

AI-Driven Talent Analytics for Identifying High-Potential Employees in Hyderabad's IT Sector: A Conceptual Framework and Research Agenda

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ABSTRACT

Information technology (IT) firms in Hyderabad are beginning to use artificial intelligence (AI) to judge which employees should be treated as “high potential,” yet research on this practice remains limited, particularly in Indian settings. Little is known about how HR professionals interpret algorithmic recommendations when building leadership pipelines, or about the conditions under which such recommendations improve decisions. This conceptual paper aims to explain how AI-driven talent analytics shapes the identification of high-potential employees and to set out a design for studying it empirically. It synthesises research on talent management, HR analytics, and algorithmic decision-making, including recent work on explainability, fairness, and AI governance, and draws on the resource-based view, signalling theory, organisational justice theory, social exchange theory, and a sociotechnical perspective. The main contribution is a proposed conceptual framework in which data foundations and a clear definition of potential shape AI-driven talent analytics; HR analytics capability moderates its effect on decisions; and human-AI integration and perceived fairness influence the quality and acceptance of high-potential decisions, with acceptance expected to improve quality over successive review cycles. Six propositions are derived from the framework. Because the paper is conceptual, no empirical data were collected. Instead, a qualitative study is proposed, involving semi-structured interviews with fifteen HR professionals from middle to top management, recruited through snowball sampling from IT organisations in Hyderabad and analysed through reflexive thematic analysis. The paper argues that the value of AI in identifying potential depends less on algorithmic sophistication than on how organisations combine machine output with contextual human judgement and explain decisions to employees. Implications are drawn for HR leaders in India's technology sector, together with an agenda for future research.

Keywords: Talent analytics; Artificial intelligence; High-potential employees; Algorithmic decision-making; Human resource management

INTRODUCTION

Background

Most organisations agree that some employees can grow into larger roles faster than others, and that finding those people early is worth the effort. Deciding who they are has always been harder. For decades, companies relied on a manager's nomination, a performance rating, and perhaps a talent review meeting where senior leaders discussed names around a table. These methods are familiar, but they are also known to be shaped by visibility, proximity to decision-makers, and the personal preferences of whoever happens to be in the room (Silzer & Church, 2009; Finkelstein et al., 2018).

The spread of HR information systems, collaboration platforms, and learning management tools has changed what organisations can observe about their people. Data on project outcomes, skill acquisition, peer feedback, mobility, and engagement is now collected routinely. Vendors increasingly offer machine-learning models that claim to turn this data into predictions about who is likely to succeed in bigger roles. This practice, often described as AI-driven talent analytics, promises to make high-potential identification more consistent, more evidence-based, and less dependent on who a manager happens to notice (Davenport et al., 2010; Tambe et al., 2019).

Hyderabad offers a useful setting in which to study this shift. Over the past two decades, the city has grown into one of India's major technology hubs, with clusters around HITEC City, Gachibowli, and the Financial District. It hosts Indian IT services firms, product companies, start-ups, and a growing number of global capability centres (GCCs) set up by multinational corporations. These organisations compete intensely for skilled professionals and face high attrition, rapid technological change, and pressure to build leadership talent from within. They are also, by the nature of their business, early adopters of data and AI tools. HR functions in these firms are therefore likely to encounter AI-based talent analytics sooner and more directly than HR functions in many other sectors.

Problem Statement

Despite growing adoption, the use of AI to identify high-potential employees raises questions that existing research has only partly answered. Much of the HR analytics literature is either prescriptive, describing what analytics should achieve, or critical, warning about what could go wrong (Angrave et al., 2016; Marler & Boudreau, 2017). Fewer studies examine how HR professionals actually interpret and use algorithmic recommendations in day-to-day talent decisions. Evidence from India is especially thin, even though Indian IT firms employ very large workforces and operate talent processes at scale. We know little about which data these firms treat as signals of potential, how much weight HR leaders give to model outputs relative to managerial judgement, and how concerns about bias, explainability, and employee trust are handled in practice. These questions have become more pressing as new data protection rules and AI governance frameworks have appeared in India and abroad.

Research Questions

This paper is guided by four questions:

1. How is “high potential” understood and operationalised in IT organisations, and how does AI-driven analytics change that understanding?
2. What organisational, technical, and human factors shape the adoption and use of AI-driven talent analytics for high-potential identification?
3. How do HR professionals balance algorithmic recommendations with human judgement when making high-potential decisions?
4. What ethical and fairness concerns arise, and how might organisations address them?

Objectives

The paper has three objectives. The first is to review and integrate relevant literature on high-potential identification, HR analytics, and AI in human resource management, including recent studies on explainability, fairness, and governance. The second is to develop a conceptual framework, with propositions, explaining how AI-driven talent analytics influences the quality and acceptance of high-potential decisions. The third is to propose a qualitative research design through which the framework can be examined among HR professionals in Hyderabad's IT sector.

Contribution

The paper contributes to the literature in two ways. Theoretically, it brings together strands of work that are usually discussed separately, namely talent management, analytics capability, organisational justice, and AI governance, and specifies how they interact when potential is assessed with the help of an algorithm. In particular, it distinguishes between factors that shape analytics outputs, a capability that conditions their effect, and processes through which decisions are made and received. Methodologically, it offers a qualitative design, including a sampling strategy, an interview guide, and a mapping of propositions to interview questions, that researchers can apply in Hyderabad or adapt for other Indian technology clusters. For practitioners, it identifies the conditions under which AI-based identification of potential is likely to be accurate, trusted, and fair.

REVIEW OF LITERATURE

Talent Management and the Idea of Potential

Talent management became a mainstream concern in the early 2000s, but the field took some time to define itself. Lewis and Heckman (2006) observed that the term was used loosely and often meant little more than a relabelling of existing HR practices. Collings and Mellahi (2009) gave the field sharper boundaries by defining strategic talent management as the identification of pivotal positions, the development of a talent pool to fill them, and the design of an HR architecture to support that pool. In this view, identifying who belongs in the talent pool is not a side activity; it is the step on which the rest of the system depends.

The notion of potential itself is contested. Silzer and Church (2009) distinguished between foundational qualities such as cognitive ability and personality, growth qualities such as learning agility and motivation, and career dimensions such as leadership and technical skill. Dries (2013) pointed out that organisations hold different, often unstated, assumptions about talent: whether it is innate or developed, whether it belongs to a few or to many, and whether it resides in the person or in the fit between person and role. Meyers and van Woerkom (2014) showed that these underlying philosophies shape which practices organisations adopt. The practical consequence is important for this paper. Any algorithm built to predict potential inherits a definition of potential, and that definition is rarely neutral.

Traditional Approaches and Their Limitations

Conventional identification relies heavily on managerial nomination and performance ratings, often combined in the well-known nine-box grid. Critics have noted that performance in the current role is an imperfect predictor of success in a larger one, and that managers tend to confuse the two (Silzer & Church, 2009). Finkelstein et al. (2018) found that the criteria organisations say they use to identify high potentials often differ from the criteria that actually influence decisions. Visibility, communication style, and similarity to the evaluator can carry more weight than they should. These weaknesses are part of the reason organisations have looked to data and algorithms for a more systematic alternative.

From HR Metrics to HR Analytics

HR analytics refers to the use of data, statistical methods, and technology to inform decisions about people. Marler and Boudreau (2017), in an evidence-based review, found that despite widespread enthusiasm, rigorous research on HR analytics was limited and adoption was slower than commentators suggested. Angrave et al. (2016) argued that many HR functions lacked the analytical skills and the strategic framing needed to make use of big data, and warned that the agenda risked being driven by software vendors rather than by HR itself. Rasmussen and Ulrich (2015) suggested that analytics could avoid becoming a passing fad only if it started from business problems rather than from available data. Davenport et al. (2010) described a progression from simple reporting to predictive and prescriptive uses, with talent identification sitting at the more advanced end.

More recent evidence suggests that the benefits of analytics depend on how it is used rather than on access to data alone. In a study of 155 Irish organisations, McCartney and Fu (2022) found that access to HR technology

enabled HR analytics, which in turn improved organisational performance by supporting evidence-based management. Charlwood and Guenole (2022) argue that AI presents HR with a series of paradoxes, and that HR professionals need to build the expertise to shape how these systems are designed and governed rather than leaving that task to technologists.

Artificial Intelligence in Human Resource Management

AI differs from earlier analytics mainly in its ability to detect patterns in large, varied, and unstructured data, and to update predictions as new data arrives. In talent management, AI applications include skills inference from project and learning records, attrition prediction, internal mobility matching, and scoring of employees for leadership readiness. Tambe et al. (2019) identified four challenges that make HR a difficult domain for AI: the complexity of HR outcomes, the small size of many HR datasets, the accountability questions raised by decisions about people, and employees' possible reactions to being managed by algorithms. Each of these challenges applies strongly to high-potential identification. Promotions into senior roles are relatively rare events, so training data is limited, and the "outcome" the model is meant to predict is itself partly a product of past human decisions.

Reviews published since 2022 point to both the rapid growth and the uneven coverage of this field. Budhwar et al. (2022) found that research on AI in international HRM was concentrated on a small number of functions, most notably recruitment, and called for studies in more varied organisational and national settings. Pan and Froese (2023) brought together studies from management, computer science, and related disciplines, and emphasised the need for research that combines technical and organisational perspectives. Chowdhury et al. (2023) proposed an AI capability framework, arguing that the value of AI in HRM depends on complementary organisational resources, such as skills, data, and governance, rather than on the technology alone. The arrival of generative AI has widened these questions further; Budhwar et al. (2023) discuss how such tools may reshape HR work and set out research priorities that include accuracy, bias, and accountability.

Fairness, Bias, and Transparency

Concern about algorithmic bias in HR became widely known after reports that Amazon had abandoned an experimental recruiting tool that disadvantaged women, because it had learned from historical hiring patterns (Dastin, 2018). Raghavan et al. (2020) examined vendors of algorithmic hiring tools and found considerable variation in how, or whether, they tested for and mitigated bias. Leicht-Deobald et al. (2019) argued that algorithm-based HR decisions can weaken personal integrity in organisations, because both managers and employees may start to defer to the system rather than exercise their own moral judgement. For high-potential identification, the risk is that historical patterns of who was promoted, which may reflect gender, caste, regional, linguistic, or educational advantages in the Indian context, become encoded in models and presented as objective.

Recent reviews have given these concerns more structure. Hunkenschroer and Luetge (2022), in a systematic review of 51 articles on AI-enabled recruitment and selection, mapped ethical opportunities alongside risks and ambiguities, and summarised measures for reducing those risks. Giermindl et al. (2022) and Tursunbayeva et al. (2022) reached related conclusions for people analytics more broadly, cautioning that opacity, surveillance, and over-reliance on quantified indicators can harm both employees and organisations. Employee perceptions matter as well: in an experimental study, Bankins et al. (2022) found that HR decisions made by humans were generally perceived as more respectful than the same decisions made by AI.

Explainability and AI Governance

Explainability has become a central requirement for AI used in decisions about people. Langer et al. (2021) argue that what counts as a satisfactory explanation depends on the stakeholder: a data scientist, an HR manager, and an affected employee need different kinds of explanation for different purposes. For high-potential identification, this means that an explanation that satisfies a model developer may still leave an employee unable to understand why they were overlooked.

Regulatory frameworks are also changing. The European Union’s Artificial Intelligence Act classifies AI systems intended to make decisions on promotion, or to monitor and evaluate the performance and behaviour of workers, as high-risk, and subjects them to requirements on risk management, data governance, transparency, and human oversight (European Union, 2024). This is relevant to Hyderabad because many global capability centres belong to multinational groups that operate in Europe. In the United States, the voluntary AI Risk Management Framework offers organisations a structured approach to identifying and managing AI risks (National Institute of Standards and Technology [NIST], 2023). In India, the Ministry of Electronics and Information Technology released the India AI Governance Guidelines in November 2025 as a voluntary, principles-based framework for responsible AI adoption (Ministry of Electronics and Information Technology [MeitY], 2025a), and in the same month notified the Digital Personal Data Protection Rules, which operationalise the Digital Personal Data Protection Act, 2023 (Government of India, 2023; MeitY, 2025b). Together, these developments make governance a practical concern for any organisation that uses AI to identify potential.

The Indian IT Context

Indian IT organisations manage large, young, and mobile workforces. Career progression is often structured around project roles and technical tracks, and many firms run formal leadership development programmes for selected employees. The sector’s scale makes manual talent reviews difficult, which strengthens the business case for automation. Malik et al. (2022), in a case study of a multinational enterprise, showed how AI-based HR applications could lower HR costs while offering employees more individualised experiences, which illustrates why such tools appeal to large technology employers. At the same time, practices vary widely. Large services firms, GCCs of multinationals, and smaller product companies differ in data maturity, HR resourcing, and the degree to which talent decisions are set centrally or locally. Hyderabad contains all these organisational types, which makes it well suited to studying variation in how AI-based talent analytics is adopted.

Employee Reactions to Talent Designation

Research on talent designation shows that being identified, or not identified, as a high potential shapes attitudes and behaviour. Björkman et al. (2013) found that employees who believed they had been identified as talent were more likely to accept increasing performance demands, commit to building competencies valued by the organisation, support its strategic priorities, and identify with their unit, and were less likely to intend to leave. Gelens et al. (2014) showed that employees’ reactions to high-potential identification were shaped by their perceptions of organisational justice. These effects are not always lasting. Tyskbo and Wikhamn (2023) found that initially positive reactions to talent status could turn into a sense of emptiness and perceived breach of the psychological contract when the designation was not followed by meaningful developmental events. Taken together, these studies suggest that the way a high-potential decision is received affects what happens after it, a point developed in Proposition 6.

Summary of Recent Literature and Research Gap

Table 1 summarises the recent studies and policy documents used in this paper and indicates how each informs the proposed framework.

Table 1. Summary of recent literature and policy documents informing the framework

Author(s) and year	Focus	Relevance to this paper
Budhwar et al. (2022)	Review of AI in international HRM	Shows research concentrated on recruitment; supports the focus on high-potential identification
Charlwood and Guenole (2022)	Paradoxes of AI for HR	Supports HR’s role in governing AI (P3)
McCartney and Fu (2022)	HR analytics and organisational performance	Value depends on use through evidence-based management (P3)

Author(s) and year	Focus	Relevance to this paper
Hunkenschroer and Luetge (2022)	Ethics of AI-enabled recruitment and selection	Risks and mitigation measures relevant to fairness (P5)
Bankins et al. (2022)	Justice perceptions of AI and human decisions	Employee reactions to AI-made HR decisions (P5)
Giermindl et al. (2022); Tursunbayeva et al. (2022)	Risks and ethics of people analytics	Data, opacity, and surveillance concerns (P1, P5)
Chowdhury et al. (2023)	AI capability framework for HRM	Complementary capabilities condition AI value (P3)
Pan and Froese (2023)	Interdisciplinary review of AI and HRM	Need to combine technical and organisational views
Budhwar et al. (2023)	Generative AI and HRM	Emerging accountability and bias questions
Tyskbo and Wikhamn (2023)	Short- and long-term reactions to talent status	Boundary condition for acceptance effects (P6)
European Union (2024)	Artificial Intelligence Act	Promotion-related AI classed as high-risk; human oversight (P4, P5)
MeitY (2025a, 2025b)	India AI Governance Guidelines; DPDP Rules	Indian governance and data protection context (P5)

Four gaps emerge from this review. First, most empirical work on HR analytics and AI in HRM comes from North American and European settings; there is little qualitative evidence from Indian IT organisations. Second, existing studies tend to focus on recruitment and attrition prediction; high-potential identification, which involves longer time horizons and more contested definitions, has received less attention. Third, recent work on explainability and AI governance has rarely been connected to talent designation, even though promotion-related AI is now explicitly treated as high-risk in some jurisdictions. Fourth, research has rarely examined the perspective of HR professionals at different levels, from middle managers who operate talent processes to senior leaders who design them. This paper responds to these gaps by developing a framework and a qualitative research design centred on HR professionals in Hyderabad's IT sector.

Theoretical Underpinnings

No single theory explains how AI changes the identification of potential. This paper therefore draws on five complementary perspectives, each of which addresses a different part of the problem.

Resource-based view. The resource-based view holds that sustained competitive advantage comes from resources that are valuable, rare, difficult to imitate, and non-substitutable (Barney, 1991). High-potential employees fit this description, because the knowledge and relationships they build are specific to the firm. The same logic applies to analytics capability. Many firms can buy the same software, so the software alone is unlikely to create advantage. What is harder to copy is the combination of good data, skilled analysts, and HR leaders who know how to use the output (Chowdhury et al., 2023). This perspective explains why two firms with identical tools may get very different results, and it underpins the treatment of HR analytics capability as a moderator in the framework.

Signalling theory. Signalling theory, developed by Spence (1973) to explain labour markets, is concerned with how parties infer hidden qualities from observable signals. Potential is, by definition, unobservable; organisations must infer it from signals such as performance, learning behaviour, and peer recognition. AI changes the signal environment in two ways. It can draw on many more signals than a human evaluator, and it can weight them in ways that are not visible to the people being assessed. This raises the question of which signals are genuinely informative about future success and which simply reflect opportunity or visibility.

Organisational justice theory. Organisational justice research distinguishes between distributive justice (fairness of outcomes), procedural justice (fairness of the process), interpersonal justice (respectful treatment), and informational justice (adequate explanation) (Greenberg, 1987; Colquitt, 2001). Being named, or not named, a high potential has real consequences for development opportunities and career progression. When an algorithm is involved, procedural and informational justice become especially salient: employees want to know what data was used and how the decision was reached. The theory predicts that even accurate decisions will be resisted if they are perceived as opaque.

Social exchange theory. Social exchange theory explains how relationships develop through reciprocal exchanges of valued resources (Blau, 1964). When employees see an organisation's investment in them as genuine and fairly allocated, they tend to reciprocate with commitment and effort. Studies of talent designation have used this reasoning to explain why employees who know they have been identified as talent respond with greater commitment (Björkman et al., 2013). In this paper, the theory is used to explain why acceptance of high-potential decisions may, over time, improve their quality (Proposition 6).

Sociotechnical perspective. Sociotechnical systems thinking, which originated in the Tavistock Institute's studies of work organisation (Trist & Bamforth, 1951), holds that outcomes depend on the joint design of the technical system and the social system around it. Applied here, the perspective suggests that the value of AI-driven talent analytics cannot be judged from the algorithm alone. It depends on how the tool is embedded in talent review meetings, how managers are trained to read its output, and who has authority to override it. Acceptance of the technology by HR users, which the Technology Acceptance Model links to perceived usefulness and ease of use (Davis, 1989), is one element of this social system; trust, which depends on perceived ability, benevolence, and integrity (Mayer et al., 1995), is another.

Taken together, these perspectives suggest that AI-driven identification of potential is best understood not as a technical prediction problem but as a sociotechnical process in which data, capability, judgement, and fairness perceptions interact.

Proposed Conceptual Framework and Propositions

The proposed framework (Figure 1) links a set of conditions to two outcomes: the quality of high-potential decisions and their acceptance by managers and employees. Decision quality refers to how accurately the process identifies people who later succeed in larger roles. Decision acceptance refers to whether the people affected regard the process as legitimate and act on it. The two outcomes are related but not identical; a process can be accurate yet distrusted, or trusted yet inaccurate.

The framework has four parts. Data foundations and clarity in the definition of potential are antecedents that determine what AI-driven talent analytics can produce (P1 and P2). HR analytics capability is a moderator: it does not produce analytics outputs itself, but it conditions how far those outputs improve decisions (P3). Human-AI integration is the process through which analytics outputs enter talent decisions (P4). Perceived fairness and transparency shape acceptance (P5), and acceptance is expected to feed back into decision quality over successive review cycles (P6).

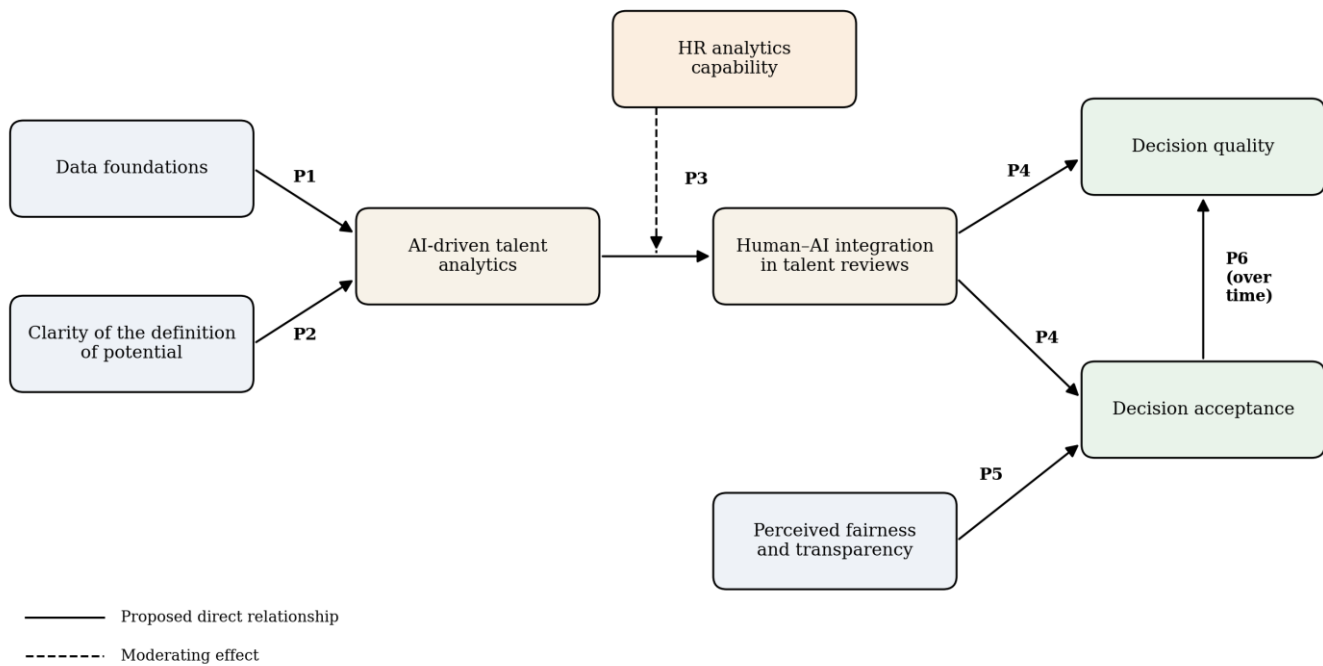


Figure 1. Proposed conceptual framework for AI-driven identification of high-potential employees. Solid arrows indicate proposed direct relationships; the dashed arrow indicates the moderating effect of HR analytics capability (Source: Authors' conceptualisation)

Data Foundations

An algorithm can only learn from the data it receives. In IT firms, useful data may include project performance, certifications, learning platform activity, peer and client feedback, and internal mobility history. However, this data is often spread across systems, inconsistently recorded, and shaped by past managerial decisions. Where historical promotion data reflects biased decisions, the model will tend to reproduce that bias (Giermindl et al., 2022).

Proposition 1: The more complete, integrated, and critically audited an organisation's employee data, the more accurate the outputs of AI-driven talent analytics, and hence the higher the quality of AI-supported high-potential decisions.

Clarity of the Definition of Potential

Because organisations hold different philosophies of talent (Meyers & van Woerkom, 2014), a model trained without an explicit definition will quietly adopt whatever definition is implied by past promotions. Organisations that first agree on what potential means for them, for example learning agility, leadership aspiration, and ability to handle ambiguity, can then choose data and model targets that reflect it.

Proposition 2: Organisations that explicitly define potential before building or buying analytics tools will achieve higher decision quality than those that allow the definition to be inferred from historical data.

HR Analytics Capability as a Moderator

HR analytics capability refers to the skills, roles, and routines that allow an HR function to question data and model assumptions, interpret outputs in context, and explain them to business leaders and employees. Consistent with the resource-based view, and with the argument that AI creates value in HRM only when it is combined with complementary organisational capabilities (Chowdhury et al., 2023; McCartney & Fu, 2022), the tool itself is unlikely to be a source of advantage.

Capability is therefore treated as a moderator rather than as a direct cause. It does not generate recommendations, but it determines whether weak outputs are noticed and challenged, and whether strong outputs are understood and used. Where capability is low, even an accurate model may be misread or accepted uncritically; where it is high, the same model is more likely to improve decisions. In Figure 1, this effect is shown by the dashed arrow acting on the path along which analytics outputs enter talent decisions.

Proposition 3: HR analytics capability moderates the relationship between AI-driven talent analytics and the quality of high-potential decisions, such that the relationship is stronger when HR analytics capability is high.

Human-AI Integration

Organisations may use AI output in different ways: as a first screen, as one input into a talent review, or as a check on managers' nominations. The sociotechnical perspective suggests that a structured combination of algorithmic and human judgement, in which each can challenge the other, will outperform both full automation and purely human decisions. Managers bring contextual knowledge about circumstances the data cannot capture, such as a difficult client, a family situation, or a recent change of role. Requirements for human oversight of high-risk AI, such as those in the EU Artificial Intelligence Act (European Union, 2024), point in the same direction.

Proposition 4: High-potential decisions that systematically combine AI recommendations with structured human review will show higher quality and acceptance than decisions based predominantly on either source alone.

Perceived Fairness and Transparency

Drawing on organisational justice theory, employees and line managers are more likely to accept outcomes when they understand the criteria, believe the data is accurate, and have a way to raise concerns. Evidence that people tend to see AI-made HR decisions as less respectful than human ones (Bankins et al., 2022) suggests that explanation and a clear route for appeal are especially important when algorithms are involved. Explanations also need to suit their audience: employees require a different kind of explanation from that needed by analysts (Langer et al., 2021).

Proposition 5: Perceived procedural and informational justice positively influence acceptance of AI-supported high-potential decisions.

Acceptance and Decision Quality over Time

Proposition 6 links the two outcomes in the framework. It proposes that acceptance does not merely follow a decision but influences whether the decision proves correct over time. Three mechanisms support this reasoning.

First, social exchange theory (Blau, 1964) suggests that employees who regard their designation as legitimate are likely to reciprocate with commitment and effort. Empirical studies of talent identification are consistent with this view: employees who know they have been identified as talent show stronger commitment to building capabilities and lower intention to leave (Björkman et al., 2013), and their responses depend on how fair they judge the process to be (Gelens et al., 2014). Second, research on the self-fulfilling prophecy shows that raised expectations can themselves improve performance (Eden, 1990). When a designation is accepted by both the employee and the line manager, the higher expectations and developmental support attached to it are more likely to be acted on. Third, acceptance by managers affects the data on which later decisions are built. Managers who trust the process are more likely to act on its recommendations and to record development and performance outcomes consistently, which improves the data available for validating and updating models in the next cycle (see Proposition 1).

The mechanism has limits. Tyskbo and Wikhamn (2023) found that positive reactions to talent status faded when the designation was not followed by meaningful development, leading to perceived breach of the psychological

contract. Acceptance is therefore expected to improve quality only when the organisation follows through on what the designation implies. The self-fulfilling nature of the mechanism also means that later success cannot be taken as simple proof that the original identification was accurate, a point that empirical studies of the framework will need to address.

Proposition 6: Over successive talent review cycles, acceptance of AI-supported high-potential decisions improves decision quality, by increasing designated employees' investment in their development and by encouraging managers to act on and consistently record decision outcomes; this effect is weaker when designation is not followed by meaningful developmental opportunities.

These propositions are stated in a form suitable for qualitative exploration. In the proposed study, they serve as sensitising concepts rather than hypotheses to be statistically tested; the interviews may confirm, refine, or challenge them.

Proposed Research Design

Research Approach

The proposed study adopts a qualitative, interpretivist approach. The aim is not to measure how widely AI is used, but to understand how HR professionals make sense of it: what they believe it captures, where they trust it, and where they override it. Qualitative interviews are well suited to this purpose, because they allow participants to describe decisions in their own terms and to raise issues the researchers may not have anticipated.

Participants and Sampling

The study will use snowball sampling. The researchers will begin with two or three initial participants from their professional networks who meet the inclusion criteria. Each participant will be asked, at the end of the interview, to suggest colleagues in other IT organisations in Hyderabad who are involved in talent identification. Snowball sampling is appropriate here because HR professionals responsible for high-potential programmes form a relatively small and professionally connected group, and access often depends on trust and personal referral (Noy, 2008).

A known risk of snowball sampling is that referral chains stay within one network and produce a narrow sample. To reduce this risk, the study will start from seeds in different types of organisations and will actively ask for referrals to people at different levels and in different firm types. Recruitment will be monitored against the target profile in Table 2.

The planned sample is fifteen participants. Guest et al. (2006) found that most themes in a relatively homogeneous interview sample appeared within the first twelve interviews. A sample of fifteen therefore allows reasonable depth while leaving room to check whether new themes are still emerging.

Inclusion criteria: participants must (a) work in an HR role in an IT organisation located in Hyderabad; (b) hold a middle-management or senior position; (c) have at least five years of HR experience; and (d) be directly involved in talent reviews, succession planning, or high-potential programmes.

Table 2. Target participant profile (n = 15)

Level	Typical designations	Target number
Middle management	HR Manager, HR Business Partner, Talent Management Manager	6
Senior management	Senior Manager HR, Associate Director HR, Head of Talent	5
Top management	Director HR, Vice President HR, CHRO	4
Total		15

The study will also aim to include participants from at least three organisation types: Indian IT services firms, global capability centres, and product or start-up companies. Participants will be recorded as P1 to P15, and organisation names will not be reported.

Data Collection

Data will be collected through semi-structured interviews of 45 to 60 minutes, conducted in person or by video call, in English. The interview guide (Appendix A) covers five areas: the participant's role and organisation; how potential is defined; the use of AI and analytics; the balance between algorithmic and human judgement; and fairness, ethics, and employee response. The guide will be piloted with one or two HR professionals who are not part of the final sample, and wording will be adjusted based on their feedback. With consent, interviews will be audio-recorded and transcribed verbatim. The researchers will keep reflective field notes after each interview.

Alignment of Propositions with the Interview Guide

To keep the empirical study consistent with the framework, each proposition is linked to the research questions and to specific questions in the interview guide (Table 3). Because Proposition 6 concerns change over time, participants will be asked to reflect on earlier talent review cycles. A cross-sectional interview study can explore this mechanism, but it cannot test it; longitudinal research will be needed for that purpose.

Table 3. Alignment of propositions, research questions, and interview guide

Proposition	Research question	Interview questions (Appendix A)	Focus of analysis
P1: Data foundations	RQ2	Q6, Q7	Data sources, integration, and auditing
P2: Definition of potential	RQ1	Q3, Q4, Q5	Explicit and implicit definitions of potential
P3: HR analytics capability (moderator)	RQ2	Q8, Q9	Whether capability changes the usefulness of outputs
P4: Human-AI integration	RQ3	Q10, Q11, Q12	Use of outputs, overrides, and final authority
P5: Fairness and transparency	RQ4	Q13, Q14, Q15	Bias concerns, explanation, and regulation
P6: Acceptance and quality over time	RQ3, RQ4	Q14, Q16	Consequences of acceptance in past review cycles

Data Analysis

Transcripts will be analysed using reflexive thematic analysis following the six phases described by Braun and Clarke (2006): familiarisation with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and writing up. Coding will combine an inductive approach, allowing themes to arise from participants' accounts, with a deductive lens informed by the six propositions and the alignment in Table 3. For Proposition 3, analysis will look for accounts in which the same kind of tool was described as more or less useful depending on the HR team's ability to question and explain it. Qualitative data analysis software such as NVivo or ATLAS.ti may be used to organise codes. Comparison between middle, senior, and top-level participants will be a specific analytic focus, as the framework suggests that their perspectives on AI and human judgement may differ.

Trustworthiness

The study will follow Lincoln and Guba's (1985) criteria for trustworthiness. Credibility will be supported through member checking, in which participants are invited to review a summary of their interview. Transferability will be supported by providing a clear description of the research context. Dependability will be supported by an audit trail of coding decisions. Confirmability will be supported by the researchers' reflexive notes and, where possible, by a second coder reviewing a subset of transcripts.

Ethical Considerations for the Proposed Study

Ethical approval will be sought from the researchers' institutions before fieldwork. Participants will receive an information sheet and sign a consent form. Participation will be voluntary, and participants may withdraw at any time. Because talent processes are commercially sensitive, participants will be asked not to share confidential documents or identifiable employee information. Recordings and transcripts will be stored securely and anonymised, consistent with the Digital Personal Data Protection Act, 2023 and the Digital Personal Data Protection Rules, 2025.

DISCUSSION AND IMPLICATIONS

The central argument of this paper is that AI does not remove the difficult judgements involved in identifying potential; it relocates them. Decisions that used to be made in a talent review meeting are now partly made earlier, when someone chooses which data to feed a model, which outcome to train it on, and what threshold separates "high potential" from everyone else. These choices are often made by vendors, data teams, or a small group in corporate HR, and they can be invisible to the managers and employees who live with the results. A framework that focuses only on algorithmic accuracy misses this shift.

Theoretical Implications

The framework extends talent management research in three ways. First, it treats the definition of potential as a design variable rather than a background assumption. Second, by modelling HR analytics capability as a moderator, it specifies why the same analytics tools may produce different results in different organisations, connecting the resource-based view with recent work on AI capability in HRM (Chowdhury et al., 2023). Third, it links organisational justice and social exchange reasoning to decision quality through Proposition 6, suggesting that acceptance is not only a matter of employee satisfaction but may also affect whether talent investments pay off. The framework also brings explainability and governance, which have been discussed mainly in relation to recruitment, into the study of high-potential identification.

Practical Implications

For HR leaders in Hyderabad's IT organisations and similar settings, the framework points to several practical steps:

- **Define potential first.** Agree on a written definition of potential that reflects the organisation's strategy before selecting or configuring analytics tools.
- **Audit the data.** Review historical promotion and rating data for patterns linked to gender, background, location, or manager, and correct for them before using the data to train models.
- **Keep humans accountable.** Use AI output as structured input to talent reviews, with clear rules for when and how managers may override it and a record of the reasons.
- **Build analytics capability in HR.** Invest in HR professionals who can question and explain models, rather than relying entirely on vendors or separate data teams.

- **Explain decisions to each audience.** Tell employees what kinds of information are used, how they can see and correct their own data, and how to raise concerns, and give managers explanations they can act on.
- **Follow through on designation.** Ensure that being identified as high potential leads to visible development opportunities, so that acceptance is sustained over time.
- **Align with data protection and AI governance.** Follow the Digital Personal Data Protection Act, 2023 and the Rules of 2025 on consent and purpose limitation, and, where relevant, the EU Artificial Intelligence Act's requirements for high-risk systems and the India AI Governance Guidelines.

Policy Implications

As AI-driven people decisions spread, industry bodies and regulators may need to set clearer expectations for fairness testing and explainability in workplace algorithms. The India AI Governance Guidelines provide a starting point, but they are voluntary and not specific to employment. Industry associations in the IT sector could play a useful role by developing shared guidelines for talent-related AI, so that individual firms are not left to set standards alone.

Limitations And Future Research

This paper is conceptual, and its propositions have not yet been examined empirically. The framework is built from literature that is largely Western, and some relationships may work differently in Indian organisations, where hierarchy, relationships with managers, and family considerations can shape career decisions in distinctive ways. Research on AI in HRM is also developing quickly, and the regulatory frameworks discussed here are new and still being implemented. The proposed study has limitations of its own. Snowball sampling may produce a sample connected through similar professional networks, and interviews with HR professionals capture only one perspective on a process that also involves line managers, data teams, and employees. In addition, Proposition 6 describes a process that unfolds over several review cycles, which interviews at a single point in time can explore but cannot test.

Several directions for future research follow. First, the proposed qualitative study should be carried out to examine and refine the framework. Second, future studies could include line managers and employees, particularly those who were not selected as high potentials, to understand how decisions are experienced. Third, once constructs are refined, quantitative surveys across a larger number of organisations could test the propositions statistically, including the moderating role of HR analytics capability. Fourth, longitudinal research could follow employees identified by AI-supported processes over several years to assess whether the predictions hold and to examine the feedback proposed in Proposition 6. Finally, comparative studies across Indian technology hubs such as Bengaluru, Pune, Chennai, and the National Capital Region could show whether the Hyderabad findings are transferable.

CONCLUSION

AI-driven talent analytics offers IT organisations a way to look more widely and more consistently for future leaders than traditional nomination processes allow. It can bring overlooked employees to attention and reduce the influence of visibility and personal preference. Its value, however, is not automatic. This paper has proposed a conceptual framework in which the quality of the underlying data and the clarity with which potential is defined shape what analytics can produce; the analytical capability of the HR function conditions how far those outputs improve decisions; and the way algorithmic and human judgement are combined, together with the fairness and transparency of the process, shapes whether decisions are sound and accepted. Acceptance, in turn, is expected to strengthen decision quality over time when organisations follow through on what designation promises. The framework, its six propositions, and the proposed qualitative design provide a starting point for examining these conditions among HR professionals in Hyderabad's IT sector. The broader lesson is that organisations should treat AI as a way to ask better questions about potential, not as a substitute for answering them.

Ethical Considerations

The present paper is conceptual in nature and draws only on published literature and publicly available legal and policy documents. Since no human participants, personal data, or animals were involved in its preparation, approval from an ethics committee was not required. The empirical study proposed in Section 5, however, involves direct engagement with HR professionals, and the authors recognise that it must be conducted with care. Before any fieldwork begins, the research protocol, interview guide, participant information sheet, and consent form will be placed before the institutional ethics committees of BV Raju Institute of Technology and KLH University, and interviews will commence only after approval has been granted.

Participation in the study will be entirely voluntary. Each prospective participant will receive a written explanation of the purpose of the research, what taking part involves, how the information will be used, and who will have access to it. Written consent will be obtained before every interview, with separate permission sought for audio recording. Participants will be free to decline any question and to withdraw from the study at any stage, even after the interview has taken place, without having to give a reason. Because the study relies on snowball sampling, particular attention will be paid to privacy within referral chains: participants will not be told who else has been interviewed, and those who make referrals will not be informed whether the colleagues they suggested chose to take part.

Confidentiality will be protected throughout. Participants will be identified only by codes from P1 to P15, and neither individual names nor organisation names will appear in any report or publication. Where a combination of details, such as an unusual designation within a named type of firm, could make a person identifiable, those details will be generalised. Talent processes and analytics tools are often commercially sensitive, so participants will be requested not to disclose trade secrets, proprietary algorithms, internal documents, or information about identifiable employees; anything of this kind shared inadvertently will be removed from the transcripts. Audio recordings will be deleted once transcripts have been verified, and anonymised transcripts will be kept on encrypted, password-protected devices accessible only to the research team, for a period consistent with institutional policy. All personal data will be processed solely for the stated research purpose and in accordance with the Digital Personal Data Protection Act, 2023 and the Digital Personal Data Protection Rules, 2025 (Government of India, 2023; MeitY, 2025b).

The authors are also mindful that conversations about high-potential decisions may lead participants to comment on colleagues or to criticise their employers. To avoid any professional risk to participants or to others, the interviews will concentrate on processes and practices rather than on named individuals, and participants will be reminded that they are under no obligation to share information they are uncomfortable disclosing. Finally, the authors confirm that this manuscript is their original work, that it has not been published previously, that it is not under consideration by any other journal, and that all sources consulted have been duly acknowledged and cited.

Conflict Of Interest

The authors declare no conflict of interest.

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Data Availability Statement

No new data were generated or analysed in this study. All sources are cited in the reference list.

Declaration On the Use of Ai Tools

During the preparation and revision of this manuscript, the authors used an AI writing assistant (Claude, Anthropic) to help draft and structure the text, paraphrase and refine the language, incorporate revisions in

response to reviewer comments, and format the manuscript according to the journal's guidelines. The authors reviewed, revised, and verified all content, including every citation and reference, and take full responsibility for the originality, accuracy, and integrity of the published work. No AI tool is listed as an author.

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Appendix A: Semi-Structured Interview Guide

Opening: Thank the participant, explain the purpose of the study, confirm consent and permission to record, and remind them they can skip any question.

Section A: Participant and Organisation Profile

1. Please describe your current role and your involvement in talent reviews or high-potential programmes.
2. How would you describe your organisation in terms of size, type (services, GCC, product), and workforce?

Section B: Understanding Potential (P2)

3. What does “high potential” mean in your organisation? Is there a written definition?
4. How were high-potential employees identified before analytics or AI tools were introduced?
5. In your experience, what are the main weaknesses of traditional identification methods?

Section C: Use of AI and Analytics (P1, P3)

6. What analytics or AI tools, if any, does your organisation use to identify or support the identification of potential?
7. What kinds of employee data feed into these tools? Who decided what data to include, and is the data checked for errors or bias?
8. What skills does your HR team have for working with analytics? Where do you rely on vendors or data teams?
9. When your HR team is able to question or explain what a tool recommends, does that change how useful its recommendations are? Could you give an example?

Section D: Human Judgement and AI (P4)

10. How are AI or analytics outputs used in talent review meetings?
11. Can you describe a situation in which a manager disagreed with what the data suggested? What happened?
12. Who has the final decision, and how are overrides recorded or explained?

Section E: Fairness, Ethics, and Employee Response (P5, P6)

13. What concerns, if any, have been raised about bias or fairness in these tools? How were they addressed?
14. How much do employees know about how they are assessed for potential? How do they react?
15. How have data protection and AI governance requirements, such as the Digital Personal Data Protection Act, 2023, affected the way employee data is used?
16. Thinking about past talent review cycles, what happened after employees and managers accepted or questioned high-potential decisions? For example, how did it affect participation in development programmes, retention, or later performance?

Closing

17. Looking ahead, how do you expect the role of AI in identifying potential to change in your organisation?
18. Is there anything else you would like to add?
19. Could you suggest one or two HR colleagues in other Hyderabad IT organisations who might be willing to take part in this study?