionals to develop skills to manage and interpret AI outputs (Kaur & Gandolfi, 2023; Morandini et al., 2023; Shanmugam et al., 2024; Vaddepalli, 2023).	Few studies offer structured frameworks for reskilling HR teams or managing resistance to AI adoption.	Provides a roadmap for structured reskilling programs and change management strategies tailored to HR needs.

**Table 2 notes:** This table compares existing literature on AI applications in HRM with the current study, highlighting gaps addressed and novel contributions across key focus areas such as recruitment, workforce analytics, ethics, and hybrid evaluation models.

**Table 3**  
Terms associated with talent in academic HRM literature.

The term associated with talent	
<b>Ability</b> (Gagné, 2000; Michaels et al., 2001; Silzer & Dowell, 2009; Slan-Jerusalim & Hausdorf, 2007; Tansley et al., 2006; Williams, 2000)	<b>Performance</b> (Stahl et al., 2007; Tansley et al., 2007)
<b>Skills</b> (Cheese et al., 2007; Gagné, 2000; Michaels et al., 2001; Silzer & Dowell, 2009; Tansley et al., 2006; Ulrich & Smallwood, 2012)	<b>Commitment</b> (Ulrich, 2008; Ulrich & Smallwood, 2012)
<b>Competence</b> (Silzer & Dowell, 2009; Ulrich, 2008; Ulrich & Smallwood, 2012; Williams, 2000)	
<b>Potential</b> (Tansley et al., 2006, 2007; Williams, 2000)	<b>Contribution</b> (Ulrich, 2008)
<b>Patterns of thought, feeling or behaviour</b> (Ashton & Morton, 2005; Buckingham & Vosburgh, 2001; Cheese et al., 2007)	<b>Experience</b> (Cheese et al., 2007)
<b>Capacity</b> (Jericó, 2001)	<b>Ability to move into leadership roles</b> (Slan-Jerusalim & Hausdorf, 2007)
<b>Knowledge</b> (Cheese et al., 2007; Michaels et al., 2001; Tansley et al., 2006; Ulrich & Smallwood, 2012)	<b>Capability</b> (Stahl et al., 2007)
<b>People</b> (Lewis & Heckman, 2006)	

**Table 3 notes:** This table presents recurring concepts linked to 'talent' as identified in academic HRM literature. It illustrates the multidimensional nature of talent through associated terms and their respective sources.

as dynamic and incremental, a quality influenced by internal factors like motivation and skills and external factors like organisational culture and developmental opportunities. This shift has important implications for how potential is identified and nurtured, influencing the ways in which individuals and organisations approach growth.

Early-career professionals who demonstrate exceptional performance are often recognised within their organisations and identified as strong candidates for future development and advancement opportunities. While performance may initially place them in the spotlight, as Ready et al. (Ready et al., 2010) argue, it is their behaviour, how they engage with challenges, adapt to feedback, and collaborate with others, that sustains their identification as a high-potential employee.

Performance and productivity, though often conflated, represent distinct constructs. Performance captures an individual's outcomes and achievements, while productivity measures the efficiency and effectiveness of their efforts. Distinguishing between the two is essential for accurately assessing potential.

Silzer and Church (Silzer & Church, 2009) define potential as the capacity to grow beyond one's current state, encompassing motivation, skills, and past experiences. High-potential employees are those who perform well and who display unique characteristics and aspirations, identifying them as candidates for future leadership or critical roles.. These individuals are regarded as capable of taking on broader roles, contributing significantly to an organisation's success. Identifying and cultivating potential requires a forward-looking approach that emphasises development and growth rather than static assessments.

Organisations face a significant challenge in aligning their talent identification processes with strategic goals. McDonnell et al. (McDonnell, 2011) highlight the difficulty of defining potential universally, stressing that talent identification must be tailored to an organisation's unique needs and direction. By aligning the development of high-potential employees with strategic objectives, organisations ensure that the suitable individuals are prepared to fill critical roles in the future.

However, potential does not develop in a vacuum. Gagné (Gagné, 2014) emphasises that a supportive organisational culture is essential for fostering growth. Investments in training, mentorship programmes, and career development opportunities create an environment where employees can thrive. This approach benefits the individuals who realise their potential and the organisation, which gains a more skilled and capable workforce.

Leadership, too, plays a pivotal role in recognising and nurturing potential. Dries and Pepermans (Dries & Pepermans, 2012) observe that effective leaders can identify their team members' unique strengths and developmental needs, providing the resources and support necessary for growth. Leadership development, therefore, becomes a crucial component of cultivating potential across the organisation.

In summary, the modern understanding of potential has shifted from a static, inherited trait to a dynamic quality shaped by various influences. Focusing solely on performance is insufficient; behaviour, motivation, and alignment with organisational goals are equally critical. By creating supportive environments and investing in leadership and

development opportunities, organisations can unlock the potential of their workforce, ensuring they are equipped to meet the challenges of the future.

### 2.3. Performance

Performance is as broad as it is vital, encompassing many dimensions defining success in individual and organisational contexts. As Tangen (Tangen, 2002) describes, performance acts as an umbrella term, covering everything from productivity and profitability to quality, delivery speed, and adaptability. It is the unifying thread that ties together diverse aspects of organisational success, illustrated by the Triple P-model in Fig. 1, which positions **productivity**, **profitability**, and **performance** as interconnected pillars. At its core, performance is shaped by two cross-cutting notions: **effectiveness**, which assesses how well resources are employed in the transformation process, and **efficiency**, which measures the achievement of desired objectives.

Understanding performance often begins with **productivity**, which focuses on the ratio of input to output. Campbell and Campbell (Campbell & Campbell, 1988) provide a foundational perspective, defining productivity as the result of dividing resources used (input) by what is generated (output). Outputs may be quantitative, such as production volume, or qualitative, such as product quality. In contemporary contexts, productivity is often framed as a driver of economic expansion and organisational advantage.

However, productivity is far from a static metric. It is influenced by an intricate web of factors that extend beyond output alone. Hough and Dunnette (Hough & Dunnette, 1992) emphasise that productivity encompasses efficiency, motivation, individual performance, organisational effectiveness, and work quality. This highlights a broader view, where productivity is not only about how much is achieved but also about the processes and motivations that drive those achievements.

Over the last two decades, the academic focus has shifted to **individual performance**, a critical concept in organisational psychology (Clegg & Cooper, 2008). Businesses increasingly prioritise enhancing individual productivity, recognising its direct impact on profitability (Gummesson, 1998). As Bluysen (Bluysen, 2010) notes, individual productivity is shaped by various factors, ranging from personal well-being and job satisfaction to technical competence, career milestones, and the balance between work and personal life. These influences, intrinsic (psychological or individual) and extrinsic (organisational or professional), underscore the complexity of fostering productivity within a workplace.

Understanding these dynamics offers a deeper appreciation of how performance functions as a multidimensional concept. It is not simply a measure of output but a reflection of the interplay between individual characteristics and organisational contexts. As shown in Table 4, factors such as interpersonal relationships, organisational challenges, and work-life balance contribute to individual productivity, shaping the broader understanding of performance. Organisations can create

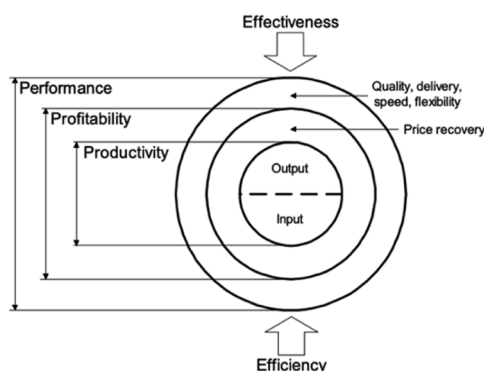


Fig. 1. The Triple P-model (Tangen, 2002).

Table 4  
Factors influencing individual productivity.

Sources	Factors Influencing Individual Productivity
(Côté, 1999)	Positive feedback.
(Hersey, 2015)	Daily emotions.
(Kaplan & Aronoff, 1996; Oseland, 1999)	The quality of the work environment, space, views outdoors, comfort, and environmental control.
(Markos & Sridevi, 2010) (Oseland, 1999)	Commitment to work.
(Lan et al., 2010)	Good working environment and employee retention.
(Herzberg, 2017)	Psychological, physiological, and neural manifestations.
(Bluyssen, 2010; Herzberg, 2017)	Position in the company, duties performed.
	Individual well-being, job satisfaction, technical competence, career achievements, work-life balance, relationships with others, personal circumstances, and organisational issues.

Table 4 notes: This table outlines various intrinsic and extrinsic factors affecting individual productivity, based on prior empirical and theoretical studies. It supports the theoretical link between performance and workplace dynamics.

environments that nurture personal and organisational success by recognising and addressing these factors.

In summary, performance is more than just a metric. It is a multifaceted concept that encapsulates the efficiency and effectiveness of individuals and organisations. Its dynamic nature demands attention to intrinsic and extrinsic factors, providing guidance for organisations to improve productivity, pursue strategic goals, and strengthen competitiveness.

### 2.4. Organisational psychology

Recent literature in organisational psychology has emphasised the central role of non-cognitive attributes in predicting high-potential performance, leadership emergence, and long-term organisational contribution. Traits such as emotional intelligence, adaptability, interpersonal sensitivity, and learning agility have been shown to influence various HR outcomes, including employee engagement, team cohesion, and retention (O'Boyle et al., 2011).

These attributes are particularly relevant in dynamic, knowledge-intensive work environments, where relational and behavioural flexibility often outweigh technical competence. Despite their recognised importance, such attributes remain difficult to evaluate through algorithmic systems, which prioritise structured, historical data over context-sensitive and situational behaviours.

This study contributes to this stream of research by operationalising these attributes through survey items and qualitative interviews, seeking to understand whether and how AI tools can meaningfully engage with behavioural complexity.

The constructs of potential and talent are grounded in this literature and are further developed in this study, where personal and professional attributes are clearly defined and linked to the empirical components of the research. In doing so, the study bridges theoretical constructs from organisational psychology with emerging practices in AI-supported evaluation, offering a novel perspective on the operationalisation of behavioural competencies in data-driven HRM.

### 2.5. Personal and professional attributes

The interplay of personal and professional attributes is a multifaceted field that shapes organisational success and innovation. As Moon (Moon, 2002) illustrates, individuals with personal talent often possess a deep understanding of their strengths and weaknesses and the resilience to achieve their goals despite setbacks. These individuals strive for self-actualisation and contribute significantly to organisational success. Psychological studies, such as those highlighted by Moon, have revealed that non-cognitive factors like self-efficacy, intrinsic motivation, and attributional style play crucial roles in goal achievement, offering a

more comprehensive view of personal talent.

The motivations behind human behaviour in the workplace are equally complex. Twenge et al. (Twenge et al., 2010), building on Herzberg's motivational theory (Herzberg & others, 1968), propose a model that categorises workplace motivators into five dimensions:

1. Extrinsic motivators, such as financial rewards or promotions.
2. Intrinsic motivators are rooted in the joy and satisfaction of the work.
3. Leisure work motivators, emphasising work-life balance and flexibility.
4. Social motivators, driven by emotional connections and teamwork.
5. Purpose-driven motivators, focused on contributing to society or helping others.

These motivators illustrate how personal attributes and preferences influence workplace behaviour and career outcomes, highlighting the intricate dynamics of professional engagement.

Talent also plays an important role in professional development and performance. According to Simonton (Simonton, 2008), individuals with inherent talent are better positioned to benefit from training and achieve high levels of proficiency in their fields. This enhanced capacity leads to superior performance, where skilled employees can deliver higher-quality results than their peers with similar experience levels. However, as Van der Heijden and Brinkman (van der Heijden & Brinkman, 2001) emphasise, talent development is a shared responsibility between the organisation and the individual. They argue that autonomy, the freedom to act and make decisions, is vital for fostering a culture of continuous learning and adaptability. Organisations can encourage innovation and knowledge transfer by empowering employees to take ownership of their roles and development, creating a more dynamic and resilient workforce.

Creativity, innovation, and initiative are pivotal in driving organisational change. As Rank et al. (Rank et al., 2004) explain, **creativity** involves generating new and valuable ideas, while **innovation** focuses on implementing those ideas to bring significant benefits to individuals, teams, and organisations. Frese (Frese, 2008) further highlights how personal initiative, characterised by proactive behaviour and persistence, acts as a catalyst for transforming creative concepts into actionable innovations. These qualities are essential for navigating the complexities of organisational change and ensuring sustained success.

High-potential employees stand out as key drivers of innovation and growth. Ready et al. (Ready et al., 2010) identify four attributes that define high-potential individuals: a strong desire to succeed, the capacity for catalytic learning, an innovative mindset, and dynamic situational awareness. These attributes enable such employees to navigate challenges, embrace new opportunities, and contribute meaningfully to their organisations. However, their success depends on the organisation's ability to identify, nurture, and align their potential with strategic goals.

Despite these insights, significant gaps remain in understanding the application of emerging technologies, such as Artificial Intelligence, to human capital management. França et al. (França et al., 2023) reveal several critical findings:

- Many HR practitioners lack reliable evidence on the effectiveness of AI for predicting future performance and potential.
- AI remains underutilised in HR, with only 22 % of organisations reporting analytics integration, often at a rudimentary level.
- While AI promises to enhance fairness and efficiency, it also poses risks of bias and misuse, highlighting the dual challenges of leveraging and regulating this technology.

This study explores the intersections of talent, potential, and personal and professional attributes. Linking these insights with predictive AI models will support organisations to address gaps in talent identification and potential evaluation processes. It is a step toward

understanding how AI can help organisations identify and nurture talent while promoting fairness and inclusivity in decision-making.

## 2.6. Personal and professional attributes contributing to potential and talent identification

Pursuing high-potential talent within organisations requires a deep understanding of the personal and professional attributes that define future leaders and technical experts. According to Ulrich and Smallwood (Ulrich & Smallwood, 2012), high-potential individuals make up just 10 to 15 per cent of an organisation's workforce. These individuals, present at all levels and often in pivotal roles, possess a unique capacity for growth, making them critical to the organisation's future success.

But what distinguishes high-potential individuals? Research offers a clear roadmap, highlighting four key characteristics that set them apart (Ready et al., 2010; Ulrich & Smallwood, 2012):

1. **Ambition:** High-potential individuals are driven by a deep sense of purpose and a willingness to invest personal time, effort, and commitment. Their perseverance fuels their capacity to overcome obstacles, making ambition a cornerstone of their success.
2. **Ability:** The skills that define high potential extend beyond technical expertise. They are adept at interpersonal communication, open to new ideas, and resilient in facing failure. Their capacity for personal growth ensures they can navigate evolving organisational challenges.
3. **Agility:** Agility is one of the most critical traits for future leaders. These individuals embrace change, experiment with new approaches, and learn from their experiences. They are adaptable, self-aware, and committed to personal and professional development, enabling them to thrive in dynamic environments.
4. **Achievement:** High-potential individuals demonstrate consistent achievement by undertaking new challenges and maintaining a record of effectiveness.

The research outlines personal and professional attributes essential for identifying and nurturing talent. As detailed in Table 5, **Personal Characteristics** include autonomy, adaptability, initiative, creativity,

**Table 5**  
Criteria corresponding to personal characteristics.

Personal Characteristics	Description	References
Autonomy	The freedom to act based on one's judgement.	(van der Heijden & Brinkman, 2001)
Adaptability	To be able to develop and adapt in a multifunctional, well-balanced manner.	(Ulrich & Smallwood, 2012; van der Heijden & Brinkman, 2001)
Initiative	Proactively seek opportunities, suggest improvements, and take ownership of one's work.	(Frese, 2008; Frese & Fay, 2001; Rank et al., 2004; Ulrich & Smallwood, 2012)
Creativity	Think outside the box, propose innovative ideas, and find new solutions.	(Frese & Fay, 2001; Rank et al., 2004; Ulrich & Smallwood, 2012)
Leadership	Demonstrate the ability to guide, inspire, and influence others in formal leadership roles or informally within teams.	(Simonton, 2008)
Desire to succeed, Ambition	Understand that progress may demand making compromises in personal lives. Willingness to go above and beyond.	(Ready et al., 2010; Ulrich & Smallwood, 2012)
Interpersonal Skills	Build positive relationships with colleagues, clients, and stakeholders.	(Ulrich & Smallwood, 2012)

Table 5 notes: This table defines key personal characteristics relevant to potential evaluation, including adaptability, leadership, and creativity, along with academic sources supporting their relevance in HRM contexts.

leadership, and ambition. Each attribute contributes to an individual’s potential by shaping their ability to navigate complex tasks and collaborate effectively with others.

**Professional characteristics**, presented in Table 6, highlight the skills necessary for organisational success, including innovation, problem-solving, teamwork, perceptiveness, mentorship, achievement, and decision-making. These attributes not only enhance individual performance but also drive collective organisational effectiveness. For instance, individuals with strong problem-solving skills and innovative mindsets are better equipped to tackle challenges and deliver meaningful results.

This approach integrates multiple dimensions of talent identification by combining personal and professional characteristics. Survey questions linked to these attributes, as outlined in Table 6, allow for a thorough evaluation of competency dynamics within the workforce. This empirical approach enables organisations to assess and align talent with their strategic objectives, fostering a more dynamic and competent workforce.

Integrating personal and professional attributes offers more than just a theoretical framework. It provides practical insights organisations can use to refine their talent identification strategies. Enhancing the accuracy and fairness of these processes improves organisational effectiveness and promotes employee development and fulfilment, contributing to both individual and organisational development.

2.7. Theoretical orientation: Framing the intersection of AI and talent in HRM

While this study is primarily empirical, its conceptual foundation is informed by three complementary theoretical perspectives that collectively support a more integrated understanding of how AI interacts with human attributes in talent identification: Human Capital Theory, the Resource-Based View (RBV), and Sociotechnical Systems Theory.

Human Capital Theory offers a foundational lens through which talent and potential are understood as value-generating assets.

Table 6  
Criteria corresponding to professional characteristics.

Professional Characteristics	Description	References
Innovation	Willingness to embrace and drive innovative solutions and practices within the organisation.	(Frese & Fay, 2001; Rank et al., 2004; Ready et al., 2010)
Problem-Solving Skills	The ability to analyse complex issues, identify solutions, and make informed decisions.	(Ulrich & Smallwood, 2012)
Teamwork	Collaborating effectively with colleagues, fostering a positive team environment, and sharing knowledge and insights.	(Ulrich & Smallwood, 2012)
Perceptive	Scan situations, have a nose for opportunity, and have a feel for time.	(Ready et al., 2010)
Mentorship and Learning	Demonstrating a commitment to personal growth and assisting others in their professional development.	(Ready et al., 2010; Simonton, 2008; Ulrich & Smallwood, 2012; van der Heijden & Brinkman, 2001)
Achievement	The ability to consistently deliver on objectives and meet performance metrics. To take on new tasks and complete them effectively.	(Ulrich & Smallwood, 2012)
Decision making	It is defined as making and taking responsibility for difficult decisions.	(Moon, 2002; Ready et al., 2010)

Table 6 notes: This table presents critical professional attributes such as innovation, problem-solving, and teamwork, which are used as indicators in talent identification frameworks.

Traditionally associated with the economic return on education and skills (Becker, 1975), this perspective frames individual attributes such as adaptability, leadership, and initiative as forms of capital that, when effectively identified and developed, can contribute to organisational success (Marginson, 2019; Nafukho et al., 2004; Wuttaphan, 2017). In this study, potential is viewed not as a fixed trait but as a latent resource that AI tools may help uncover and activate, provided such tools are implemented with contextual sensitivity.

The Resource-Based View (RBV) (Barney, 1991) complements this by focusing on the strategic value of internal resources, including human capital and technological capabilities. From this perspective, AI systems can enhance the firm’s capacity to identify and retain unique, inimitable talent when appropriately aligned with organisational needs. The hybrid evaluation model examined in this research is thus conceived as dynamic capabilities (Teece et al., 1997), enabling the organisation to better sense, select, and support high-potential individuals.

Lastly, Sociotechnical Systems Theory (Trist & Bamforth, 1951) underscores the necessity of integrating AI tools within the broader social fabric of the organisation. This theory foregrounds the interdependence of human and technical subsystems, warning against technological determinism and advocating for the co-design of systems that respect the complexity of human judgement, workplace culture, and ethical considerations. It is particularly relevant to this study’s emphasis on a hybrid evaluation model, in which human oversight is essential for interpreting qualitative traits such as emotional intelligence and cultural fit, dimensions that AI continues to struggle to assess reliably.

Together, Human Capital Theory, the Resource-Based View, and Sociotechnical Systems Theory provide a complementary foundation for the hybrid model developed in this study. Human Capital Theory highlights the value of individual attributes as a core organisational resource, while the Resource-Based View emphasises that such resources become a source of sustained competitive advantage when they are valuable, rare, and difficult to replicate. Sociotechnical Systems Theory, in turn, underscores that the effective integration of technology into organisational processes requires balancing technical efficiency with human and social considerations. When combined, these perspectives suggest that AI can strengthen HR decision-making by enhancing the analysis of structured data, but its contribution to sustainable advantage depends on human judgement to interpret non-cognitive attributes and maintain fairness. This theoretical integration frames the hybrid evaluative model not as an eclectic combination of theories, but as a coherent response to the dual challenge of harnessing technological potential while preserving the strategic and human dimensions of talent management.

These theoretical orientations do not function as formal frameworks to be tested within this study. Instead, they offer conceptual guidance for interpreting the role of AI in talent identification and shaping the proposed conceptual model (Fig. 2), which links AI capabilities, human attributes, and HRM outcomes through a hybrid evaluative model. This theoretical grounding reinforces the study’s interdisciplinary contribution and opens pathways for future research to test and refine the

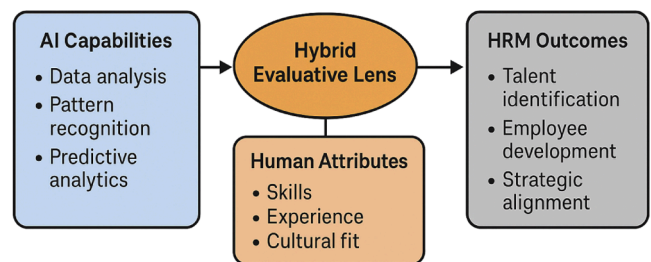


Fig. 2. Conceptual Model of AI-Driven Talent Identification Through a Hybrid Evaluative Model.

proposed relationships empirically. Building on this integration, Fig. 2 presents the conceptual model that operationalises these theoretical insights into the hybrid evaluative model.

For clarity and consistency, this study adopts the term **Hybrid Evaluative Model** as the primary descriptor of the integration between AI-driven analytics and human judgement in talent identification. Related terms, such as **AI-human collaboration** and **sociotechnical systems**, are not used interchangeably but rather serve as complementary perspectives. AI-human collaboration captures the operational dimension of joint decision-making, while sociotechnical systems theory provides the conceptual basis for balancing technological and social considerations. Throughout the manuscript, these terms are employed in a complementary manner, with 'hybrid evaluative model' serving as the overarching concept that frames the proposed model.

This conceptual model illustrates how AI capabilities (data analysis, pattern recognition, and predictive analytics) interact with human attributes such as individual skills, prior experience, and cultural fit through a hybrid evaluative model. The model positions this integration as central to achieving key HRM outcomes: talent identification, employee development, and strategic alignment. It emphasises the complementarity between algorithmic processing and human judgement in capturing both measurable and qualitative dimensions of potential, aligning with the broader goal of supporting the development of inclusive, context-sensitive, and effective workplaces.

### 3. Methodology

This study employs a mixed-methods research design with an inductive orientation. While relevant theoretical perspectives inform the research questions, no formal hypotheses are proposed *a priori*. Instead, quantitative and qualitative data are analysed in an exploratory manner, aimed at identifying relationships and interpreting patterns across diverse data sources. The integration of findings is not aimed at statistical confirmation but rather at theory development and the generation of new conceptual insights.

This study investigates the potential of AI in evaluating talent and identifying high-potential employees within HRM. To address the complex questions surrounding AI's role in HR, the research adopts a mixed-methods approach, blending quantitative and qualitative methods to offer empirical evidence and contextual insights. This dual methodology reflects the multifaceted nature of AI adoption, acknowledging both its opportunities and its challenges.

The mixed-methods framework was designed to capture both broad patterns and detailed insights into the impact of AI. The quantitative analysis identifies trends and relationships within the data, while the qualitative analysis examines the human and contextual dimensions of AI implementation.

The quantitative findings derive from a global survey conducted with a diverse and representative sample of individuals across multiple industries and roles, capturing a wide range of personal and professional attributes that define the talent landscape. The survey employed closed-ended questions to evaluate key variables such as accuracy, comparative effectiveness, and organisational outcomes. Statistical techniques, including Pearson correlation analysis, reveal significant relationships between key competencies such as creativity, innovation, and teamwork, underscoring areas of potential while also highlighting opportunities for improvement in talent evaluation processes.

While the quantitative data clarifies attribute metrics, the qualitative component provides complementary insights through semi-structured interviews with HR professionals. These interviews explored critical areas such as perceptions of bias, workforce readiness, and cultural resistance, providing contextual perspectives on challenges that numbers alone cannot illuminate. Together, the findings support a comprehensive understanding of AI's role in HRM by integrating measurable evidence with practitioner perspectives.

This mixed-methods approach integrates quantitative and

qualitative perspectives to provide a comprehensive understanding of AI's role in HRM. Quantitative insights into the talent landscape are complemented by qualitative accounts of ethical and operational challenges, resulting in a multifaceted analysis. Patterns observed in survey data are further contextualised through interview findings, enhancing the empirical robustness of the study while incorporating practitioner perspectives. This study examines AI's potential in HRM through the combination of statistical analysis and qualitative inquiry. The findings offer actionable recommendations for organisations seeking to integrate AI into their talent management strategies while maintaining a commitment to fairness and ethical integrity. In doing so, the research contributes to understanding AI's role in HRM by highlighting how innovation can be balanced with responsibility in the evolving landscape of workplace practices.

#### 3.1. Research design

This study examines the personal and professional attributes that underpin potential evaluation and talent identification. It investigates whether characteristics such as ambition, adaptability, and technical expertise, individually or in combination, are associated with the identification of high-potential employees. The analysis focuses on identifying patterns and correlations that link personal traits to professional competencies.

The research takes a **dual perspective on potential**, recognising that assessing an individual's capacity for growth and success requires considering both personal characteristics and professional skills, their characteristics, such as resilience and creativity, alongside their professional skills, like problem-solving and teamwork. This approach ensures that evaluation extends beyond basic performance metrics to include the nuanced qualities that characterise high-potential employees.

The study contributes beyond theoretical insights by linking these attributes to the processes of evaluation and identification. It provides practical guidance for organisations to refine their talent strategies. The capacity to accurately identify which individual qualities align with organisational objectives and to understand how these attributes contribute to broader strategic outcomes provides a valuable foundation for decision-making. Such insight enables the formulation of targeted strategies that support individual development while enhancing overall organisational performance.

The study aims to enhance decision-making in potential development by mapping personal and professional attributes to talent identification processes. This approach enables organisations to make better-informed decisions about where to invest in employee development and how to support growth. The outcome is not only more effective talent management but also a workforce better prepared to address future organisational demands.

#### 3.2. Data collection

##### 3.2.1. Surveys

Surveys provide a systematic means of capturing the perspectives and experiences of professionals that shape the talent management landscape. In this study, surveys are the foundation for gathering quantitative data from a broad and varied sample of individuals across industries and roles. The survey comprises 31 questions, divided into 14 competency-related items and 17 demographic and employment-related queries. Competency questions scored on a five-point scale, assess professional behaviours and capacities, such as leadership, problem-solving, and teamwork. Demographic questions provide context, ensuring the data reflects the diverse realities of the workforce.

The survey was developed based on constructs identified in the literature on talent, potential, and professional competencies. To evaluate the internal consistency of the survey instrument, Cronbach's alpha was calculated for the 14 competency-related items (Q1 to Q14). The

analysis yielded a reliability coefficient of  $\alpha = 0.90$ , indicating excellent internal consistency and confirming that the items reliably capture coherent dimensions of personal and professional attributes relevant to potential and talent identification in organisational settings.

Table 7 reports descriptive statistics (mean, standard deviation, minimum, and maximum) for the 14 Likert-scale items (Q1 to Q14) used to measure respondents' perceptions of personal and professional competencies associated with talent and potential evaluation. All items were measured on a five-point scale ranging from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). These metrics provide a preliminary overview of item distribution and respondent variability before inferential analysis.

The survey design prioritised inclusivity and neutrality. Demographic questions on gender, age, and employment status included options such as 'other' and 'prefer not to say' to ensure representation of all respondents. Professional experience questions were framed to elicit authentic behaviours without suggesting preferred responses. This approach was intended to encourage accurate reporting and to provide a reliable foundation for subsequent analysis.

In the quantitative phase, the study employed a non-probabilistic purposive sampling strategy, complemented by snowball sampling. The survey was initially distributed via professional networks (LinkedIn and academic mailing lists) to reach individuals in HR-related roles across industries. Participants were invited to forward the survey to relevant contacts, broadening participation across roles, seniority levels, and geographical locations. While this approach increased participation, it also introduced potential biases, as certain regions and sectors were more strongly represented than others, a limitation addressed in the discussion of findings.

To assess whether organisational size influenced competency evaluations, subgroup analyses were conducted by comparing SMEs ( $\leq 500$  employees) and large enterprises ( $> 500$  employees). Independent-sample *t*-tests were used to examine mean differences between groups under the assumption of approximately normal distribution. At the same time, Mann-Whitney U tests provided a non-parametric robustness check that does not rely on distributional assumptions. This dual testing strategy ensured that potential deviations from normality or unequal variances did not bias the analysis. Conducting these tests strengthened the robustness of the findings by confirming whether observed differences between SMEs and large enterprises were statistically meaningful.

The survey was intentionally distributed broadly, leveraging networks across email and LinkedIn to gather responses from diverse organisational levels and departments. Participants were invited to share the survey within their professional and personal networks to expand coverage. The survey was compatible with desktop and mobile platforms, ensuring global accessibility for employees in various locations and time zones.

While the survey was distributed globally through LinkedIn and

professional mailing lists, participation was not evenly distributed across regions. For example, 30 % of responses were from the United States, whereas countries such as Canada and Turkey had fewer than ten participants each. This imbalance reflects the limitations of network-based distribution and introduces potential bias in the dataset.

Between December 21st, 2023, and January 21st, 2024, this world-wide survey on "Competencies Related to Potential and Talent in an Organisational Context" gathered 240 unique responses. Participants represented a broad spectrum of job roles and industries, ranging from entry-level employees to senior executives. This diverse sample captured a wide range of demographic variables, including gender, age, and working conditions, offering insights into how competencies influence potential evaluation across organisational contexts.

The 14 competency-related items (Q1–Q14) were designed to capture respondents' self-perceptions of personal and professional attributes. These self-reports provide insight into how professionals characterise themselves, but do not directly measure the traits they prioritise when evaluating others. This distinction is acknowledged as a limitation, as respondents may value attributes in employees that differ from those they identify in themselves.

These responses provide a robust dataset supporting the analysis of attributes shaping potential and talent identification. The survey not only reflects the current state of talent management practices but also provides a foundation for crafting future policies and programmes that are inclusive, effective, and impactful.

### 3.2.2. Interviews

The study turns to in-depth interviews, providing a qualitative counterpart to the rich survey data. Picture a series of candid conversations with seasoned HR professionals, each offering a unique lens into how they recognise and nurture talent within their organisations. These dialogues unravel the nuances, successes, and challenges that define talent management practices in today's dynamic workplace.

The interviews are structured to address four essential areas. First, they explore the personal and professional qualities most valued in high-potential employees, uncovering traits such as adaptability, creativity, and leadership. Next, the focus shifts to the processes and criteria used in potential evaluation, providing a detailed understanding of the methods and standards that guide decision-making. Participants also share insights on the effectiveness and challenges of current talent identification practices, shedding light on what works and where gaps remain. Finally, the interviews bring these strategies to life through real-world examples, illustrating how practical approaches can lead to tangible success.

The qualitative phase followed a purposive expert sampling approach, selecting participants with at least 3 to 5 years of HR or leadership experience and/or demonstrated engagement with AI-related tools in recruitment or evaluation processes. These criteria ensured the

**Table 7**  
Descriptive statistics for competency-related survey items (Q1–Q14).

	Mean	Standard Deviation	Minimum value	Maximum value
Q1	3.6458333333333335	1.1220420589923705	1.0	5.0
Q2	3.6833333333333333	0.9505192004103206	1.0	5.0
Q3	3.5833333333333335	1.067459607641901	1.0	5.0
Q4	3.7208333333333333	1.0829524059387796	1.0	5.0
Q5	3.7666666666666666	0.9658030095612381	1.0	5.0
Q6	3.6	1.1045739821344553	1.0	5.0
Q7	3.7875	0.928765095441501	1.0	5.0
Q8	3.6625	1.1159972180946416	1.0	5.0
Q9	3.7666666666666666	0.8748779552264095	1.0	5.0
Q10	3.8208333333333333	0.9535132863095085	1.0	5.0
Q11	3.7541666666666667	0.9734892454558145	1.0	5.0
Q12	3.7666666666666666	1.0607752224314098	1.0	5.0
Q13	3.8958333333333335	0.9515365977156053	1.0	5.0
Q14	3.7583333333333333	0.9238434663668272	1.0	5.0

**Table 7** notes: Summary of mean, standard deviation, minimum, and maximum scores across items assessing personal and professional attributes relevant to talent identification.

relevance and depth of the data collected.

These experts, drawn from various industries and organisational contexts, offer perspectives grounded in practical experience, adding depth and credibility to the findings.

The semi-structured format of the interviews strikes a balance between flexibility and focus. While participants can explore emerging themes, the structured questions align the discussions with the study's objectives. The sessions were conducted via video conferencing for convenience and accessibility. Each 30-minute session allows participants to share their perspectives in detail while accommodating their demanding schedules.

Through these interviews, the study identifies the criteria and processes central to talent evaluation and incorporates the personal insights and experiences of participants. These qualitative findings enrich the quantitative survey results, providing an integrated account of how organisations approach talent management. By combining the rigour of structured analysis with the depth of personal storytelling, the study provides practical insights into factors associated with effective talent identification and how it can be enhanced for the future.

### 3.3. Data analysis

#### 3.3.1. Quantitative analysis

Once the survey responses are collected, uncovering insights begins with a thorough statistical analysis. This involves examining a comprehensive dataset encompassing the experiences and perspectives of professionals from diverse industries and identifying patterns and trends. This process translates raw numerical data into an evidence-based account about how organisations evaluate potential and identify talent. After collecting survey responses, insight generation begins with a rigorous statistical analysis. This process entails examining a diverse dataset that captures the experiences and perspectives of professionals from multiple industries and distilling it into discernible patterns and trends. This analytical approach translates quantitative data into meaningful narratives that reveal how organisations assess employee potential and identify talent.

The analysis employs a combination of descriptive and inferential statistics to explore the data in depth:

- **Descriptive Statistics** is the first step, summarising the data and providing a clear snapshot of the participants' responses. These summaries reveal overarching trends, such as the most commonly valued personal and professional qualities or the general perception of AI's effectiveness in talent identification.
- **Inferential Statistics** further analyses, tests hypotheses and examines the relationships between various factors. For instance, the analysis might explore how organisational size, industry, or leadership style influences the criteria for potential evaluation.

The study identifies correlations and trends that reveal how different attributes and competencies align with successful talent management practices. The statistical tools confirm existing theories and uncover new insights, providing a robust foundation for practical recommendations.

This rigorous analysis transforms the survey data into actionable insights, equipping organisations with the knowledge to refine their talent identification strategies and align them with their broader goals. It is a process that bridges individual experiences with organisational outcomes, ensuring that every data point contributes to a more comprehensive understanding of potential evaluation in the modern workplace.

#### 3.3.2. Qualitative analysis

The rich conversations captured during the interviews hold a wealth of insights waiting to be uncovered through careful analysis. Once the interviews are conducted, the next step involves transforming these discussions into actionable knowledge by identifying recurring themes

and patterns. This meticulous process begins with transcribing each interview verbatim, ensuring every word, tone, and nuance is preserved for analysis.

With the transcripts in hand, the exploration deepens. Patterns and relationships emerge as the qualitative data is combed for recurring themes, shared experiences, challenges, and strategies that illuminate the processes of potential evaluation and talent identification. For example, HR professionals might consistently highlight adaptability or ambition as key traits or reveal common barriers to integrating AI tools into their workflows. These themes act as threads that weave together the diverse perspectives shared during the interviews.

To ensure analytical rigour and methodological transparency, the interview data underwent a structured process of thematic analysis, combining deductive and inductive coding strategies. Initial codes were developed deductively, drawing on key themes identified in the literature, such as personal and professional attributes, AI limitations and bias mitigation. These categories provided a foundational structure for the initial coding frame. As analysis progressed, new subthemes emerged inductively from the data, capturing insights specific to participant experiences, contextual variables, and organisational practices. This iterative approach allowed for analytical flexibility while maintaining conceptual coherence. Qualitative data were analysed using NVivo. An initial round of open coding was conducted to capture recurring concepts across interviews. These codes were subsequently refined through axial coding, in which related codes were grouped into broader categories. Themes were finalised through iterative review by the author, ensuring alignment with both the empirical material and the theoretical framework. Reliability was strengthened through repeated coding cycles and peer debriefing, which enhanced consistency in theme identification and the robustness of the qualitative analysis.

Finally, the findings are interpreted to create a nuanced understanding of the qualitative data. Each insight is contextualised within the broader talent management landscape, connecting participants' individual experiences to organisational trends and challenges. This interpretive step ensures that the qualitative analysis complements the quantitative findings and adds depth and richness to the study's conclusions.

The study uncovers themes that resonate across industries and roles by systematically analysing the interview transcripts, offering a detailed and human-centred perspective on talent identification and potential evaluation. These insights provide valuable guidance for organisations seeking to refine their strategies and create more effective, inclusive talent management practices.

### 3.4. Ethical considerations

Every step of this research was conducted with a strong commitment to ethical integrity, ensuring participants' views were considered while safeguarding their rights and privacy. Before participating, each individual provided informed consent, acknowledging their understanding of the study's purpose and procedures. This step was important to promote participant confidence and willingness to share their experiences and insights.

All data were anonymised during collection and analysis. This measure guaranteed that no identifiable information was linked to the responses, allowing participants to contribute openly without privacy concerns. The anonymity extended to reporting findings, where aggregated data and thematic summaries protected individual identities.

Throughout the research process, strict adherence to ethical guidelines was maintained. From the collection of survey responses to the analysis of interview transcripts, every aspect of the study was designed to uphold the dignity and autonomy of participants. Following these principles, the research upheld academic integrity and reinforced its commitment to ethical responsibility.

This rigorous approach to ethics ensures that the study's findings are credible, trustworthy, and grounded in respect for those who

contributed to them. It underscores the importance of conducting research that values the data and the people behind it, creating a foundation for meaningful and impactful insights.

### 3.5. Integration of findings

The integration of findings from quantitative and qualitative analyses provides findings from both quantitative and qualitative analyses, offering a rich and comprehensive understanding of the research problem. By weaving together the numerical clarity of the survey data with the nuanced insights from interviews, the study paints a complete picture of how personal and professional qualities influence talent identification and potential evaluation.

The mixed-methods approach serves as the foundation for this integration, allowing for data triangulation, a process that enhances the validity and reliability of the results, using different perspectives to examine the same phenomenon. The survey data reveals overarching trends and measurable outcomes, while the interview insights bring those patterns to life with context and real-world examples. Together, they validate each other, ensuring the findings are robust and profoundly informed by practical realities.

These integrated findings are more than just theoretical observations. They lead to practical recommendations for organisations aiming to optimise talent identification processes. Organisations craft strategies beyond surface-level evaluations by leveraging personal and professional attributes, aligning talent management practices with broader organisational goals. For instance, identifying ambition, adaptability, and problem-solving as key traits can guide the development of tailored training programmes and recruitment strategies.

Ultimately, this data integration transforms the research into a roadmap for action, helping organisations make informed decisions that enhance their talent identification processes' fairness, accuracy, and effectiveness. It bridges the gap between theory and practice, ensuring that the study's conclusions have a tangible impact on the evolving landscape of HR management.

## 4. Analysis and findings

The intersection of personal and professional attributes in talent identification and potential evaluation is critical for improving organisational outcomes. This section explores the study's empirical analysis findings, combining data from surveys and statistical evaluations to uncover the nuanced relationships between individual competencies and workplace dynamics.

### 4.1. Unveiling insights through surveys: A comprehensive exploration

The study began with the design of a survey aimed at uncovering the intricate connections between personal and professional attributes in assessing potential and talent. Acknowledging the interplay of ambition, adaptability, and leadership, qualities influenced by personal backgrounds and professional environments, the survey sought to capture these dynamics comprehensively.

The survey was structured into 31 questions, each carefully crafted to explore the subject from two critical angles. Fourteen competency-related questions (Table 8) delved into attributes like problem-solving, teamwork, and creativity, using a 1–5 scale to quantify these essential traits. Meanwhile, seventeen demographic and employment-related questions (Table 9) provided the contextual backdrop, gathering information on factors such as age, education level, years of experience, and organisational role. These dual categories offered a balanced view, enabling the study to draw meaningful connections between individuals' attributes and professional contexts.

Inclusivity and authenticity were at the forefront of the survey's design. Questions were framed neutrally to ensure fairness, with options like "other" or "prefer not to say" for gender and employment-related

**Table 8**

Relationship between the personal and professional attributes and competency-related questions.

#	Personal Characteristics	Competency related questions
Q1	Autonomy	In your current role, how frequently do you take the lead on tasks and projects without needing explicit instructions?
Q2	Adaptability	How do you typically handle changes in work processes or unexpected challenges?
Q3	Initiative	When you identify an opportunity for improvement in a work process, what steps do you take to address it?
Q4	Creativity	How often do you contribute new and innovative ideas to your team or projects?
Q5	Leadership	Describe your recent contributions to guiding and inspiring your team towards achieving common goals.
Q6	Ambition	What steps have you recently taken to pursue and achieve your career goals?
Q7	Interpersonal Skills	How do you ensure effective communication and collaboration with team members and stakeholders?
Q8	Innovation	How frequently do you explore and implement new ideas or processes in your role?
Q9	Problem-Solving Skills	When faced with a complex issue, how do you approach identifying and resolving it?
Q10	Teamwork	How have you contributed positively to recent team collaborations?
Q11	Perceptive	How frequently does your attention to detail help you navigate complex work scenarios effectively?
Q12	Mentorship and Learning	How often do you actively seek opportunities for continuous learning and growth?
Q13	Achievement	How consistently do you strive to meet or exceed performance expectations in your role?
Q14	Decision making	How do you navigate challenging situations that require decision-making?

Table 8 notes: This table maps survey questions (Q1Q14) to the specific personal and professional attributes they aim to assess. It forms the empirical basis for the competency analysis conducted in the study.

**Table 9**

Survey demographic and employment-related questions.

#	Demographic and employment-related questions
Q15	What is your gender?
Q16	What is your age?
Q17	Do you have dependent children?
Q18	What is the highest level of education you have completed?
Q19	In which country do you currently reside?
Q20	What is your nationality?
Q21	What is your current work location?
Q22	Are you currently working remotely, in an office, or a combination of both?
Q23	How long is your average daily commute?
Q24	What is your current employment status?
Q25	What is your current job title?
Q26	Which department or team are you a part of?
Q27	How many years of experience do you have in your current role?
Q28	How many years of experience do you have in the organisation?
Q29	What are your annual gross earnings?
Q30	What is the size of your company (number of employees)?
Q31	What industry or field of work are you in?

Table 9 notes: This table lists demographic and employment-related variables (Q15 to Q31) used to contextualise the analysis of competency-related responses and control for diversity in the sample.

queries. This thoughtful approach encouraged participants to respond honestly, fostering an environment of trust and openness. By prioritising inclusivity and precision, the survey laid a strong foundation for collecting reliable and meaningful data, setting the stage for deeper exploration into the dynamics of potential and talent in the workforce.

#### 4.1.1. Global reach and rich diversity

Between December 21st, 2023, and January 21st, 2024, the survey

was conducted globally to examine the dynamics of personal and professional attributes in talent evaluation. Two hundred forty (240) professionals participated, contributing perspectives from diverse industries, roles, and regions. The responses reflected the diversity and inclusivity of the workforce.

The survey revealed a balanced gender representation, with 52 % male and 48 % female respondents, reflecting a balanced gender representation among respondents. The demographic data showed the majority of participants aged between 25 and 44, representing early- to mid-career professionals. The work arrangements of the respondents ranged widely, encompassing hybrid setups and fully remote roles, which underscored the growing adaptability of organisations to modern workplace demands.

Educational diversity was another hallmark of the dataset, with 70 % of respondents holding bachelor's degrees or higher qualifications. This level of academic attainment illustrated a well-educated sample aligned with the professional rigour required for high-potential roles.

The survey's geographic reach was equally striking. Fig. 3 captures this global scope, visualising the broad range of participant locations and highlighting the inclusion of perspectives from various cultural and professional backgrounds. This dataset enabled robust insights into the complex interplay between personal attributes and professional success, offering a rich foundation for understanding talent dynamics in diverse organisational contexts.

Using a stacked column chart, Fig. 4 illustrates the responses to the competency-related survey questions (Q1–Q14). Each column corresponds to one of the 14 questions, with segments within the columns representing the range of response options scored on a 1 to 5 scale. The colour-coded segments make it easy to identify trends, such as the proportion of respondents selecting higher or lower scores for specific competencies.

The chart visually summarises how participants rated various professional capacities and behaviours, such as leadership, teamwork, creativity, and problem-solving. For example, questions receiving a higher proportion of 4 s and 5 s indicate attributes that participants widely recognise as critical for potential evaluation and talent identification.

This visual representation allows for quickly identifying patterns, highlighting the most valued competencies or where opinions vary. It complements the survey's statistical analysis by offering a clear, accessible snapshot of how personal and professional attributes are perceived

within the workforce.

#### 4.1.2. Analysing correlations: Patterns and relationships

The study examines the relationships between key competencies, using Pearson correlation coefficients to analyse how these attributes are associated with individual and organisational outcomes. This statistical method provided statistical evidence of how combinations of different skills are associated with effective talent management. It is important to recognise the exploratory nature of the statistical approach adopted in this study to interpret the Pearson correlation analysis findings. Correlation coefficients provide insight into the direction and strength of associations between personal and professional attributes without implying causality or structural interdependence. Nonetheless, these results are analytically valuable as they illuminate coherent patterns in how competencies relate to one another and perceived potential within organisational settings.

The choice of correlation analysis reflects the exploratory and inductive orientation of the study. In nascent research domains such as AI in HRM, methodological literature recommends the use of simpler, pattern-seeking approaches to uncover associations and guide subsequent theory development (Edmondson & McManus, 2007; Eisenhardt, 1989). More complex multivariate techniques, including regression or SEM, presuppose mature constructs and established theoretical models (Sarstedt et al., 2014; Spector, 2019), conditions that are not yet fully present in this domain. Correlation analysis is therefore an appropriate first step, providing empirical grounding while leaving scope for future studies to apply multivariate modelling once the theoretical landscape becomes more developed.

At the core of this analysis lies the robust association between creativity and innovation, evidenced by a statistically significant correlation of  $r = 0.65$  ( $p < 0.01$ ). This finding not only quantifies their relationship but also highlights the transformative impact of cultivating creative thinking within organisations. It suggests that environments which actively promote creativity are more likely to foster breakthrough ideas that lead to meaningful innovation. Complementing this dynamic, the correlation between leadership and innovation ( $r = 0.59$ ,  $p < 0.01$ ) underscores the role of effective leadership in enabling innovative outcomes. Leaders who do more than manage—those who inspire, empower, and guide teams—play a pivotal role in translating ambitious ideas into implementable strategies. But the story does not end with leadership and creativity. Interpersonal skills and teamwork also play

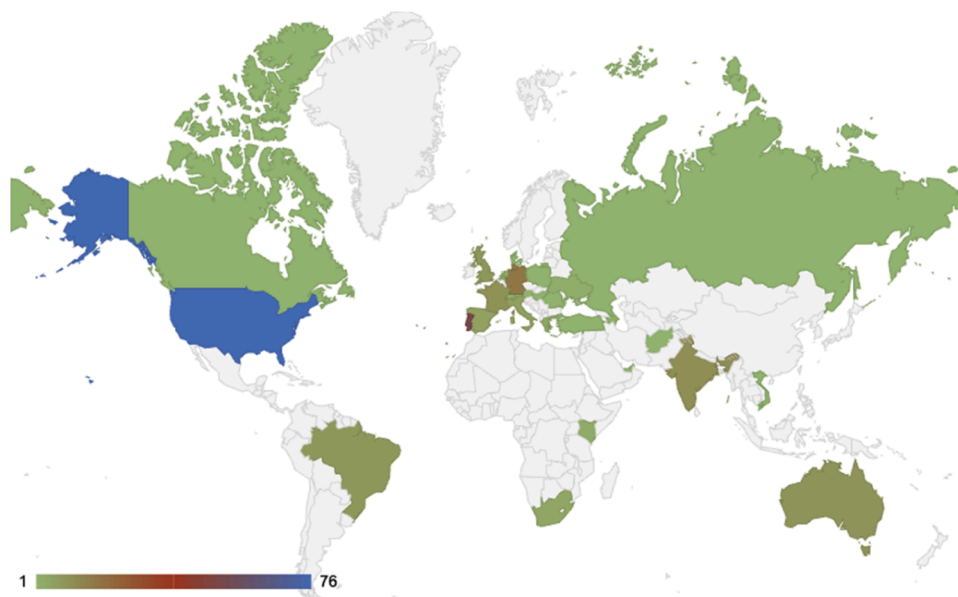


Fig. 3. A global map showing participant nationalities, with counts per country ranging from 1 to 76.

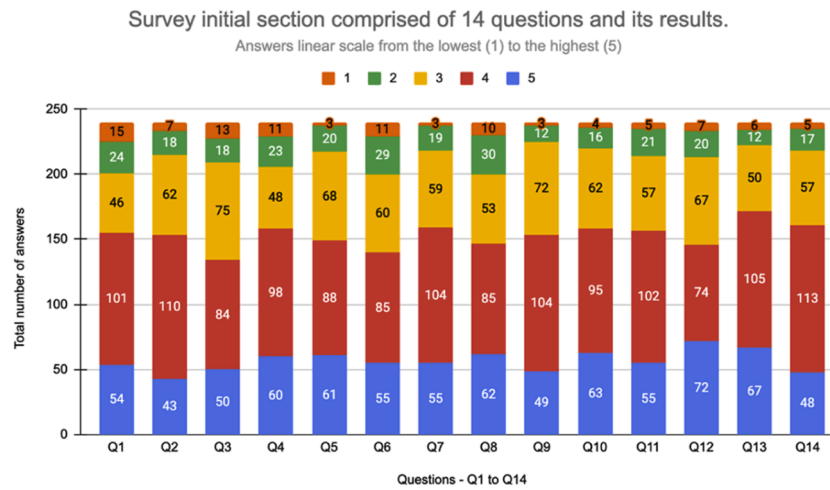


Fig. 4. A column stack chart depicting the results of the questions ranging from Q1 to Q14.

pivotal roles, exhibiting a meaningful correlation of  $r = 0.56$  ( $p < 0.01$ ). This highlights how empathy, communication, and collaboration form the backbone of team success, fostering environments where collective effort triumphs over individual ambition. Decision-making is shown to be tightly linked to innovation,  $r = 0.54$  ( $p < 0.01$ ). This connection reveals that sound, strategic decisions bridge creative ideas and their practical implementation, ensuring that innovation does not remain a lofty ideal but becomes a tangible outcome.

These insights come to life in Fig. 5, a matrix that captures the most significant correlations among the 14 competency-related survey questions. This matrix illuminates the strength of each relationship using a colour-coded gradient, with deep green cells drawing attention to the most compelling connections. Creativity (Q4) and innovation (Q8) shine as a dynamic duo, while leadership (Q5) anchors innovation (Q8) and teamwork (Q10), revealing its pivotal role in organisational dynamics.

The findings tell a story of interconnected strengths, suggesting a path forward for organisations looking to refine their talent strategies. By nurturing creativity and leadership, businesses can ignite a chain reaction that amplifies innovation and teamwork. This ripple effect, driven by the cultivation of these competencies, promises enhanced individual growth and broader organisational success. These insights resonate with the pressing demands of the modern workplace, where aligning talent development with broader strategic goals is no longer optional but necessary. Organisations prioritising this integration are better positioned to manage uncertainty, pursue opportunities, and

contribute to long-term competitiveness in a rapidly changing world.

The strongest observed correlation between creativity and innovation ( $r = 0.65$ ,  $p < 0.01$ ) suggests that respondents who self-report higher creative engagement are more likely to contribute to innovative processes. This finding reinforces literature that links creative thinking to applied innovation within dynamic work environments. Likewise, leadership and innovation ( $r = 0.59$ ) and teamwork and interpersonal skills ( $r = 0.56$ ) indicate that social and strategic competencies tend to cluster, particularly in contexts requiring collaborative problem-solving and initiative.

These relationships are interpreted as preliminary associations that warrant further investigation, both in theoretical terms and for organisational practice. The observed correlations were further interpreted through qualitative interview insights, highlighting how these competencies are recognised and valued in real-world evaluation processes. As such, the quantitative results serve a dual role: they inform theory-building by identifying consistent competency patterns and anchor the mixed-methods integration by aligning with practitioners' narratives.

#### 4.1.3. Diving deeper: Insights from data

The dataset predominantly features male respondents, with a notable concentration in the 25 to 64-year-old age range. The most common age bracket among these is 25 to 34, which suggests a youthful demographic that potentially brings a dynamic and perhaps more technologically inclined perspective to their roles. This demographic skew towards

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	
Q1		0,24	0,39	0,44	0,34	0,23	0,25	0,40	0,22	0,20	0,17	0,27	0,21	0,36	Q1
Q2	0,24		0,34	0,42	0,43	0,35	0,44	0,38	0,50	0,43	0,50	0,39	0,43	0,42	Q2
Q3	0,39	0,34		0,50	0,48	0,46	0,38	0,59	0,31	0,31	0,36	0,44	0,39	0,38	Q3
Q4	0,44	0,42	0,50		0,52	0,49	0,37	0,65	0,34	0,33	0,32	0,37	0,23	0,37	Q4
Q5	0,34	0,43	0,48	0,52		0,35	0,46	0,59	0,52	0,45	0,52	0,41	0,39	0,51	Q5
Q6	0,23	0,35	0,46	0,49	0,35		0,4	0,48	0,33	0,34	0,38	0,42	0,38	0,40	Q6
Q7	0,25	0,44	0,38	0,37	0,46	0,40		0,46	0,44	0,56	0,49	0,34	0,44	0,54	Q7
Q8	0,40	0,38	0,59	0,65	0,59	0,48	0,46		0,39	0,36	0,42	0,46	0,35	0,56	Q8
Q9	0,22	0,50	0,31	0,34	0,52	0,33	0,44	0,39		0,40	0,57	0,39	0,50	0,44	Q9
Q10	0,20	0,43	0,31	0,33	0,45	0,34	0,56	0,36	0,40		0,45	0,41	0,41	0,47	Q10
Q11	0,17	0,50	0,36	0,32	0,52	0,38	0,49	0,42	0,57	0,45		0,47	0,56	0,57	Q11
Q12	0,27	0,39	0,44	0,37	0,41	0,42	0,34	0,46	0,39	0,41	0,47		0,52	0,48	Q12
Q13	0,21	0,43	0,39	0,23	0,39	0,38	0,44	0,35	0,50	0,41	0,56	0,52		0,47	Q13
Q14	0,36	0,42	0,38	0,37	0,51	0,40	0,54	0,56	0,44	0,47	0,57	0,48	0,47		Q14

Fig. 5. Pearson correlation coefficient (r) matrix.

younger male professionals may reflect industry-specific trends or recruitment practices favouring this demographic, especially in sectors like technology and finance, where younger workforces are often prevalent.

Understanding the representation of this age group and gender within the dataset is crucial, as it provides insights into the career stages at which these competencies are being developed and assessed. Moreover, it offers an opportunity to explore how competencies are perceived and valued differently across age groups and genders within professional settings. This can lead to targeted strategies for competency development tailored to the needs and characteristics of the most represented groups, thereby enhancing professional growth and addressing any demographic-specific challenges or biases within organisational or industry practices.

This suggests that a workforce potentially is at a mid-level stage in their career, which is also supported by the most common education level being a bachelor's degree. Many respondents have attained post-graduate qualifications, indicating a highly educated workforce. This level of education might correlate with the more senior job titles and responsibilities reported, such as managers and directors.

A notable aspect is the diversity in work arrangements, with a substantial prevalence of hybrid work (both remote and in-office), which could indicate evolving work practises, possibly accelerated by recent global shifts towards more flexible work environments. Most respondents live in urban areas, typically offering closer proximity to office locations and a broader range of job opportunities. However, the presence of fully remote workers who do not commute at all suggests that companies are adapting to allow for more excellent work-life balance or are leveraging technology to broaden their hiring pool beyond geographic limits.

Respondents are primarily full-time employees, which might indicate stable employment conditions within the represented industries. The sample covers a range of departments with a significant focus on IT and technology, reflecting this sector's ongoing demand and growth. Interestingly, most respondents have between 3 and 5 years of experience in their current roles, suggesting either a dynamic job market where individuals switch roles or companies relatively frequently or significant growth in new positions, allowing for rapid career development.

The heatmap presented in Fig. 6 is a visual representation designed to illustrate the distribution of employees across various job titles concerning their tenure in their current roles within an organisation. This data visualisation highlights career progression patterns and employee

role longevity.

Each row in the heatmap corresponds to a specific job title, indicating the diversity of roles. The columns represent different ranges of years employees have spent in their current positions, from less than one year to more than ten years. The cells within the heatmap contain numeric values, and these numbers reflect the number of employees who align with the row's job title and the column's experience category. For example, a cell intersecting the "Senior Manager" row and the "3–5 years" column with a value of 4 indicates that four senior analysts have been in that position for between three and five years.

Fig. 7 depicts the average annual gross earnings by industry. Annual earnings varied, with a significant portion of the workforce earning less than €30,000. This could suggest entry-level positions or roles in lower-paying industries despite high levels of education. The dataset shows a prevalence of smaller companies (1 to 50 employees), which could be startups or smaller enterprises typical in fast-growing sectors like technology. This size of company often offers rapid advancement opportunities but might also lack the salary benefits of larger corporations.

The dataset provides a nuanced view of annual gross earnings across industries, roles, and experience levels, illustrating how economic positioning, organisational structures, and job seniority influence earning potential. High-paying sectors such as Banking & Financial Services and Computers & ICT stand out, with a substantial number of professionals earning between €75,001 and €100,000 and a smaller but notable group exceeding €100,000. These earnings are primarily associated with senior roles such as managers, directors, and executive-level positions, where specialised expertise and leadership responsibilities are key compensation drivers. Similarly, fields like Business Management & Human Resources and Engineering, Manufacturing, & Energy show higher average earnings, particularly for professionals with advanced skills and longer tenure in the workforce. This trend reflects the association between higher earnings and knowledge-intensive, innovation-oriented industries.

In contrast, service-oriented and traditionally lower-paying sectors such as Community & Voluntary, Clerical & Administration, and Tourism & Hospitality are predominantly represented in the "Less than €30,000" category. These roles often involve administrative tasks or customer-facing responsibilities, reflecting limited earning opportunities compared to more specialised fields. Notably, even within high-paying sectors, disparities emerge based on job roles and seniority. For example, assistants and entry-level employees are often clustered in the lower-earning ranges, even in industries like Banking or Healthcare, highlighting the importance of progression opportunities. The dataset

		Years of Experience in Current Role				
		< 1 year	1 to 2 years	3 to 5 years	6 to 10 years	more than 10 years
Job Title	Analyst	3	3	3	3	4
	Assistant	5	15	13	2	3
	Associate		3	3	5	1
	Chief [Job Title] Officer	2		1	4	2
	Coordinator	1	1	4		1
	Director	2	1	6	2	5
	Executive Director			1	1	4
	Head of [Department]		1	1		
	Intern	3	2	1		
	Lead [Job Title]	2		5		2
	Manager	4	13	20	12	7
	President			3		
	Senior [Job Title]	1	1	5	6	4
	Senior Director					1
	Senior Manager	1	1	4	2	2
	Senior Vice President (SVP)			1		1
	Specialist		1	7	8	5
Supervisor		1	4	3	1	

Fig. 6. Heatmap displaying job titles against years of experience in current roles.

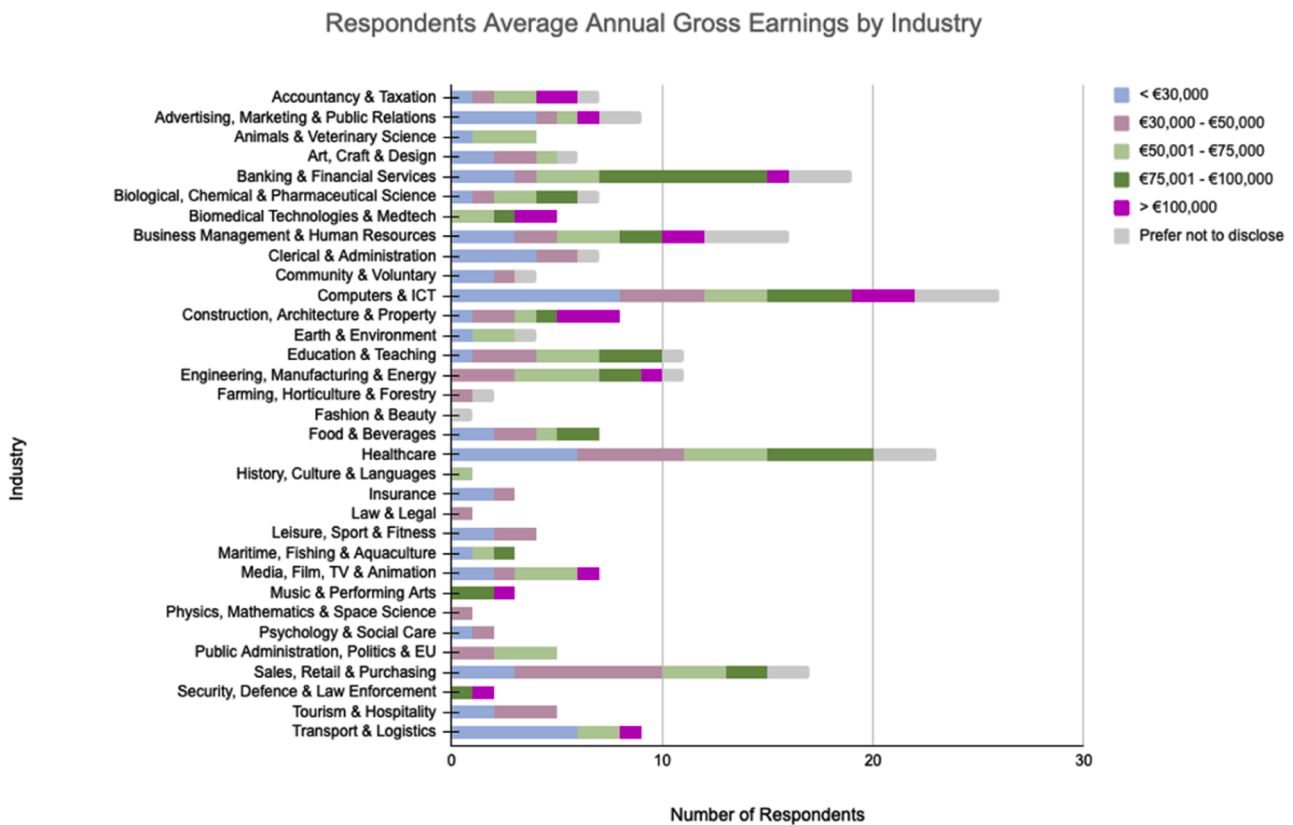


Fig. 7. Average annual gross earnings by industry.

also reveals that years of experience play a critical role, with professionals in "More than 10 years" categories often securing higher-paying positions, particularly in leadership roles such as directors and managers. These findings illuminate the interconnectedness of sector dynamics, role specificity, and career trajectory in shaping income distribution.

4.1.4. Education, earnings, and career progression

The study embarked on an in-depth analysis to uncover the influence of educational attainment on career outcomes, deploying statistical methodologies to draw meaningful connections between learning and professional advancement. By applying techniques such as Analysis of Variance (ANOVA) and Chi-square tests, the research aimed to reveal the significant variations in earnings and career progression across industries.

ANOVA served as a critical tool in this analysis, grouping earnings data by educational levels, high school, bachelor's, master's, or doctoral degrees, and determining whether these variations were statistically significant or merely coincidental. The results were striking. A p-value of less than 0.05 confirmed significant earnings disparities across industry educational levels. Knowledge-intensive fields such as banking, technology, and healthcare exhibited the most pronounced differences. In banking, for instance, individuals with postgraduate degrees reported earning approximately 30 % more than their counterparts with undergraduate qualifications. This underscores the premium on advanced education, particularly in sectors requiring specialised expertise.

The Chi-square test further explored the relationship between education and career stages and entry-level, mid-level, and senior roles. The test revealed a statistically significant association by organising data

into a contingency table that compared academic qualifications to career levels ( $p < 0.05$ ). In the technology sector, bachelor's degree holders were more likely to occupy mid-level roles, while advanced degrees often became prerequisites for leadership positions. Similarly, in healthcare, advanced qualifications were essential for progressing into specialist or managerial roles.

The findings validate the hypothesis that educational background profoundly impacts earnings and career trajectories, but the degree of this influence varies by industry and geography. Knowledge-intensive industries showed stronger correlations, while geographic disparities highlighted differences between urban and rural job markets. Urban professionals often benefit more financially from higher education due to the competitive nature of metropolitan economies.

These insights emphasise the critical role of higher education in fostering career advancement, particularly in specialised and regulated fields. They also spotlight the need for targeted initiatives to address disparities. Educators could align curricula more closely with industry needs to enhance employability. Employers might implement professional development programmes to close educational gaps, while policymakers could invest in regional education and training to mitigate geographic inequalities.

Future research could adopt longitudinal approaches to enrich these findings, tracking career trajectories over time. Incorporating qualitative methodologies could also shed light on personal and socioeconomic factors influencing these outcomes, providing a more nuanced understanding of education's role in professional success.

The survey's implications extend into actionable strategies for organisations. Fostering creativity and leadership emerged as pivotal in driving innovation and decision-making. Employees encouraged to

think creatively often contribute transformative ideas that reshape organisational strategy. Leadership development initiatives could cultivate essential skills like strategic thinking and emotional intelligence, empowering leaders to guide teams effectively through challenges.

Training programmes tailored to demographic and industry-specific needs also emerged as a crucial recommendation. Younger employees might benefit from mentorship, while experienced professionals could require upskilling in emerging technologies. Industry-focused training, whether emphasising digital proficiency in technology or leadership in healthcare, ensures that organisational efforts are relevant and impactful. Flexible delivery methods like e-learning platforms and virtual workshops are essential to accommodate hybrid work models and geographically dispersed teams.

Mentorship and educational support were highlighted as critical tools for bridging career progression gaps, particularly in underserved regions. Structured mentorship fosters knowledge-sharing and inclusivity, while targeted educational initiatives like scholarships or regional training programmes can improve accessibility. These efforts ensure that individuals in rural or economically disadvantaged areas are not left behind in the evolving workforce.

By integrating these insights into strategic goals, organisations can prepare for future challenges, enhance workforce resilience, and promote inclusivity. Metrics to measure the impact of these initiatives, such as employee engagement, innovation output, and retention rates, are essential for adapting strategies to dynamic environments.

#### 4.1.5. SMEs vs. large enterprises

Subgroup analyses were conducted to examine whether organisational size influenced the evaluation of competencies. Table 10 presents the mean scores for SMEs ( $\leq 500$  employees) and large enterprises ( $> 500$  employees) across the 14 competency items (Q1–Q14), together with statistical tests of difference.

The results show that mean values were highly consistent across groups, with differences generally below 0.2 points on a five-point scale. Neither independent-sample  $t$ -tests nor Mann-Whitney U tests revealed statistically significant differences (all  $p > 0.05$ ). These findings indicate

**Table 10**

Subgroup analysis of competency items (Q1–Q14) by organisational size (SMEs vs. large enterprises).

Competency (Q1–Q14)	SME Mean ( $\leq 500$ employees)	Large Enterprise Mean ( $> 500$ employees)	$t$ -test p-value	Mann-Whitney p-value	Significance Marker
Q1	3.633	3.683	0.746	0.999	
Q2	3.767	3.983	0.143	0.083	
Q3	3.722	3.85	0.336	0.476	
Q4	3.722	3.9	0.23	0.349	
Q5	3.906	3.867	0.778	0.699	
Q6	3.783	3.683	0.488	0.739	
Q7	3.644	3.8	0.299	0.16	
Q8	3.594	3.55	0.761	0.401	
Q9	3.683	3.833	0.343	0.345	
Q10	3.744	3.833	0.564	0.476	
Q11	3.6	3.6	1.0	0.931	
Q12	3.806	3.733	0.61	0.563	
Q13	3.694	3.567	0.463	0.498	
Q14	3.756	3.8	0.723	0.669	

**Table 10** notes: The table reports mean scores for competency items Q1–Q14, comparing SMEs ( $\leq 500$  employees) and large enterprises ( $> 500$  employees). Independent-sample  $t$ -tests and Mann-Whitney U tests were conducted to assess statistical significance of group differences. No differences reached statistical significance (all  $p > 0.05$ ). The column “Significance Marker” indicates significance at the 5 % ( $* p < 0.05$ ) and 1 % ( $** p < 0.01$ ) levels. In this analysis, no differences reached statistical significance, and therefore no markers ( $*$  or  $**$ ) appear in the table.

that perceptions of key attributes are broadly stable across organisations of different sizes, lending support to the consistency of the survey results.

#### 4.2. Expert insights on personal and professional attributes related to potential and talent identification

##### 4.2.1. Harnessing the power of semi-structured interviews

Semi-structured interviews were employed as a primary qualitative method of this study, providing a dynamic blend of structure and flexibility to delve into complex topics while capturing the richness of lived experiences. Following Galletta’s framework (Galletta & Cross, 2013), this method harmonised theoretically driven inquiries with open-ended opportunities, allowing participants to share profound, experience-based insights. This approach ensured a systematic yet adaptive exploration of the key constructs underpinning talent identification and evaluation.

The interviews focused on understanding how personal and professional attributes contribute to assessing potential and how these attributes can integrate effectively with AI-driven tools. The protocol was meticulously crafted to elicit unbiased responses. Open-ended questions let participants articulate their thoughts freely, fostering authentic and comprehensive discussions. The interviews were conducted via video conferencing to ensure global accessibility, with each session lasting approximately 30 min. These interactions were systematically transcribed, preserving the accuracy and depth of the perspectives shared.

The structure of the interviews, outlined in Table 11, provided a clear roadmap for exploring various dimensions of talent evaluation. The interview questions were designed to meet the study’s objectives, address thematic areas, and be valuable for understanding and improving HR practices. The framework spanned key topics, including identifying attributes, current evaluation processes, AI integration, practical applications, and future advancements.

A significant portion of the interviews examined key attributes. Participants were encouraged to reflect on the personal qualities, such as adaptability, emotional intelligence, and integrity, that they considered crucial in identifying potential. They also discussed professional competencies like leadership, problem-solving, and teamwork, providing evidence of how these skills are associated with talent identification.

The discussions then shifted to evaluation processes, where participants detailed the tools and criteria employed within their organisations to assess these attributes. By highlighting existing methodologies and their effectiveness, these conversations identified areas with potential for improvement.

The integration of AI into HRM was another central theme. Participants provided nuanced perspectives on AI’s role in evaluating attributes, emphasising its strengths, scalability and efficiency alongside challenges like contextual understanding and bias. These insights underscored the complexities of combining technology with human judgement in talent evaluation.

Practical applications were illustrated through participants’ real-world examples of successful talent identification. They highlighted specific attributes and competencies contributing to these outcomes, providing implications relevant to HR professionals and researchers.

Finally, the interviews explored future trends, probing participants’ visions for advancing AI capabilities and improving evaluation processes. These discussions emphasised the need for innovative, ethical, and inclusive approaches to talent identification, setting the stage for continued evolution in HRM practices.

Through this comprehensive approach, the interviews painted a vivid picture of the current landscape and future potential of talent evaluation. They captured the intricate interplay between human expertise and AI-driven tools, offering actionable insights to bridge gaps and drive innovation in HR practices.

**Table 11**

Interview questions.

Q#	Section / Question
Determining Personal and Professional Qualities	
Q1	Key Attributes: What personal qualities do you consider important for evaluating an employee's potential? Can you provide examples of how these qualities might be observed in employees? (Examples: autonomy, adaptability, initiative, creativity, leadership, ambition, interpersonal skills)
Q2	Professional Competencies: What professional competencies do you believe are essential for identifying high-potential employees? How do these competencies typically manifest in the workplace? (Examples: innovation, problem-solving skills, teamwork, perceptiveness, mentorship, achievement, decision-making)
Q3	Critical Characteristics: Are there any additional personal or professional characteristics that you think are strong indicators of high potential in employees? Can you describe situations where these characteristics were particularly evident?
Connection Between Attributes and Potential Evaluation	
Q4	Correlation: In your experience, how do personal qualities like ambition and adaptability relate to professional competencies such as problem-solving and innovation? Can you provide examples or scenarios that illustrate this relationship?
Q5	Attribute Impact: How do personal and professional attributes influence the outcomes of potential evaluations and talent identification processes in your organisation? Can you share specific examples of how these attributes affected the evaluation results?
Q6	Practical Examples: Can you provide specific examples of how certain personal or professional attributes have been used to identify high-potential employees in your organisation? How did these attributes contribute to their selection and subsequent performance?
Evaluation Process	
Q7	Assessment Methods: What methods or tools do you use to assess personal and professional qualities during potential evaluation and talent identification processes? How effective do you find these methods in identifying high-potential employees?
Q8	AI Integration: How do AI tools evaluate personal and professional attributes in your experience? Are there specific qualities that AI tools assess more accurately than others? Can you provide examples of AI assessments and any limitations you have observed?
Q9	Challenges: What challenges have you encountered in linking personal and professional attributes with AI-driven potential evaluations? How have you addressed these challenges, and what solutions or improvements would you suggest?
Improvement and Insights	
Q10	Enhancements: Based on your experience, what improvements would you suggest for AI tools to assess better and connect personal and professional attributes with potential evaluations? Are there specific features or functionalities that you think would enhance these tools?
Q11	Best Practices: What practices do you find effective for integrating personal and professional qualities into AI-driven talent identification processes? Are there particular strategies or approaches that have proven successful in your organisation?
Q12	Future Trends: How do you foresee the evaluation of personal and professional attributes evolving with advancements in AI? What future trends should organisations prepare for, and how can they leverage these advancements to improve talent identification and potential assessment processes?

**Table 11** notes: This table provides the semi-structured interview guide used in the qualitative phase of the study. It was designed to align with key themes such as personal attributes, professional competencies, and AI integration in HRM.

#### 4.2.2. Validation of the interview framework

The interview structure was subjected to rigorous validation by four HR professionals, each bringing a wealth of expertise to the process. This validation aimed to refine the study's framework, ensuring its relevance, clarity, and precision. These experts, selected through purposive sampling, represented diverse roles and industries, offering invaluable perspectives on potential evaluation and talent identification.

The experts meticulously reviewed the interview questions during the validation process, identifying gaps, ambiguities, and potential biases. Their feedback was instrumental in refining the structure, ensuring that the questions were neutral, inclusive, and aligned with the study's objectives. The validation process enhanced the interview's ability to capture meaningful and authentic participant insights by

addressing these elements.

The group included a Leadership Development Expert, an HR Team Lead, a Manager in Communication and Marketing, and a Vice President of HR. Their collective insights spanned healthcare, workplace advisory, financial services, and marketing sectors. This cross-industry representation provided a comprehensive view of talent management practices, highlighting universal principles and sector-specific nuances. Each professional's organisational context ranged from small agencies to large multinational corporations, underscoring the scalability and adaptability of talent identification strategies.

Between June 2 and June 15, 2024, a diverse group of seven seasoned professionals gathered to share their expertise and insights on potential evaluation and talent identification. **Table 12** details these experts' professional roles, industry backgrounds, years of experience, and organisational contexts. It reveals a balance of leadership expertise and specialised knowledge in AI-driven HR tools, ensuring the study captures traditional and innovative practices. For instance, while some participants offered decades of experience in leadership and strategic HR management, others provided insights rooted in cutting-edge

**Table 12**

List of the expert's professional role and experience.

Role	Experience
Leadership Development Expert	With over 21 years of experience in leadership development training, this respondent has minimal hands-on experience with AI, primarily using tools like <i>ChatGPT</i> . Works in a medium-sized organisation of about 200 employees.
HR Team Lead	With 3–5 years of experience in human resources, specifically recruitment, this respondent has moderate hands-on experience with AI tools such as <i>Hirevue</i> , the Applicant Tracking System (ATS), resume scanning tools, chatbots, and <i>Fetcher</i> . This respondent works in an organisation with 201–500 employees.
Manager at a Customer Experience Management Agency	Bringing over 21 years of experience in communication and marketing, this respondent has moderate experience with AI, using tools like <i>ChatGPT</i> , <i>Gemini</i> , <i>Claude</i> , and <i>Monica</i> . Their organisation is relatively small, consisting of five people.
Vice President of HR	With over 21 years of experience in the infrastructure industry, this respondent has no hands-on experience with AI tools. Works in a large organisation with over 10,000 employees, reflecting a significant management and operational scope.
Market Manager in Home Healthcare	This respondent has 3–5 years of experience in home healthcare, managing a team of approximately 65 office staff and hundreds of Home Health Aides (HHAs) and Certified Nursing Assistants (CNAs). Has moderate experience with AI, using <i>JobDiva</i> and the built-in ATS for screening applicants.
Executive Vice President, Head of Diversity, Equity, and Inclusion (DEI) Advisory	With 16–20 years of experience in healthcare and workplace advisory, this respondent has some hands-on experience with AI tools such as <i>ChatGPT</i> , <i>Textio</i> , <i>Jodi AI</i> , and <i>Praxis Labs</i> . They are part of a large organisation with around 7000 employees.
Director of Global Talent Development	This respondent has 15 years of experience in the financial and insurance industries, overseeing global talent development for an organisation with over 60,000 employees. Has some experience with AI tools, including <i>Copilot</i> , an internal generative AI solution, and <i>ChatGPT</i> .

**Table 12** notes: This table summarises the roles, sectors, organisational size, and AI familiarity of the expert interviewees, offering transparency on the diversity and relevance of the qualitative sample.

technology and data-driven evaluation methods.

The diversity of the experts' backgrounds also enriched the study by incorporating perspectives from varying degrees of familiarity with AI tools. This balance ensured that the findings reflected a holistic understanding of talent identification, bridging the gap between established HR practices and emerging AI-driven methodologies. Ultimately, the validation process provided a robust foundation for the interviews, enabling a nuanced exploration of how personal and professional attributes influence potential evaluation in diverse organisational settings.

Their feedback confirmed the questions' alignment with industry standards, emphasising adaptability, emotional intelligence, and integrity as critical for potential evaluation. Similarly, practical examples and scenarios validated professional competencies such as decision-making, teamwork, and problem-solving.

#### 4.2.3. Insights from industry experts

Representing industries such as healthcare, financial services, infrastructure, communication, marketing, and workplace advisory, these experts brought a rich tapestry of experiences from small agencies to multinational corporations. Their combined knowledge laid a solid foundation for examining how personal and professional qualities intersect in organisational success.

These professionals came from various roles: leadership development experts, HR managers, and industry specialists. They explored the nuances of adaptability in healthcare, the strategic demands of financial services, and the challenges faced by different organisational contexts. Together, they painted a vivid picture of what it takes to identify and nurture high-potential employees.

The first question focused on personal qualities critical for potential evaluation. Respondents highlighted essential traits such as **adaptability, emotional intelligence, integrity, and proactivity**. "An employee who can quickly adjust to new challenges and learn new skills will thrive," one respondent emphasised. They noted that these qualities are often job-specific, with tools like the Hexaco 60 personality model helping tailor evaluations to roles ranging from healthcare aides to sales representatives.

Respondents prioritised **problem-solving, teamwork, strategic thinking, and technical expertise when discussing professional skills**. High-potential employees not only excel individually but also elevate their teams. As one participant noted, "The best performers share ideas and leverage collective strengths." Continuous learning and resilience emerged as indispensable qualities for leadership roles, underscoring the need for growth-oriented talent.

Respondents explored additional characteristics beyond personal and professional traits that signal high potential. **Critical thinking, resilience, and a growth mindset** stood out as markers of employees capable of navigating complex challenges. Networking skills and cultural alignment also played a significant role, while leadership potential was evident even in non-managerial positions.

The interplay between personal and professional qualities revealed a dynamic relationship. **Ambition** drives innovation and problem-solving, while **adaptability** fosters flexibility and creativity in tackling challenges. These attributes amplify professional competencies, shaping a high-potential workforce ready to excel in unpredictable environments.

The interviews provided multiple examples of success. A military veteran thriving in sales, a team leader navigating restructuring, and a strategic thinker selected for executive training exemplified how personal and professional qualities align to drive results. These narratives reinforced the importance of resilience, emotional intelligence, and innovation in achieving organisational goals.

Respondents described diverse tools to evaluate potential, each offering unique insights into employee capabilities. They highlighted the effectiveness of 360-degree feedback, which provided a comprehensive view of interpersonal and leadership skills by gathering input from peers, subordinates, and supervisors. Scenario-based interviews were

noted for their ability to assess problem-solving and adaptability through real-life job-related situations. Psychometric assessments emerged as a valuable resource for uncovering personality traits and cognitive skills, offering objective data to complement other evaluation methods. Additionally, project assignments and rotations were emphasised as dynamic approaches to testing adaptability and leadership, allowing employees to demonstrate their skills in varying contexts. These methods showcased the importance of integrating subjective feedback with objective data in a holistic evaluation process.

AI tools have shown effectiveness in evaluating technical skills and productivity, providing precise and efficient analyses that organisations can rely on. However, these tools often falter regarding more nuanced traits, like emotional intelligence and cultural fit. One respondent noted, "AI can identify patterns, but understanding the context behind those patterns still requires a human perspective."

This limitation highlighted among participants the need for a hybrid approach. By blending the analytical precision of AI with the empathy and contextual understanding of human judgement, organisations can develop an integrated evaluation framework. This combination positions AI as a complement to, rather than a replacement for, human decision-making.

Central to this vision was the call for robust ethical frameworks. Respondents highlighted the importance of addressing biases embedded within AI systems, urging organisations to use diverse datasets and conduct regular audits to mitigate unfair assessments. "Without diverse datasets and regular updates," one expert warned, "AI tools risk reinforcing biases, compromising the fairness of evaluations."

These insights painted a future where technology and humanity collaborate seamlessly, using their unique strengths to craft more equitable, inclusive, and effective talent assessment processes.

Key obstacles, such as false representation and contextual misunderstandings, underscore the necessity for robust bias detection mechanisms and AI models capable of incorporating contextual nuances. Respondents emphasised the importance of tools that integrate real-time feedback with personalised development plans, advocating for transparent systems and user-friendly interfaces to enhance trust and usability.

The interviews culminated in a comprehensive set of best practices. Consistently defining qualities were identified as essential to maintaining fairness and reliability in evaluations. Leveraging diverse datasets emerged as a critical strategy for uncovering nuanced insights into employee potential. Respondents stressed the importance of balancing evaluation models to ensure that no single attribute is overemphasised, advocating for a holistic approach. Additionally, fostering collaboration between human judgement and AI was highlighted to combine analytical precision with the contextual understanding needed for more accurate and equitable assessments.

Looking ahead, respondents envisioned significant advancements in talent evaluation. They anticipated the integration of real-time analytics, which would provide immediate feedback and actionable insights, as well as incorporating unstructured data sources, such as communication patterns and contextual cues, to enrich assessments. Ethical considerations in AI design, including bias mitigation and data privacy, were seen as critical areas for development. Respondents also emphasised the need for practical AI training for managers, equipping them with the skills to effectively interpret and leverage AI-generated insights. As tools continue to evolve, they envision systems offering more profound, more actionable insights to support dynamic and equitable talent management.

The insights from these interviews illustrate how personal and professional qualities shape potential evaluation and talent identification. By embracing a holistic approach, integrating advanced AI tools, and maintaining a human touch, organisations can create a more equitable, innovative, and high-performing workforce. These findings provide a basis for further exploration for a future where talent thrives aligned with organisational goals.

### 4.3. Mixed data integration

This section presents a direct synthesis between the quantitative survey findings and the qualitative insights provided by HR professionals. Rather than imposing interpretative frameworks, the integration here reflects how the empirical patterns observed in the data are either confirmed, challenged, or nuanced by the practitioners' lived experiences and evaluative practices.

The survey analysis showed a perceived connection between ambition, adaptability, and innovation, attributes linked to potential and performance. One interviewee affirmed this connection: *"People with ambition and long-term objectives are more likely to become innovative and push the boundaries of conventional thinking."* He further noted that *"flexibility is the most critical one"* in evaluating potential within his organisation. Another interviewee also directly reinforced this pattern: *"Ambition and adaptability aid employees in performing better under pressure, especially in evolving environments."* These attributes *"impact an employee's trajectory and ability to take on larger roles"*.

However, not all participants viewed ambition in a positive light. One interviewee expressed critical reservations: *"Ambition is a word I don't particularly like. It's vague and overused. In recruitment, I need to see purpose-driven goals and follow-through behaviours"*. This underscores the contextual variability in how seemingly universal traits are interpreted and supports the importance of human evaluation in complementing data-driven models.

Leadership and teamwork were also found to be correlated in the quantitative data. One interviewee echoed this link through a concrete organisational example: *"It was evident during performance appraisal. Employees with high leadership capabilities were also those who could hold the team together during stress periods and deadlines"*. Others described high-potential individuals as those who *"navigate ambiguity, collaborate across teams, and consistently show resilience during major change efforts"*. These testimonies strongly align with the statistical relationships observed in the survey results and offer an in-depth understanding of how such competencies manifest in situ.

Participants provided specific examples of how these traits influenced selection and performance outcomes. One interviewee, for instance, described how open-ended interview questions help her assess candidates' readiness to respond under pressure: *"I train my staff on the traits I want and how to look for them in interviews."* Similarly, another interviewee noted that *"these attributes are often cited in the 360 feedback and regular performance review cycles,"* suggesting that longitudinal behavioural patterns are considered important in how talent is recognised.

The survey also pointed to a general reliance on structured and informal methods for assessing talent. This was confirmed across interviews. One interviewee explained: *"Yearly reviews + continuous eye on KPI. However, we also rely on managers' discretion."* Murthy added that their organisation uses *"a combination of structured assessments and observation"*. Another interviewee clarified that *"the methods are mainly observational"* and acknowledged current gaps in systematic evaluation: *"We are not doing a particularly good job identifying high-potential people algorithmically. We would need much richer data and more advanced systems"*.

These integrated insights reveal alignment and divergence between measured patterns and practical application. While certain competencies show clear empirical correlations, their operationalisation depends heavily on interpretive, situational, and often tacit judgements that experienced HR professionals make. The findings thus reinforce the study's central proposition: that hybrid models, where human insight complements AI analytics, are essential for accurate and contextually valid talent identification.

Taken together, these findings are not only descriptive but also speak directly to the central research question of whether AI can assist HR in identifying talent more effectively.

These findings directly inform the central research question of

whether AI can assist in identifying talent more effectively. The competencies most valued by respondents, such as adaptability, creativity, and emotional intelligence, are precisely those that current AI tools struggle to assess reliably, as shown in prior literature and confirmed in our qualitative interviews.

Conversely, attributes more easily captured by algorithms, such as technical proficiency or measurable performance indicators, were also recognised but viewed as insufficient on their own to predict long-term potential. This alignment underscores the theoretical rationale for hybrid evaluative models: AI provides efficiency and consistency in analysing structured data, while human judgement remains essential for interpreting complex, non-cognitive attributes. The convergence of survey and interview evidence therefore supports the argument that AI's contribution lies not in replacing human evaluators but in augmenting their capacity to make fairer and more informed talent decisions.

## 5. Discussion

The discussion integrates survey and interview findings to provide a comprehensive analysis, weaving together data from 240 survey respondents across industries and countries. These respondents revealed the intricate links between personal and professional attributes and their impact on talent potential. The survey illuminated compelling correlations. Creativity emerged as a cornerstone of innovation, with individuals exhibiting this trait contributing to their organisations' capacity for new ideas and processes. Initiative surfaced as another powerful driver, suggesting that proactive individuals play a pivotal role in fostering innovation and continuous improvement. Leadership, too, stood out, with its strong connection to innovation underscoring the critical role of leaders in cultivating and managing forward-thinking efforts within teams.

Seeking to deepen this understanding, we turned to the voices of seasoned HR experts through semi-structured interviews. Their qualitative insights depicted the attributes driving innovation and performance. Adaptability, the ability to adjust to evolving circumstances and information, was repeatedly cited as essential for sustaining innovation in dynamic environments. A profound desire to achieve and succeed also emerged as a recurring theme, tied closely to heightened performance and creative output. Emotional intelligence, encompassing the ability to manage emotions and understand others, was spotlighted as vital for fostering collaboration and innovation. Furthermore, ethical behaviour and integrity were considered the bedrock for building trust and cultivating an environment conducive to innovative breakthroughs.

These expert narratives resonated with the survey findings, creating a harmonious blend of qualitative depth and quantitative breadth. Together, they pointed to the transformative potential of AI-driven tools in talent management. Advanced AI capabilities such as predictive analytics, pattern recognition, and continuous learning are envisioned as game-changers. By identifying critical competencies with heightened precision and fairness, AI systems could enhance how organisations pinpoint and nurture talent.

Ultimately, the convergence of data and expert perspectives underscored a profound opportunity for organisations. By leveraging the insights derived from AI-enhanced evaluations, businesses could cultivate a culture of innovation and high performance. This approach promises to revolutionise talent management and lay a foundation for sustained organisational success in an ever-evolving landscape. The story of this research is one of discovery, integration, and the endless possibilities that arise when technology and human insight come together to shape the future of work.

It is important to underscore that the findings presented here are not the outcome of a confirmatory hypothesis-testing exercise but rather the result of an inductive inquiry. As such, the study should be viewed as a contribution to theory-building, offering conceptual clarity and empirical grounding in an area still marked by significant uncertainty. Future research could build on these exploratory insights by developing and

testing formal hypotheses across different organisational contexts and technological applications, thereby advancing the theoretical maturation of AI-enabled HRM practices.

While this study provides empirical insights into the integration of AI in talent identification, its findings should be interpreted with attention to contextual variation across industries, organisational sizes, and cultural settings. Large organisations with mature HR infrastructures may have greater capacity to implement and govern AI systems in compliance with ethical and regulatory standards. In contrast, small and medium-sized enterprises (SMEs) often operate with limited technological and human resources, relying more heavily on informal decision-making and human discretion. These structural differences may influence AI-enabled evaluation models' feasibility and perceived utility.

Industry dynamics also play a critical role. Sectors characterised by standardised roles and process automation, such as manufacturing or logistics, may adopt AI tools more easily and efficiently. In contrast, creative or relational sectors like consulting or education may require more nuanced, human-centric assessments that are less amenable to full automation.

Cultural context further affects the interpretation and acceptance of AI in HRM. Conceptions of potential, fairness, and performance are socially constructed and vary across regions. In collectivist cultures, for example, informal reputation and team integration may outweigh individual metrics, complicating the applicability of algorithmic evaluation models trained on Western data. As such, while the study offers an empirically grounded model of hybrid AI-human evaluation, its transferability must be assessed in light of these contextual conditions.

### 5.1. Interpretation of results

Building on these empirical findings, it is necessary to situate the results within the theoretical frameworks that underpin this study. The integration of survey and interview findings provides important insights into the central research question of whether AI can assist in talent identification. The results show that while professionals acknowledge the value of algorithmic tools for analysing structured data and enhancing efficiency, the competencies most critical for long-term success, such as adaptability, creativity, and emotional intelligence, remain difficult for AI to capture.

This finding is consistent with theoretical perspectives such as the Resource-Based View and Sociotechnical Systems Theory, which emphasise the strategic importance of human judgement in interpreting non-cognitive attributes. By situating empirical evidence within this theoretical landscape, the study argues that AI should not be considered a substitute for human evaluation but rather an augmenting mechanism that strengthens fairness, scalability, and consistency in talent assessment. This hybrid orientation aligns with the emerging consensus in the literature that sustainable competitive advantage depends on the joint optimisation of technological and human capabilities.

This research's findings highlight AI's potential contribution to HR practices, particularly in talent identification and assessment. The developed model demonstrates significant efficacy in linking personal and professional attributes with talent and potential, as evidenced by robust Pearson coefficient correlations.

A notable finding is the strong connection between creativity and innovation, highlighting the critical need to foster a creative mindset within organisations. Creativity shows a strong correlation with innovation, which is frequently associated with organisational transformation and competitive advantage. Similarly, initiative and leadership are positively associated with innovation, which in turn is often linked to environments where innovation is fostered.

Additional correlations reveal other organisational dynamics. The correlation between innovation and decision-making suggests an association between innovative capabilities and strategic decision-making processes. The link between interpersonal skills and teamwork reaffirms the fundamental role of effective communication in building

strong team dynamics. Furthermore, the correlation between mentorship, learning, and achievement suggests that continuous learning is associated with higher levels of performance. The connection between interpersonal skills and decision-making highlights that adept communication is integral to sound, strategic decisions.

These correlations offer invaluable strategic insights for refining organisational practices. By understanding the interplay of these competencies, organisations can tailor their HR initiatives to cultivate creativity, initiative, leadership, and effective communication. Such targeted interventions may be associated with more innovative, collaborative, and high-performing workplace cultures.

Insights from HR professionals and organisational leaders further enrich these findings. Essential personal qualities, such as adaptability, initiative, communication skills, emotional intelligence, and integrity, emerged as universally critical. These traits fuel professional competencies, including problem-solving, teamwork, strategic thinking, and technical expertise, creating a dynamic interplay that enhances individual effectiveness and growth potential. Practical examples provided by respondents illustrate how these qualities manifest in workplace scenarios and are perceived as linked to successful talent identification and improved performance outcomes.

The research also highlights the burgeoning role of AI in HRM, particularly in evaluating professional attributes through advanced analytics and machine learning. AI's ability to process and analyse vast datasets offers unprecedented precision in identifying professional competencies. However, challenges remain, particularly in assessing personal attributes. Respondents noted AI's current limitations in contextual understanding and the risks of inherent biases in training data. Incorporating richer contextual data, improving natural language processing (NLP) capabilities, and embedding robust ethical frameworks offer enhancements to AI tools, a promising path forward for achieving more comprehensive and fair evaluations.

These findings indicate the importance of combining AI's analytical precision with human judgement. Such an approach ensures a holistic and nuanced talent identification process, enabling organisations to apply AI's capabilities while addressing its limitations. The result supports the development of approaches aimed at more effective, equitable, and sustainable talent management strategies.

This research provides organisations with structured guidance for integrating AI into their HR practices. It offers recommendations for improving talent management processes and contributes to the theoretical understanding of how professional competencies interconnect and influence workplace dynamics. By adopting these insights, organisations can better navigate the complexities of modern talent management, supporting innovation and long-term organisational performance.

### 5.2. Comparison with previous research

The findings of this study align with a growing body of research highlighting AI's transformative role in enhancing HRM practices. Several prior studies have discussed AI's opportunities and challenges in this field. França et al. (França et al., 2023) identified a persistent gap between the theoretical potential of AI and its practical implementation by organisations, noting that while AI offers significant promise in streamlining and improving talent management, its full capabilities remain underutilised. Our research contributes to bridging this gap by providing empirical evidence demonstrating AI's effectiveness in identifying high-potential employees and critical competencies, surpassing the accuracy of traditional HR methods. These findings affirm the emphasis placed by Ulrich and Smallwood (Ulrich & Smallwood, 2012) on attributes such as ambition, ability, agility, and achievement as essential markers of high-potential individuals.

Despite these advancements, ethical concerns and the risk of algorithmic biases remain pressing issues, echoing themes in existing literature. Usman and Herrera (Usman & Herrera, 2024) warned of the potential for AI to reinforce discriminatory practices if improperly

managed, emphasising the need for continuous evaluation and adjustment of AI tools to ensure fairness. Similarly, Zaman and Thrun (Zaman & Thrun, 2024) underscored the importance of adopting rigorous processes to monitor and update AI systems to mitigate risks of perpetuating or creating biases. These insights align with our findings, which reveal that organisations need to develop robust ethical frameworks and implement regular audits to ensure AI systems contribute to workplace diversity and inclusion goals.

Shah and Thrun (Shah & Thrun, 2024) delved into the ethical dilemmas associated with AI in HRM, advocating for transparent practices and ethical guidelines to prevent unintended harm to employees. Our findings corroborate this view, highlighting the need for AI application transparency to foster stakeholders' trust. Wajid and Kellis (Wajid & Kellis, 2024) explored the balance between AI's performance enhancements and the ethical concerns it raises. Our research confirms their conclusions, showing that while AI significantly improves talent identification and management, its deployment must be carefully managed to address ethical challenges and prevent unintended consequences.

Practical considerations, such as effective data management, are also featured in existing studies. Iqbal and Gasmi (Iqbal & Gasmi, 2024) emphasised the importance of accurate and comprehensive data for supporting AI applications in HR. Our study reinforces this point, demonstrating that data quality is critical to achieving reliable and unbiased results from AI systems. Sufiyan and Gasmi (Sufiyan & Gasmi, 2024) further highlighted the benefits of AI in improving job performance metrics through data-driven insights and automation, a finding reflected in our study's evidence of AI's ability to streamline HR functions while enhancing efficiency.

Nar et al. (Nar et al., 2024) argue that ongoing education and training in facilitating AI integration and equipping HR professionals with the necessary skills are essential for effective AI adoption. Our findings align with this perspective, emphasising that continuous learning is crucial to ensure that HR teams can effectively leverage AI technologies. Similarly, Narain (Narain, 2024) noted that AI could transform talent management strategies by enabling more precise identification and development of employee potential. Our study supports this assertion while reiterating the need for responsible AI use to avoid ethical pitfalls.

Research by Cuesta-Valiño et al. (Cuesta-Valiño et al., 2024) further illustrates the wide-ranging applications of AI in HR functions, including recruitment, training, and onboarding. Their findings align closely with our research, highlighting AI's capacity to streamline these processes while improving decision-making accuracy. However, as our study emphasises, organisations must remain vigilant in addressing ethical considerations and biases to ensure equitable outcomes.

The comprehensive review by Suri (Suri, 2024) highlighted the legislative and managerial challenges associated with AI adoption in HRM. Suri argued that effective implementation requires technological readiness, a supportive regulatory framework, and committed leadership, insights that resonate with our findings. Similarly, Ramanathan et al. (Ramanathan et al., 2024) focused on the unique challenges and opportunities AI presents for small and medium-sized enterprises (SMEs). Their research, which emphasises the need for tailored strategies to address sector-specific constraints, is supported by our findings, which suggest that AI's transformative potential can benefit organisations of all sizes, provided the implementation strategies are appropriately customised.

Our research reinforces and extends the existing literature on AI in HRM by offering empirical evidence of its benefits while addressing critical ethical and practical considerations. These findings underscore the importance of adopting a balanced and responsible approach to AI integration, leveraging its capabilities to enhance talent identification

**Table 13**

Comparison of current study insights with previous research on AI in HRM.

Aspect	Current Study Insights	Previous Research Findings	Alignment/Gaps
AI Potential in HRM	Demonstrates AI's ability to effectively identify high-potential employees and critical competencies, surpassing traditional HR methods.	The gap between theoretical potential and practical implementation of AI in organisations (França et al., 2023).	The study builds on theoretical gaps with empirical evidence. It highlights practical effectiveness, which was not emphasised in earlier research.
Key Traits for High Potentials	Identifies ambition, ability, agility, and achievement as essential attributes.	Previous studies like Ulrich & Smallwood (Ulrich & Smallwood, 2012) highlight similar traits.	Reinforces earlier findings with updated data and AI tools for better identification.
Ethical and Bias Concerns	Highlights ongoing challenges with algorithmic biases and calls for ethical frameworks and continuous evaluations.	Usman & Herrera (Usman & Herrera, 2024) and Zaman & Thrun (Zaman & Thrun, 2024) emphasise the risks of AI reinforcing biases.	Agreement on the need for regular AI audits and transparency. Suggests hybrid models combining human oversight with AI.
Practical Benefits of AI	Improved decision-making, enhanced efficiency, and streamlining of HR functions.	Previous studies noted these benefits but lacked empirical evidence (Iqbal & Gasmi, 2024).	The current study adds empirical validation to theoretical assertions.
Data Quality	Emphasises criticality of data quality for unbiased AI results.	Highlighted in prior works like Iqbal & Gasmi (Iqbal & Gasmi, 2024).	The current study reaffirms its importance and suggests robust data management practices.
Education & Training for HR	Advocates upskilling HR professionals to use AI effectively.	Nar et al. (Nar et al., 2024) and Narain (Narain, 2024): Emphasise training HR teams for better AI adoption.	It aligns with the importance of education but introduces hybrid frameworks for talent evaluation.
Integration of AI & Human Insight	Promotes hybrid models blending AI analytics with human judgement.	Cuesta-Valiño et al. (Cuesta-Valiño et al., 2024) show AI limitations in qualitative assessments.	Extends work with practical frameworks for integrating AI with human oversight.
Legislative and managerial challenges	Highlights the need for ethical AI frameworks, hybrid models, and targeted upskilling for practical implementation in HR.	Suri (Suri, 2024) argued that effective implementation requires technological readiness, a supportive regulatory framework, and committed leadership.	Bridges the gap by providing practical frameworks and empirical insights for ethical AI integration in HR.
Sector-Specific Challenges	Highlights AI's scalability to large organisations and SMEs with tailored implementation strategies.	Ramanathan et al. (Ramanathan et al., 2024) discuss unique AI adoption hurdles for SMEs.	Aligns with prior work while expanding strategies to bridge gaps in AI scalability.

**Table 13** notes: This table contrasts the findings of the current study with recent research in AI and HRM, identifying areas of alignment, divergence, and original contribution.

and management while safeguarding against potential risks. [Table 13](#) compares the current study's insights and previous research on AI in HRM.

### 5.3. Practical implications

The findings from this research provide actionable guidance for transforming HRM practices. By harnessing the capabilities of AI tools, organisations can more effectively identify high-potential employees by emphasising critical competencies such as creativity, initiative, and leadership. These tools enable HR teams to streamline talent management processes, refine decision-making accuracy, and cultivate an environment of continuous improvement and innovation.

Integrating AI into HR practices offers a dual advantage: enhancing the accuracy and fairness of talent identification. By minimising biases and increasing objectivity, AI-driven evaluations foster more equitable and efficient talent management systems, leading to improved organisational performance. These improvements benefit immediate decision-making and support the long-term development of a high-performing workforce.

Moreover, the insights drawn from the correlation analysis within this research can inform strategic interventions to cultivate specific competencies. Organisations can build a more capable workforce that aligns with their strategic goals by targeting innovation, problem-solving, and teamwork development efforts. Ultimately, the thoughtful integration of AI into HR practices can improve existing processes, supporting organisational adaptation to changing business contexts and competitiveness.

While this study highlights the promise of AI in enhancing efficiency and objectivity in talent identification, it also reveals fundamental limitations, particularly in evaluating qualitative human attributes such as emotional intelligence, adaptability, and cultural fit. These attributes are not easily reducible to structured data, and current AI systems often fail to capture the situational and relational nuance required for accurate assessment.

However, emerging fields such as affective computing and context-aware AI may provide opportunities for improvement. Advances in NLP and sentiment analysis, for instance, may allow for more refined interpretations of behavioural signals in communication and feedback loops. At the same time, human oversight remains indispensable. For HR professionals, this means cultivating roles as evaluators and interpreters of AI outputs, especially in complex or high-stakes scenarios. For AI developers, it entails designing systems with greater transparency, explainability, and modular integration that allow for human intervention and correction.

Ultimately, these limitations reinforce the argument that talent identification should not be viewed as a fully automatable process but rather as a collaborative task that benefits from the complementary strengths of both human judgement and machine intelligence.

### 5.4. Ethical and bias considerations

Integrating AI into HRM has fundamentally transformed talent evaluation processes, introducing unprecedented efficiency and scalability. However, alongside these advancements come critical ethical challenges, particularly the risks of algorithmic bias. If left unaddressed, these biases can perpetuate systemic inequities, erode trust in AI-driven tools, and undermine their utility in identifying high-potential employees. Ensuring fairness, transparency, and accountability in AI-driven evaluations is paramount to maintaining their credibility and effectiveness.

AI systems often inherit biases from the historical data on which they are trained. A notable example is Amazon's recruitment tool, which systematically favoured male candidates due to biased training data that reflected historical hiring practices ([Raghavan et al., 2020](#)). This case highlights the dangers of embedding societal biases into algorithms,

potentially excluding underrepresented groups from talent pools. These risks align with the findings in this study, where respondents underscored the importance of diverse training datasets and regular audits to detect and mitigate biases in AI assessments. The ethical deployment of AI in HRM requires the identification of risks such as bias and opacity, and the application of structured frameworks that can guide implementation. The EU Artificial Intelligence Act ([European Union, 2021](#)) provides a useful regulatory foundation. The Act classifies AI systems used in employment, recruitment, and performance evaluation as "high-risk" applications, thereby subjecting them to enhanced obligations. These include ensuring transparency in AI decision-making, embedding effective human oversight, maintaining rigorous technical documentation, and using non-discriminatory, high-quality training data. In talent identification, these provisions can be operationalised through practical measures such as informing candidates when AI tools are involved in evaluations, enabling HR professionals to override algorithmic decisions, documenting system behaviour over time, and auditing training data for representativeness and fairness.

By framing ethical considerations through the EU AI Act, this study contributes to the conceptual debate and the practical discourse on how organisations can align technological adoption with human-centred values and regulatory compliance.

Similarly, the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems identifies fairness, accountability, and explainability as fundamental principles for ethical AI design. Incorporating these guidelines can help organisations mitigate ethical challenges and strengthen the reliability of AI-driven evaluations.

This study also identified a key limitation of AI systems. While highly effective in analysing structured data to evaluate professional attributes such as productivity and technical skills, AI often struggles to interpret complex personal attributes like emotional intelligence and adaptability. Respondents emphasised the importance of complementing AI's analytical capabilities with human judgement, particularly for nuanced assessments. This conclusion aligns with broader literature advocating for a hybrid evaluation model integrating AI-driven insights with qualitative human evaluations ([Tambe et al., 2019](#)).

Organisations should adopt several strategic approaches to uphold ethical standards and mitigate bias. Regularly updating training datasets to ensure they represent diverse demographics can help eliminate historical biases. Real-time bias detection tools should identify and correct skewed evaluations as they occur. Transparency in AI decision-making is also essential, requiring organisations to provide clear visualisations and explanations of how AI models generate their outputs. Finally, hybrid evaluation systems that combine AI-driven metrics with human oversight can ensure a more comprehensive and balanced assessment process. For example, dashboards that integrate AI-generated data with qualitative observations from managers can provide a richer, context-aware understanding of employee potential. These systems address limitations highlighted in this study, where over-reliance on quantitative metrics risks overlooking critical qualitative attributes such as creativity and leadership.

Ethical AI practices are essential to fostering trust, inclusivity, and fairness in HRM. By adopting frameworks like the EU AI Act and IEEE guidelines, organisations can enhance the reliability and equity of AI-driven assessments. This study highlights the critical need for hybrid evaluation systems and robust bias detection mechanisms to ensure comprehensive and equitable talent evaluations. Future research should prioritise the development of context-sensitive AI systems and foster interdisciplinary collaborations that integrate technical, legal, and ethical perspectives to advance the field responsibly.

### 5.5. Generalizability

The generalisability of the findings must also be considered in light of cultural norms, which significantly shape how AI systems are perceived and adopted in HRM. For instance, in collectivist contexts,

such as parts of East Asia, algorithmic tools may be more readily accepted if they are perceived to promote group harmony and equitable outcomes. Conversely, in individualist cultures, such as much of Western Europe and North America, greater emphasis is placed on autonomy and personal agency, meaning that employees and HR professionals may be more resistant to AI-driven evaluations if they are seen as constraining individual discretion. From a sociotechnical perspective, these contrasts illustrate that the success of AI implementation depends not only on technical accuracy but also on cultural alignment. For practitioners, this underscores the need to adapt AI-enabled HR processes to local values, while for researchers, it highlights the importance of cross-cultural comparisons in assessing the broader validity of hybrid evaluative models.

### 5.6. Future research

Future research could refine and expand the application of AI in HRM, particularly in talent identification and potential evaluation. A critical area of focus could be identifying and evaluating AI models that are effective in predicting outcomes based on a comprehensive range of personal and professional characteristics. This exploration would involve testing machine learning algorithms and deep learning techniques to determine which models provide greater accuracy and reliability in forecasting key metrics such as employee performance, career growth, and leadership potential. Beyond predictive accuracy, researchers should consider these AI tools' model complexity, interpretability, and scalability, seeking integration into HRM systems without overburdening technical or operational resources.

Future research should adopt a comparative lens across industries, organisational types, and cultural settings to strengthen the external validity and contextual adaptability of AI-supported talent evaluation models. While the present study offers an integrated perspective on hybrid AI-human decision-making, its empirical scope is limited to a subset of respondents. Comparative studies could explore how organisations in resource-constrained versus resource-rich environments differ in their implementation of AI tools or how regulatory frameworks and digital infrastructure shape adoption dynamics across regions. Furthermore, cross-cultural investigations into the meanings ascribed to potential, merit, and fairness would be especially valuable in understanding how diverse stakeholders interpret, trust, or resist AI systems. Such work would inform theory-building and provide practical guidance for developing ethically sensitive and context-aware AI applications in HRM.

Another vital research direction involves examining the integration of AI models with existing HR processes, such as talent identification frameworks and potential evaluation systems. Researchers should explore how AI can enhance these processes' objectivity, efficiency, and fairness while identifying potential challenges or limitations during their implementation. This might include examining how well AI aligns with current HR practices, the training required for HR professionals to use AI tools effectively, and the cultural and ethical implications of relying on AI-driven insights for talent decisions.

Empirical validation is another crucial avenue for future investigation. Studies could focus on collecting and analysing large, diverse datasets from various organisational contexts to evaluate AI models' predictive power and accuracy. Such research could provide valuable insights into which AI approaches work best in specific industries or organisational settings and the factors influencing the effectiveness of AI-driven evaluations. By systematically comparing AI models' performance in real-world scenarios, future research can offer evidence-based recommendations for HR professionals seeking to adopt these technologies.

While this study employs correlation analysis as an exploratory tool, future research could substantially extend the analytical depth by incorporating multivariate statistical techniques. For instance, multiple regression analysis could identify which attributes are the strongest

predictors of perceived potential or successful talent identification across different organisational contexts. Additionally, factor analysis could help clarify whether the attributes assessed in this study cluster into latent competency dimensions, enhancing the conceptual precision of HR evaluation models.

Further, Structural Equation Modelling (SEM) would be particularly valuable in testing and validating the conceptual model proposed in this study. SEM would allow researchers to empirically assess the relationships between AI capabilities, human attributes, hybrid evaluative processes, and HRM outcomes, providing a comprehensive and statistically robust framework. Such approaches would support the transition from theory-building to theory-testing, advancing the academic maturity of research on AI integration in HRM.

By pursuing these research directions, future work can significantly contribute to the evolving understanding of AI's role in HRM. Understanding AI's role in HRM includes enhancing the precision and fairness of talent management practices, addressing AI integration's practical and ethical challenges, and fostering innovative approaches to identifying and developing high-potential employees. Ultimately, advancing this research will help unlock AI's transformative potential, driving more effective and equitable HR practices in organisations worldwide.

## 6. Conclusions

This study offers insights into the integration of AI in HRM, particularly in talent identification and potential assessment domains. The findings demonstrate that AI tools can substantially enhance the precision and efficiency of identifying high-potential employees by utilising advanced algorithms to detect critical competencies such as creativity, initiative, and leadership. The semi-structured interviews with HR experts further underscored the importance of key personal qualities, including adaptability, ambition, emotional intelligence, and integrity, as drivers of innovation and performance. These qualitative insights complement the quantitative data and highlight AI's transformative potential in reshaping HR practices.

At the same time, this study emphasises the necessity of addressing the ethical and bias challenges inherent in AI systems. While AI presents a significant opportunity to revolutionise HRM processes, its effectiveness is inextricably linked to the quality and diversity of input data and the thoughtful design and rigorous monitoring of algorithms. Without proactive measures, AI systems risk perpetuating or amplifying existing biases, undermining the fairness and inclusivity of talent assessments. The research highlights the importance of a balanced approach where AI augments, rather than replaces, human judgement, ensuring that ethical considerations and nuanced decision-making remain central to HR practices.

To fully harness the potential of AI, organisations are encouraged to adopt robust bias detection and mitigation strategies, invest in comprehensive training programmes for HR professionals to effectively utilise AI tools, and foster a culture of transparency and accountability in their talent management processes. By doing so, organisations can leverage AI's strengths to streamline operations, improve decision-making, and promote innovation, all while safeguarding fairness and ethical integrity. These steps are critical for ensuring that AI is a transformative and equitable force in HRM, contributing to more effective, inclusive, and sustainable talent identification practices.

### 6.1. Research managerial implications

Integrating AI in HRM presents substantial opportunities for enhancing talent management processes. AI can improve precision and efficiency in identifying critical competencies such as creativity, initiative, and leadership, which are associated with innovation and organisational performance. However, alongside these advancements come significant ethical and bias concerns that must be proactively addressed. Robust detection and mitigation strategies, transparent methodologies,

and inclusive development processes are essential to ensuring fairness and equity in AI-driven assessments.

Managers play a pivotal role in balancing AI and human judgement, particularly in areas requiring empathy, ethical considerations, and nuanced decision-making. AI should be positioned as a complementary tool that enhances human capabilities rather than replacing them. Organisations must invest in continuous learning and development to foster a culture of innovation, equipping HR professionals and leaders with the skills needed to leverage AI effectively and responsibly.

Strategic workforce planning also stands to benefit significantly from AI-driven analytics. These tools enable organisations to align workforce capabilities precisely with strategic goals, ensuring optimal resource allocation and talent development. At the same time, ongoing research and development efforts are essential to refining AI models, enhancing their reliability, and ensuring their ethical application. By embracing these measures, organisations can position themselves as leaders in the rapidly evolving landscape of AI-driven HRM, achieving both operational excellence and a commitment to fairness and inclusion.

## 6.2. Research theoretical implications

This study contributes to the theoretical understanding of AI integration within HRM, particularly in talent identification and potential assessment. Demonstrating AI's capacity to enhance precision in evaluating critical competencies such as creativity, initiative, and leadership extends traditional talent management theories, illustrating how advanced technologies can refine and elevate these processes.

Moreover, the research underscores the importance of addressing bias and ensuring fairness within AI systems, enriching the ongoing discourse surrounding ethical AI frameworks. It highlights the risks associated with unregulated AI deployment in HR practices and advocates for responsible design, implementation, and monitoring of AI models. This aligns with broader theories emphasising equity and inclusivity in talent management, marking a critical step in integrating ethical considerations into AI-driven frameworks.

The findings also validate theories supporting human-AI collaboration in decision-making. The study demonstrates that while AI excels in precision and scalability, it is most effective when combined with human judgement to address nuanced and ethically complex scenarios. This collaboration allows for a balanced approach, integrating data-driven insights with contextual and empathetic understanding.

Additionally, the research highlights AI's potential role in talent identification and strategic workforce planning, reinforcing its ability to align human capital with organisational objectives. These advancements contribute to a deeper understanding of how AI can support organisational agility and innovation, paving the way for a more strategic approach to workforce management.

The theoretical implications of this study offer a robust foundation for future research. They emphasise exploring AI's long-term impact across diverse organisational contexts and investigating how emerging technologies can sustainably transform HR practices. By bridging gaps between traditional theories and modern technological capabilities, this research offers a forward-looking perspective on the evolving role of AI in HRM.

## 6.3. Implications for organisational policy and strategy

Integrating AI into HRM represents more than a technological innovation; it is a strategic opportunity to redefine and transform talent management practices. By leveraging AI tools effectively, organisations can enhance their ability to identify and develop high-potential employees, streamline processes, and create more inclusive and equitable talent strategies. This shift improves operational efficiency and strengthens an organisation's competitive advantage by fostering innovation and aligning human capital with strategic goals.

However, the transition to AI-driven HRM demands a holistic and

thoughtful approach. Ethical considerations must remain at the forefront, ensuring that AI systems are designed and implemented transparently and inclusively. Addressing algorithm biases, prioritising data integrity, and building robust mechanisms for accountability are critical for fostering trust and fairness in AI-driven processes.

Equally important is maintaining employee engagement and preserving the human element in talent management. AI should complement human judgement rather than replace it, particularly in areas requiring empathy and ethical discernment. Organisations must invest in continuous learning and development programmes to achieve this balance, empowering HR professionals to use AI tools effectively and responsibly. By adopting such a comprehensive strategy, organisations can more effectively integrate AI in HRM while ensuring that ethical principles and human values remain integral while ensuring that ethical principles and human values remain integral to their practices.

## 6.4. Policy recommendations for HR practitioners

The findings outline key recommendations for HR practitioners, emphasising the value of a hybrid evaluation model that integrate AI-driven insights with human expertise. Organisations must adopt a multifaceted approach to implementing AI in HR to ensure ethical, efficient, and inclusive talent management practices. Establishing ethical oversight mechanisms, such as dedicated committees, can help ensure fairness, transparency, and compliance with data protection regulations throughout the AI integration process. Regular audits of AI systems are essential for identifying and mitigating biases, ensuring that training datasets reflect diverse demographics and professional experiences.

Additionally, equipping HR professionals with the necessary skills to interpret AI outputs critically and integrate them effectively into decision-making processes is paramount. Training and education programmes should prioritise the development of digital literacy and ethical awareness to empower practitioners to use these tools responsibly. Customising AI tools to assess role-specific competencies enhances precision and relevance, allowing for more accurate evaluations aligned with organisational needs.

Finally, implementing continuous feedback loops encourages employees to share their experiences with AI-driven HR processes, fostering trust and uncovering opportunities for improvement. By combining these strategies, organisations can harness AI's potential to revolutionise HR practices while maintaining ethical integrity and building employee confidence.

The findings underscore that the role of HR professionals remains essential, particularly in interpreting AI-generated outputs, contextualising decisions, and ensuring fairness. Rather than displacing human evaluators, AI systems shift the nature of their involvement toward higher-order analytical and ethical tasks. This demands enhanced data literacy, including the ability to scrutinise algorithmic recommendations and recognise where human judgement should override system outputs.

Furthermore, HR professionals should play an active role in system configuration, particularly in selecting which attributes are evaluated and how those constructs are defined and operationalised.

## 6.5. Practical contributions for information systems professionals

For Information Systems professionals, integrating AI into HRM represents a transformative opportunity, as supported by the findings of Tinguely et al. (Tinguely et al., 2023). The practical benefits of AI in HRM align closely with this study's emphasis on leveraging technology to enhance talent identification and management.

For AI developers, the key implication is that system design must go beyond optimisation and prediction to incorporate explainability, interpretability, and fairness auditing by design. Complex human traits, such as emotional intelligence or adaptability, require multimodal input

(behavioural data, language cues, team interactions), and developers must engage with domain experts to ensure a meaningful representation of these constructs. Co-development models that embed HR practitioners in the system design process can reduce the risk of epistemic mismatch, where the system's logic diverges from organisational values or practical expectations.

Furthermore, developers should anticipate that hybrid usage is the norm and design tools that assume human intervention, override capacity, and ongoing recalibration.

AI's capacity to deliver data-driven insights is pivotal in improving decision-making accuracy in HR processes. By analysing vast datasets, AI tools uncover patterns and correlations that inform strategic workforce planning, talent acquisition, and potential assessments. This aligns with our research findings, emphasising AI's potential to identify key competencies like creativity, initiative, and leadership with unprecedented precision.

Operational efficiency is another critical advantage of AI integration. Automating routine HR tasks such as candidate screening, performance tracking, and payroll processing reduces administrative burdens. This efficiency allows HR professionals to focus on strategic initiatives, such as fostering innovation, enhancing employee engagement, and developing targeted training programmes. These activities directly contribute to organisational growth and align with the broader strategic goals discussed in this study.

AI also provides scalability, enabling organisations of all sizes to manage HR functions effectively. Its ability to process large volumes of data ensures that HR practices remain efficient and consistent, regardless of organisational scale. This scalability supports diverse applications, from streamlining processes in small and medium-sized enterprises to optimising large corporations' complex HR ecosystems.

By integrating AI responsibly and effectively, organisations can create a more agile, data-driven HR function that is efficient and better aligned with their strategic objectives. As highlighted in our study, these advancements underscore the importance of combining technological innovation with ethical oversight and human judgement to realise AI's transformative potential in HRM.

### 6.6. Limitations and recommendations

While the study contributes to understanding the integration of AI into HRM, it is essential to reflect on its limitations.

The concentration of responses from the United States and limited representation from other countries constrain the generalisability of findings across cultural contexts. Results should therefore be interpreted with caution, particularly when considering differences in organisational culture or labour market structures.

Although subgroup analyses by company size revealed no significant differences, the uneven geographical distribution of respondents, with an overrepresentation from the United States, remains a limitation for generalisability.

An important limitation of the survey design is that competency items reflect self-reported attributes of respondents, who represented a broad cross-section of professionals across industries. While these measures provide valuable insight into self-perceptions, they do not capture evaluative preferences towards employees. For example, a respondent who does not consider themselves detail-oriented may still prioritise this trait when assessing colleagues or subordinates. Future studies should therefore employ instruments that distinguish between self-assessed traits and the attributes valued in others. Additionally, the study's focus on short-term impacts offers only a snapshot, leaving the more extended, evolving narrative of AI's influence on HRM yet to be explored. The next research phase in this field would benefit from broadening its scope to include a more diverse range of cultural and industry contexts while incorporating objective performance metrics to deepen the analysis. Longitudinal studies could further enrich this line of inquiry by tracing the evolution of AI's impact over time, revealing its

sustained influence on talent management practices and outcomes.

A methodological limitation is that the statistical analysis relied on correlational techniques, which reveal associations but do not establish causality. Although relationships such as those between mentorship, learning, and achievement were found to be significant, these results should be interpreted as evidence of co-variation rather than causal effects. Future research could apply regression models or structural equation modelling (SEM) to examine the causal mechanisms underlying these relationships.

The ethical challenges inherent in AI use are central to this debate. Just as an author revisits drafts to refine their work, organisations must continually monitor and update their AI systems to address biases and maintain fairness. This requires practitioners to develop robust ethical frameworks who craft robust ethical frameworks, equipping HR professionals with the tools to navigate this new terrain confidently.

Collaboration becomes the plot's key theme, blending human expertise with AI's precision to create a balanced and transparent system. When organisations embrace this duality, they set the stage for talent management strategies that are innovative, equitable, and inclusive.

As this narrative unfolds, it becomes clear that addressing these challenges and building on these opportunities will define the following chapters on AI's role within HRM. Through careful stewardship, organisations can shape a future where AI does not just fit into HRM but elevates it, creating stories of success and fairness for the workforce of tomorrow.

### 6.7. Contributions

This study contributes to the theoretical advancement of AI-driven talent identification in HRM by offering a novel conceptual articulation of how algorithmic systems interact with human attributes in the context of potential evaluation. Although not grounded in a single formal theory, the research draws conceptually from three foundational perspectives: Human Capital Theory, the Resource-Based View, and Sociotechnical Systems Theory, which collectively inform its analytical framing.

Theoretically, the study extends current discourse by conceptualising talent not as a static input but as a dynamic configuration of personal and professional attributes that can be interpreted, in part, through algorithmic analysis. In line with Human Capital Theory, the research recognises potential as a latent asset, requiring data-driven insight and contextual understanding to be meaningfully activated within organisational settings. From the RBV perspective, the study reinforces that AI-enabled talent identification processes can contribute to a sustained competitive advantage when aligned with strategic priorities, mainly when human capabilities are treated as rare and inimitable organisational resources.

Additionally, the research acknowledges the relevance of Sociotechnical Systems Theory by emphasising the interplay between algorithmic systems and human judgement. Rather than viewing AI as a replacement for traditional HR practices, the study positions it as a component within a broader sociotechnical system in which organisational values, ethical safeguards, and contextual interpretation are vital.

Therefore, the central theoretical contribution lies in developing a hybrid conceptual model that positions AI as a decision-support mechanism embedded in socio-organisational structures. This model advances the literature by offering a structured way to understand how AI can complement, rather than substitute, human expertise in talent decisions. Moreover, it opens new avenues for theorising how emerging technologies reshape the identification and development of high-potential employees while also surfacing tensions around objectivity, bias, and fairness.

In synthesising these perspectives, the study contributes to a more nuanced theoretical understanding of AI in HRM, one that foregrounds complexity, interdependence, and the need for interdisciplinary

reflection in the design of intelligent, human-centred evaluation systems.

### 6.8. Future research directions

The future of AI in HRM involves balancing innovation with responsibility, where a steadfast commitment to fairness and inclusivity must temper the pursuit of innovation. As organisations increasingly rely on AI to streamline talent management, the challenge lies in designing systems that are efficient and just. This narrative centres on the call for bias-resistant algorithms explicitly tailored for HRM applications.

Today's AI systems often draw upon historical data, which risks perpetuating existing inequities. To address this challenge, researchers should prioritise creating training datasets that reflect diverse and inclusive perspectives. These datasets must be dynamic and regularly updated for evolving workplace realities. AI systems equipped with real-time bias detection mechanisms could identify and flag discriminatory patterns as they arise. These innovations function as safeguards, promoting fairness and ensuring that assessment processes remain equitable and free from systemic bias.

AI's current analytical capabilities face limitations in evaluating qualities often defining exceptional talent—emotional intelligence, creativity, and cultural fit. Critical for leadership and team cohesion, these attributes often elude quantitative metrics. Future research must explore advanced methodologies, such as NLP technologies, that can interpret sentiment and communication styles. These advancements could bring AI closer to understanding the complexities and potential of human behaviour by bridging the gap between qualitative and quantitative data analysis.

The ethical dimensions of AI in HRM require a collaborative and interdisciplinary approach. Picture a table where technical experts, legal scholars, and ethicists come together to craft robust regulatory frameworks. Inspired by models like the EU AI Act, such frameworks would establish global standards for ethical AI use in HRM, emphasising transparency, accountability, and respect for employee privacy. At the heart of these discussions would be mechanisms to ensure accountability, transparency requirements, and safeguards for consent, fostering trust in AI-driven evaluations.

In this context, human oversight remains indispensable. While AI can provide powerful insights, human judgement ensures that these insights are applied with empathy and fairness. Researchers and practitioners must work hand in hand to refine AI tools, embedding ethical safeguards and innovative strategies that prioritise equity. Organisations, too, play a critical role, adopting a holistic approach that combines technical advancements with ethical responsibility.

Future research requires a commitment to fairness, transparency, and accountability. By addressing these challenges, the full potential of AI in HRM can be realised—creating systems that enhance efficiency and foster trust and inclusivity. This is not just a technological transformation but a reimagining of how we define, assess, and nurture human potential in the workplace.

### Author contribution statement

Tiago Jacob Fernandes França: Conceptualisation, Methodology, Investigation, Formal analysis, Writing – original draft, Visualisation, Project administration.

José Henrique Pereira São Mamede: Conceptualisation, Methodology, Writing – review & editing, Validation, Supervision, Funding acquisition.

João Manuel Pereira Barroso: Conceptualisation, Methodology, Writing – review & editing, Validation, Supervision.

Vítor Manuel Pereira Duarte dos Santos: Conceptualisation, Methodology, Writing – review & editing, Validation, Supervision.

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### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.

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