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| RESEARCH ARTICLE

Generative AI in Recruitment: Implications for Recruiter Fairness, Professional Identity and Talent Acquisition

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| ABSTRACT
The impact of Generative Artificial Intelligence (GenAI) on recruitment is undeniable, as it quickly creates new opportunities and challenges for recruiters and the recruitment process; however, HRM research has only recently begun to explore the implications of this technology for recruiters and talent acquisition processes. The purpose of this study is to examine the design and organisational implications of a GenAI-based recruitment assistant designed to facilitate the analysis of curriculum vitae (CVs) and evaluate candidates. The paper is inspired by organisational justice theory, role identity theory, and contingency theory and proposes a theoretical framework that examines how OCRs shape the perceptions of the recruiter concerning the perceived fairness of recruitment systems, role adaptation and talent acquisition outcomes. The study investigates the development and pilot implementation of a recruitment assistant which unifies the automated analysis of CVs with conversational access to the information about the candidate in a large enterprise environment, using a design-science approach. Initial implementation evidence indicates that the system enhances the effectiveness and uniformity of screening processes and transforms the recruiters' job from information processing tasks to verification, interpretation and judgment-based ones. The results also showed that having AI outputs that are transparent, explainable and still under human control increases acceptance by recruiters. The study advances the ongoing HRM research on the use of GenAI in recruitment by showing how GenAI can support rather than supplant the role of recruiters and highlighting the factors that affect GenAI's effectiveness in recruitment. Some practical tips are provided for HR leaders looking to incorporate generative AI in talent acquisition while staying fair, accountable and professional.

| KEYWORDS

Generative AI; CV Analysis and Parsing; Algorithmic Fairness; Recruiter Role Identity; HR Technology Adoption; People Analytics

| ARTICLE INFORMATION

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1. Introduction
Recruitment is one of the most impactful roles of HRM that affects the quality, diversity and long-term performance of an organisation's staff (Jamil et al., 2023). For big companies, the number of applications for job openings can easily be in the thousands, and the manual review of curriculum vitae (CVs) with required job skills is still a time-consuming and labour-intensive process, often lacking uniformity. Traditional screening methods are heavily dependent on the individual judgment of the recruiter, which can lead to inconsistencies, fatigue effects, and unconscious bias in screening decisions, especially at the initial stages, and are also difficult to scale as the volume of applications increases (Boubrik, 2025).
Over the last ten years, Artificial Intelligence (AI) has been firmly integrated into the field of recruitment technology, most notably with predictive and rule-based solutions like keyword-matching resume parsers, automatic candidate ranking systems, and chatbot scheduling. In the last decade, AI has firmly become a part of recruitment technology, especially in the form of predictive and rule-based applications such as keyword-matching resume parsers, automatic candidate ranking systems and

chatbot scheduling. More recently, Generative AI (GenAI) has started to be used for other recruitment-specific tasks, including candidate summary, creating interview questions, and conversational and query-based interaction with candidate databases (Udani, 2025). GenAI is unique in that it utilises large language models that return natural, contextually relevant text, instead of a score or even a label. Amidst this evolution, the majority of empirical research on AI in HRM continues to explore earlier generation predictive systems, and there is limited peer-reviewed HRM research that explores GenAI-based assistants which generate information about candidates, instead of simply classifying or ranking information about candidates. In spite of this evolution, most research on AI in HRM remains focused on earlier-generation predictive systems, and there is comparatively little peer-reviewed research on GenAI-based assistants that generate information regarding candidates, rather than just classifying or ranking information regarding candidates (Holmstrom, 2026).

The introduction of GenAI assistants into recruitment workflows surfaces three tensions that motivate this study. The first is between efficiency and fairness: a system that accelerates screening may also raise new questions about the transparency, consistency and contestability of the judgements it produces (Bakir, 2026). The second is between automation and professional discretion. As routine screening tasks are delegated to AI, recruiters' day-to-day work, required skills and sense of professional identity can shift in ways that some experience as threatening and others as empowering (Ellemers & de Gilder, 2022). The third is between scalability and strategic fit. A CV assistant designed for high-volume, low-complexity hiring, such as graduate or entry-level recruitment, may be poorly suited, or even counter-productive, for specialist or leadership roles where human judgement is central to selection decisions (Bhatt, 2025)

Against this backdrop, the paper addresses three research questions:

- RQ1: How can a GenAI-powered CV analysis assistant be architected and implemented within a secure, enterprise-grade environment to support natural-language interaction with candidate data?
- RQ2: How does the introduction of such an assistant affect recruiters' perceptions of procedural fairness, and their professional identity and skill requirements?
- RQ3: Under what organisational conditions (role complexity, hiring volume, and the structure of the HR function) is a GenAI CV assistant likely to deliver strategic talent-acquisition value, and what are the boundary conditions of its usefulness?

These tensions show up throughout a fast-growing body of recent HRM scholarship. Talwar et al. (2025) propose an integrated risk-analysis framework for GenAI in HRM, drawing on Leavitt's Diamond model to map the ethical, bias, privacy and role-disruption risks associated with GenAI adoption, and they argue that these risks need to be actively governed rather than treated as incidental by-products of efficiency gains. Yang et al. (2026) take a related but distinct angle, developing a multi-stage, organisational-justice-based framework for AI-based selection systems that spans pre-assessment, in-assessment and post-assessment stages. They argue for human-AI joint decision-making, transparency of AI involvement, and personalised communication with candidates as ways of improving fairness perceptions throughout the selection process. Abdelhay et al. (2025), based on a survey of 469 professionals, find that generative AI tools are associated with reductions in perceived bias and improvements in screening efficiency, though the strength of these effects depends on users' familiarity with the technology and on organisational size. This is an early empirical hint at the kind of contingency effects discussed further in Section 2.4. More broadly, GenAI-enabled recruitment is part of a wider trend in which AI tools are being adopted across an increasing share of the recruitment funnel, from sourcing and screening through to interview support and onboarding (Zhang, 2024). which makes it increasingly important for HRM research to keep pace with practice. Much of this practice-level innovation is documented in technical and vendor literature rather than peer-reviewed HRM outlets, leaving a gap between what is being deployed inside enterprises and what is being theorised and evaluated academically. The present paper aims, in part, to narrow that gap by combining a detailed system account with an explicit HRM-theoretic framing.

The paper makes three contributions. On the theoretical side, it brings organisational justice theory, role identity theory and contingency theory in strategic HRM to bear on the GenAI recruitment context, and sets out a conceptual model (Figure 1) linking system design features to recruiter-level and organisation-level outcomes. On the practical side, it documents a replicable, secure cloud architecture (Figures 2 and 3, Table 1) and works through a set of design principles and a practitioner checklist for HR managers (Table 3). And on the empirical side, it reports early, qualitative observations from a single-enterprise deployment (Table 2) and sets out a longitudinal, mixed-methods research agenda for future evaluation of GenAI recruitment assistants.

2. Theoretical Background and Conceptual Model

2.1 Generative AI in HRM: From Predictive to Generative Systems

The typical predictive AI systems employed in recruitment make a binary decision (either accept or reject), a shortlist position, or classify the candidates, giving them a score. The way GenAI systems work is different. Created with the help of large language models, they can produce context-sensitive text-based responses to interview questions, such as what the advantages of the course are, what the difficulties are, and what the result would look like. They are context-sensitive and can produce natural language responses to interview questions, such as what are the advantages of the course, what are the difficulties, what would the result look like, etc., which are not reducible to a single score, and are built on large language models (Bernasconi et al., 2025). This generative ability brings in new types of interaction between the recruiter and the system. For example, a recruiter may want to know from the system which candidates in a shortlist have experience leading cross-functional teams. It also introduces new governance issues; however, since the results are probabilistic, they may differ across runs and are more difficult to audit than the ranking algorithm (Abdelhay et al., 2025). To advance HRM research on AI-powered recruitment, there is a need for frameworks that can support the generative mode of human-AI interaction, and not simply a quick way to implement predictive screening.

2.2 Organisational Justice and AI-Based Screening
Organisational justice theory is divided into procedural justice, distributive justice, interpersonal and informational components of interactional justice (Rasooli et al., 2019). In relation to AI-based selection, questions of procedural justice include: Are the criteria employed by the AI system communicated to recruiters and candidates? Do recruiters have access to, and have the option to review, question or challenge AI-generated outputs? Do the underlying source documents used by the AI system remain accessible for review? (Mori et al., 2024). A GenAI CV assistant that produces opaque summaries with no link back to the original CV, and that recruiters cannot question or adjust, risks being seen as a 'black-box gatekeeper', which would undermine procedural justice even if the system improves average decision accuracy (Almeida et al., 2025). Design features that preserve recruiter voice work in the opposite direction: retaining the original document alongside the AI-generated summary, allowing follow-up queries, and logging the rationale for a generated response all sit within a broadly 'human-in-the-loop' approach to fairness in AI selection, an approach that is also reflected in multi-stage frameworks for embedding HR judgement throughout AI-assisted selection processes. On this basis, the paper proposes Proposition 1 (P1): the procedural justice perceptions of recruiters using a GenAI CV assistant will depend less on the existence of automation per se, and more on the explainability, verifiability and overridability built into the system's design.

2.3 Professional Identity and Role Redesign
Role identity theory holds that people derive part of their professional identity from the tasks, skills and decision authority associated with their role (Fitzgerald, 2020). Technological change may be experienced as ‘competence-destroying', which means that it devalues a set of skills that are already learned, or as ‘competence-enhancing', meaning that it is based on the existing expertise and generates new skills and higher valued tasks (Ahsan, 2018). Some research on GenAI and job crafting indicates that some employees find it to be an identity threat, whereas others see it as an opportunity for identity growth (Law and Varanasi, 2025). Usually, in a way that involves moving around tasks that demand judgment, interpretation of context, or interpersonal skills. For recruitment, when a GenAI assistant performs the initial reading and summarising of CVs, recruiters could shift their attention from reading CVs to reviewing the summaries, asking GenAI to explain, making decisions on edge cases, and communicating with candidates. In short, a shift from 'screener' to 'curator' or 'verifier' of AI output (Hawrysz, 2025). Whether this shift feels competence-enhancing probably depends on whether recruiters are given a meaningful evaluative role, in line with augmentation, or are reduced to passively accepting AI outputs, in line with displacement. This leads to Proposition 2 (P2): the introduction of a GenAI CV assistant will be associated with a shift in recruiters' task composition from manual searching and reading towards verification, interpretation and judgement-based tasks, and this shift will be experienced as competence-enhancing to the extent that recruiters retain meaningful evaluative discretion.

2.4 Contingency Theory and Strategic Fit
Contingency perspectives in strategic HRM argue that the value of a given HR practice or technology is not universal. It depends on its fit with organisational characteristics such as the structure of the HR function, the complexity of the roles being filled, and the volume of recruitment activity (Arokiasamy et al., 2024). A GenAI CV assistant that standardises the extraction of skills, experience and qualifications, and surfaces candidates matching a defined profile, is likely to generate the largest efficiency gains where role requirements are relatively well-specified and application volumes are high, as in graduate or high-volume operational hiring. For specialist, senior or highly idiosyncratic roles, where selection criteria are less codified and depend heavily on tacit organisational knowledge, the same system may be more useful as research and drafting aid than as a primary screening mechanism. This leads to Proposition 3 (P3): the efficiency and decision-quality benefits of a GenAI CV assistant will be greater for high-volume, lower-complexity roles than for specialist or senior roles, where the assistant is more likely to act as a complement to, rather than a substitute for, recruiter judgement.

2.5 Conceptual Model
Figure 1 pulls Propositions 1 to 3 together into a conceptual model. The GenAI-powered CV analysis assistant is positioned as influencing three sets of outcomes: (a) recruiters' fairness perceptions, viewed through organisational justice theory; (b) recruiters' professional role and identity, viewed through role identity theory; and (c) talent-acquisition outcomes such as time-to-screen, time-to-hire, quality-of-hire and shortlist diversity. These relationships are proposed to be moderated by organisational contingencies, namely role complexity, hiring volume, and how centralised the HR architecture is, in line with a contingency view of strategic HRM. The model provides the interpretive lens for the implementation observations discussed in Section 5, and a structured agenda for the empirical research called for in Section 7.

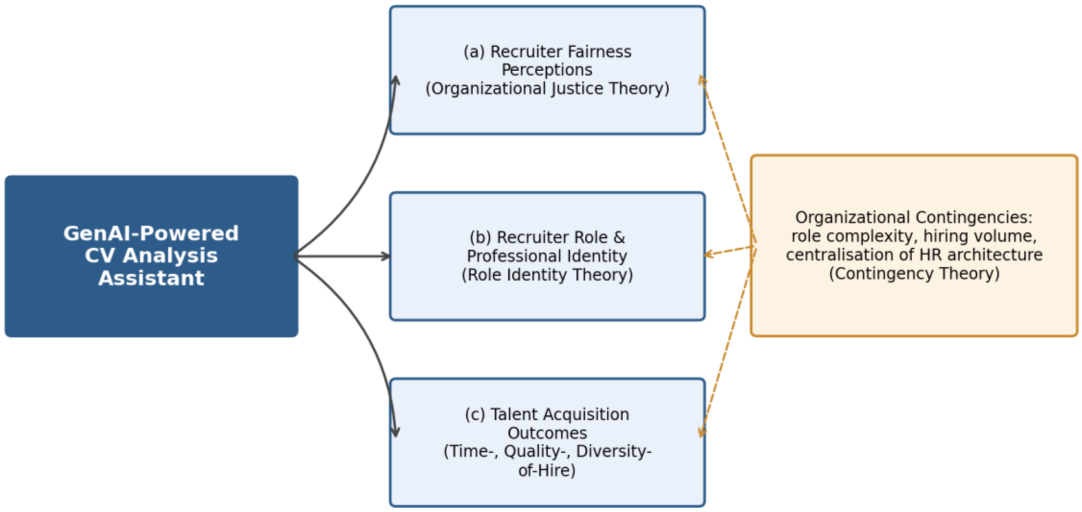

Figure 1. Conceptual model linking the GenAI HR Assistant to recruiter fairness perceptions, professional identity, and talent acquisition outcomes, moderated by organisational contingencies.

3. Methodology

3.1 Research Design and Philosophy

This study takes a design-science research approach (Rieskamp et al., 2023), where the main contribution is a purposefully designed and implemented artefact, the GenAI-powered HR Assistant, evaluated in its real organisational context. This is combined with a single-organisation case study, set in a large enterprise operating multiple business units with high-volume recruitment activity. The paper reports on the iterative design, build and pilot deployment of the system, and reflects on early implementation observations in light of the theoretical framework and propositions developed in Section 2. In keeping with design-science conventions, the emphasis here is on documenting the artefact, the design rationale, and the practical and theoretical implications of its initial use, rather than on testing statistically generalisable causal effects. That kind of testing is left as a priority for future research in Section 7.

3.2 System Development Process

This was designed through an agile and iterative process with HR practitioners as co-design partners (Fox et al., 2022). Development took place in phases of requirements gathering with recruiters and hiring managers, prototyping of the conversational interface and CV-parsing pipeline, internal testing with sample CV datasets, and refinement based on feedback on the relevance, accuracy and usability of the summaries and responses generated (Anthony et al., 2025). The features of explainability and overridability, encouraged by Proposition 1, were especially considered during the co-design process, ensuring that the content of the CVs that were parsed was available alongside the summaries produced by AI, and permitting the ability to ask further or clarifying questions instead of just the automated output.

3.3 Setting and Participants

The system was deployed in a large enterprise that had many business units and high-volume recruitment processes. End users include recruiters and hiring managers who use the assistant via a natural language-based front end to upload and manage CVs, search for candidate information and view AI-generated summaries of candidates and supporting evidence based on CV content indexed within the system.

3.4 Data Sources and Analytical Approach

The implementation observations reported in Section 5 draw on system design documentation, architecture artefacts, configuration and usage logs generated during the pilot rollout, and informal feedback gathered from HR users during early use of the system. These sources were analysed thematically, with themes organised around the three propositions set out in Section 2: explainability/overridability and procedural justice, task shift and professional identity, and contingent value across role types. At this stage, the study does not include a controlled pre-post quantitative survey of recruiter attitudes, formal interviews analysed using a documented qualitative protocol, or objective HR metrics such as time-to-hire collected over a defined evaluation period. The observations reported below are therefore best read as preliminary, practitioner-based reflections that motivate, rather than substitute for, the structured empirical evaluation outlined in Section 7.

4. System Architecture and Implementation

4.1 Design Principles

The design of the GenAI HR Assistant was guided by four principles derived from the co-design process and from the theoretical considerations in Section 2:

- Co-design with HR practitioners, so that the system reflects how recruiters actually search for and reason about candidate information, rather than imposing a purely technical workflow.
- Explainability and traceability, so that AI-generated summaries can be traced back to the underlying CV content, supporting recruiter verification and procedural justice (Proposition 1).
- User control, so that recruiters retain the ability to query, refine and challenge AI outputs rather than receiving a single automated decision.
- Security and compliance by design, given that CV data constitutes sensitive personal data requiring enterprise-grade access control and data protection.

4.2 Overall Architecture

The system follows a layered, cloud-native architecture made up of a user interface layer, an application services layer, an AI processing layer, and a data management layer (Figure 2). Each layer operates independently, which allows flexibility in deployment and future enhancement. The architecture is deployed on Microsoft Azure and brings together Azure Application Gateway with a Web Application Firewall for secure ingress and DDoS protection, private endpoints for storage, key management, search, AI and database services, and Microsoft Entra ID for enterprise authentication. A 'ChatUI' front end and a separate 'AI Engine' back end are each deployed across multiple zones for resilience, with Application Insights and Azure Monitor providing telemetry and usage monitoring. The aim of this design is to support scalability, modular deployment, and real-time query processing in an enterprise environment with multiple business units.

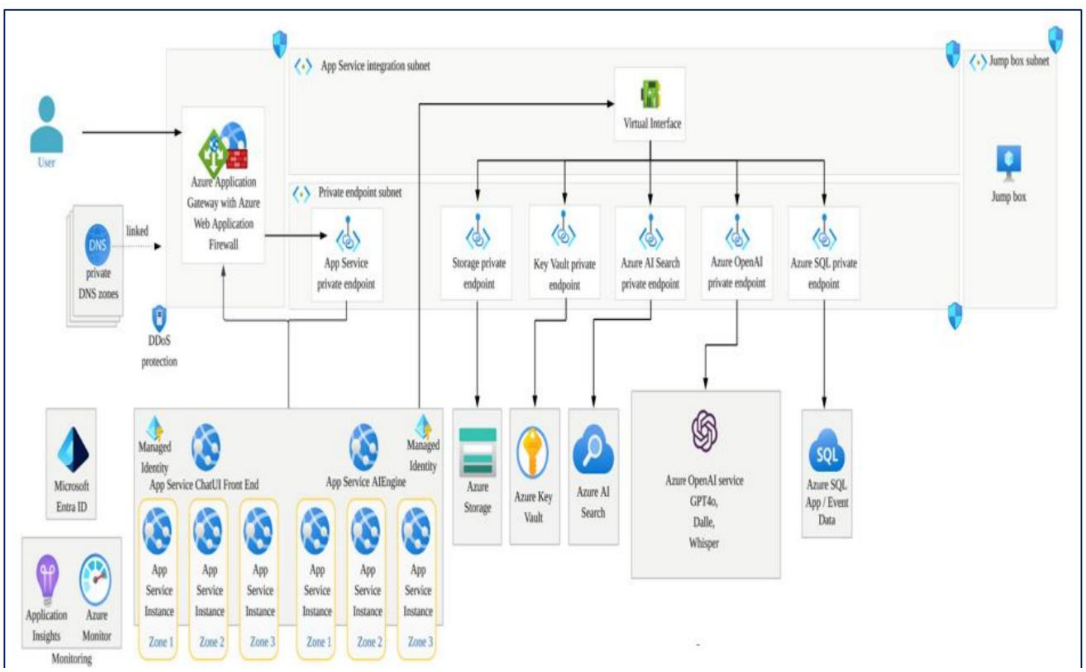

Figure 2. Overall architecture of the GenAI-powered HR Assistant, showing the interaction between the ChatUI front end, the AI engine, Azure AI services, and enterprise data and security infrastructure.

4.3 Core Technologies

Table 1 summarises the principal technology components of the system and their role within the GenAI HR Assistant.

Component / Technology	Role in the GenAI HR Assistant
Azure OpenAI Service (GPT-4o, with DALL·E and Whisper available)	Natural language understanding and generation; powers the conversational interface, candidate summaries, and query responses.
Azure Document Intelligence	Parses uploaded CVs (PDF, DOC, DOCX) and extracts structured data on skills, experience, education and certifications.
Azure AI (Cognitive) Search	Indexes parsed CV content to enable fast, context-aware retrieval in response to recruiter queries.

Azure SQL Database	Stores structured candidate profile data and application/event records (the 'candidate database').
Azure Storage	Provides secure, centralised storage of uploaded CV documents in multiple formats.
Azure Key Vault	Manages credentials and secrets used by application and AI services.
Microsoft Entra ID and role-based access control	Provides enterprise authentication and ensures only authorised users access candidate data.
Azure Application Gateway with Web Application Firewall and DDoS protection	Secures inbound traffic to the ChatUI front end and routes requests to application services.
Application Insights and Azure Monitor	Provide system monitoring, usage logging and performance telemetry across the deployment.

4.4 End-to-End Workflow

The operational workflow of the system (Figure 3) has three stages. The first, CV ingestion and processing, begins when a CV is uploaded in PDF, DOC or DOCX format and its document format is validated. Valid documents move on to data extraction via Azure Document Intelligence, after which key fields, such as skills, experience and education, are parsed, cleaned and structured, and the resulting record is stored in the candidate database. Invalid documents are rejected at this stage. The second stage, data indexing, takes the structured candidate data and indexes it in Azure AI Search, creating a searchable index of attributes such as skills, experience and education that stays in step with the candidate database. In the third stage, query handling and response generation, a recruiter enters a natural-language query through the ChatUI. The API layer receives the query, enriches it with relevant context through a form of prompt engineering, retrieves relevant records from the search index, sends the enriched query and retrieved context to Azure OpenAI, and generates and displays an intelligent response to the HR user. The workflow is designed to keep latency low and to improve the accuracy of candidate insights at enterprise scale.

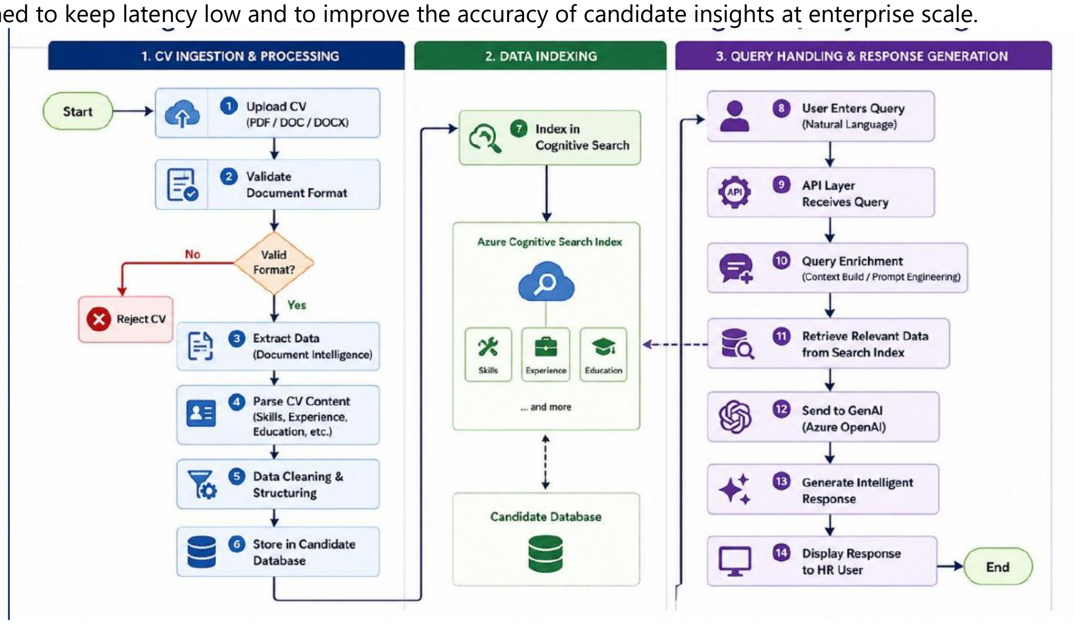

Figure 3. End-to-end workflow of the GenAI-powered HR Assistant, covering CV ingestion and processing, data indexing, and query handling and response generation.

4.5 CV Management

The CV management module handles centralised storage and management of candidate profiles in multiple formats, mainly PDF and DOCX. The system stores documents securely using cloud-based repositories and supports efficient retrieval for downstream processing. Version control and document-tracking mechanisms keep the data consistent, and this module is the entry point for the entire processing pipeline.

4.6 Information Extraction

The information extraction component leverages document intelligence powered by AI to convert the data in CVs from unstructured to structured formats. Pre-trained models are used to identify key attributes of skills, work experience, education and certifications, and the data extracted from these CVs is normalised to ensure consistency across various CV formats from different sources and templates. The aim is to minimise manual work and enhance the consistency of key candidate attributes identification with large applicant pools.

4.7 AI-Based Conversational Interaction

The system includes a conversational interface, powered by Azure OpenAI, that lets HR users interact with candidate data using natural-language queries. The model processes a user's query, retrieves relevant information from the indexed candidate data, and produces a context-aware response by combining that retrieved data with the language model's generative capabilities. The idea is to give non-technical HR users an intuitive alternative to building complex search filters, while keeping the link between generated responses and the underlying candidate records, in line with the explainability principle set out in Section 4.1.

4.8 Security and Access Control

Security is handled through enterprise-grade authentication and role-based access control, integrated with directory services so that only authorised users can access sensitive candidate data. Data encryption and secure communication protocols protect information during processing and storage, and private network endpoints keep core AI, search, storage and database services off the public network. Together, these measures are meant to support organisational data-governance policies and the applicable data-protection requirements for processing candidates' personal data.

5. Early Implementation Observations and Discussion

This section walks through preliminary, qualitative observations from the pilot deployment of the GenAI HR Assistant, organised around the three research questions and the propositions set out in Section 2. As noted in Section 3.4, these observations come from practitioner reflection, design documentation and informal user feedback rather than a controlled empirical evaluation, and they are presented here as a basis for the structured research agenda proposed in Section 7.

5.1 RQ1 Architecture, Feasibility and Scalability

From an implementation point of view, the layered, cloud-native architecture described in Section 4 turned out to be feasible to deploy and operate within an enterprise environment supporting multiple business units. Separating the CV ingestion, indexing and query-handling layers meant each component could be developed, tested and scaled relatively independently, and using managed cloud services for document parsing, search and language generation cut down the amount of custom infrastructure that had to be built and maintained. Early use suggested that the system could process CVs in common formats (PDF, DOC, DOCX) and handle natural-language queries without any noticeable slowdown as the volume of indexed candidate records grew, which fits with the architecture's intended support for enterprise-scale deployment (Chafiq et al., 2025).

5.2 RQ2 Fairness Perceptions and Professional Identity (Propositions 1 and 2)

The design choice to keep the original CV alongside the AI-generated summary, and to let recruiters ask follow-up questions, mattered for how recruiters engaged with the assistant, which is in line with Proposition 1. Rather than treating the AI-generated summary as a final verdict, early users tended to treat it as a starting point: a first-pass synthesis they then checked against the underlying CV, particularly for candidates close to a shortlisting threshold (Goodman et al., 2024). This fits the broader claim that procedural justice perceptions depend on whether explainability and verification mechanisms are available, not on automation as such.

There was also a noticeable shift in the nature of recruiters' screening work, which speaks to Proposition 2. Rather than reading each CV from the outset, recruiters increasingly began their review with the AI-generated summary and the indexed skills/experience/education fields, saving their own time for verifying borderline cases, querying the system for additional detail, and exercising judgement on candidates whose profiles did not map cleanly onto the structured fields. That looks like a move from a 'screener' role focused on reading and searching, towards a 'curator' or 'verifier' role focused on checking, querying and judging AI-generated output, which is the kind of role redesign that Tushman and Anderson (1986) describe as competence-enhancing when it preserves and reorients, rather than eliminates, professional expertise (Lauring & Jonasson, 2024). Whether recruiters experience this shift positively probably depends on whether they feel they retain meaningful evaluative authority, which is why the user-control design principle in Section 4.1 matters, and why this is flagged as a priority for the structured evaluation proposed in Section 7.

These early patterns also line up with the multi-stage fairness framework proposed by Yang et al. (2026), which points to transparency of AI involvement, human-AI joint decision-making, and personalised communication as key levers for improving fairness perceptions across the pre-assessment, in-assessment and post-assessment stages of AI-based selection. The system's retention of source CVs and its conversational, query-based interface map onto the first two of these levers reasonably well: recruiters were not handed a final AI verdict but an AI-generated synthesis they could interrogate, and a joint recruiter-AI assessment effectively emerged from that back-and-forth. The third lever, personalised communication with candidates about the role of AI in their assessment, was not implemented in the pilot. That is an area where the system's current design lags behind the fairness framework it otherwise broadly supports, and it is worth flagging here as a design gap for future iterations rather than as evidence against Proposition 1.

One further observation concerns informational justice. Because the indexed skills, experience and education fields were visible to recruiters as discrete, labelled attributes (Figure 3), rather than buried only inside free-text AI summaries, recruiters seemed able to trace a given AI statement back to a specific structured field. This kind of structured traceability may partly substitute for a more elaborate, dedicated explanation interface, which suggests informational justice in GenAI selection tools can come from careful data architecture as much as from bespoke explainability features.

5.3 RQ3 Talent Outcomes and Contingencies (Proposition 3)

The benefit most consistently mentioned during early use was a cut in the time needed for manual CV screening, with the development team estimating that the system has the potential to reduce CV-screening effort by up to 60-70% for high-volume roles, based on automating tasks that previously required manual reading and data extraction. This efficiency benefit appeared most pronounced for roles with well-specified requirements and high application volumes, such as entry-level and operational positions, where the structured extraction of skills, experience and qualifications maps fairly directly onto the criteria used for shortlisting, which is in line with Proposition 3. For specialist and senior roles, where selection criteria are less codified and depend more on tacit organisational knowledge, the assistant tended to be used more as research and drafting aid, for instance to quickly pull up a candidate's stated experience in a particular domain, than as a primary screening mechanism. This points to a contingency view in which the strategic value of a GenAI CV assistant depends on how well it fits the complexity and volume of the roles it is applied to, and suggests organisations should expect, and plan for, differentiated use of such systems across their HR architecture rather than one uniform deployment model.

This pattern broadly lines up with survey evidence from Abdelhay et al. (2025), who find that the relationship between generative AI tool use and recruitment efficiency is shaped both by users' familiarity with the technology and by organisational size, which implies the same system can produce different efficiency outcomes depending on who is using it and what kind of organisation they are in. In the present case, recruiters who were more confident formulating natural-language queries seemed to get more out of the conversational interface than those who used it mainly as a passive summary generator. That suggests familiarity-related variation in benefits may operate at the level of individual recruiters as well as organisations, and points to training as a lever organisation can use to shape the benefits they actually realise.

From a risk perspective, Jamil et al, (2023) flag role-disruption risk as one of the main categories of risk associated with GenAI adoption in HRM, particularly for roles where human judgement has traditionally been central to task performance. The pattern observed here, where the assistant was used as a primary screening aid for high-volume roles but as a secondary research tool for specialist roles, can be read as an informal, emergent form of risk mitigation. By limiting the assistant's role in specialist hiring to information retrieval rather than candidate evaluation, the pilot deployment appears to have implicitly contained role-disruption risk in exactly the contexts where Rieskamp et al. (2023) suggest it is most acute, even though this containment was not the result of an explicit, documented risk-management process. Formalising such differentiated-use patterns, rather than leaving them to emerge informally, may be a low-cost way for organisations to put risk-based guidance on GenAI deployment into practice.

5.4 Summary: Mapping Theory, Design Features and Observations

Table 2 summarises how the theoretical lenses introduced in Section 2 map onto specific design features of the system described in Section 4, along with the status of the corresponding observation: whether it reflects an implemented design feature, a preliminary observation from early use, or a proposition that still needs structured empirical testing.

Theoretical Lens	System Design Feature	Conceptual Linkage	Status
Organisational justice (Proposition 1)	Retention of original CV alongside AI-generated summary; conversational follow-up queries; query-enrichment/logging	Explainability and verifiability support procedural and informational justice in AI-assisted screening	Implemented; preliminary positive use pattern observed
Role identity (Proposition 2)	Conversational interface positions recruiter as initiator of queries rather than passive recipient of a single score	Shift from 'screener' to 'curator/verifier' role; potential for competence-enhancing redesign	Preliminary observation; requires identity/role survey to confirm
Contingency theory (Proposition 3)	Structured extraction of skills, experience, education and certifications mapped to role requirements	Efficiency gains expected to be larger for high-volume, lower-complexity roles than for specialist roles	Preliminary pattern observed; requires

			comparative evaluation across role types
Strategic HRM / scalability	Layered cloud-native architecture (Figure 2); independent ingestion, indexing and query layers	Supports modular deployment and enterprise-wide scaling across business units	Implemented and operating in pilot deployment

5.5 Discussion: Situating the Findings within the Broader GenAI-in-HRM Literature

The observations above connect to, and add to, three strands of the emerging literature on GenAI in recruitment. The first is Dutta and Naveen's (2026) structuration-based account of recruitment and selection, which describes the emergence of 'human-technology-conjoined agencies', where task delivery and role-performance responsibilities are shared between recruiters and AI systems, based on an exploratory qualitative study of 43 HR and talent-acquisition leaders. The shift from 'screener' to 'curator/verifier' observed here is a concrete, system-level instance of that kind of conjoined agency: the assistant handles the initial extraction and synthesis, the recruiter handles verification, judgement and communication, and neither role is fully reducible to the other. Dutta and Naveen (2026) document this transformation mainly through retrospective accounts of HR leaders across many organisations, so the present paper offers something complementary: an architecture-level account of how such conjoined agency actually gets built into a specific system, which may help explain why and how those broader transformations come about in practice.

Second, these findings extend Acikgoz et al.'s (2020) work on justice perceptions of AI in selection from predictive, scoring-based systems to a generative, conversational system. Acikgoz et al. (2020) show that justice perceptions of AI-based selection are shaped by how consistent, job-related and transparent the system seems. The design features examined here, retaining source documents, allowing conversational follow-up, and making structured attributes visible, are one way of building transparency and job-relatedness into a generative system, where there is no single 'score' whose job-relatedness can be judged on its own, unlike with a fixed scoring algorithm. Future justice research on GenAI selection tools may therefore need to look at the transparency and contestability of generative outputs as an ongoing process of interaction, rather than treating the fairness of a single, discrete decision as the endpoint.

Third, these findings speak to the risk-governance perspective of Jiang et al. (2025) and the fairness-by-design perspective of Yuan et al. (2025). They show how design choices made early in a system's development, before any formal risk assessment or fairness audit, can already embody partial responses to the risks and fairness levers those frameworks identify. Risk and fairness frameworks for GenAI in HRM may therefore be useful not just as post-hoc audit tools, but as design heuristics that get embedded into the co-design process described in Section 3.2, which is exactly what the practical recommendations in Table 3 try to do.

Put together, these three points of comparison suggest the present case is not an isolated technical exercise but one instance of a broader shift in recruitment practice, a shift that HRM scholars are starting to theorise from several complementary angles: structuration, organisational justice, and risk governance. A single, well-documented implementation like the one described here can connect these otherwise separate strands of theory, and gives a concrete reference point against which the propositions developed in Section 2 can be tested in future, larger-scale studies.

6. Practical Implications for HR Managers

The design and early implementation experience reported here point to a set of practical recommendations for HR managers thinking about deploying GenAI-powered CV assistants. Table 3 sets these out as 'do' and 'avoid' recommendations, organised around the theoretical considerations discussed in Section 2.

Recommendation	Rationale	Related Theory / Proposition
Co-design the system with recruiters and hiring managers, and pilot it with a representative subset of roles before wider rollout.	Ensures the system reflects how recruiters actually evaluate candidates, and surfaces role-specific differences in usefulness early.	Contingency theory (P3)
Preserve access to the original CV and underlying data alongside any AI-generated summary, and allow recruiters to query and challenge outputs.	Supports procedural and informational justice; avoids the system being perceived as a 'black-box gatekeeper'.	Organisational justice (P1)
Communicate the system explicitly as an augmentation of recruiter	Frames the change as competence-enhancing rather than	Role identity theory (P2)

judgement, not a replacement for it, and define the residual decision rights recruiters retain.	competence-destroying, supporting positive professional identity adjustment.	
Provide training on how to interpret, verify and, where necessary, override AI-generated summaries and recommendations.	Builds the new evaluative and 'AI-literacy' skills required in a curator/verifier role.	Role identity theory (P2)
Differentiate how the system is used across role types: as a primary screening aid for high-volume, well-specified roles, and as a research/drafting aid for specialist or senior roles.	Matches system use to the contingencies under which it adds the most value, avoiding a one-size-fits-all deployment.	Contingency theory (P3)
Monitor fairness-relevant metrics over time (e.g., shortlist composition across candidate groups, override rates, recruiter feedback on AI summaries) rather than relying solely on efficiency metrics.	Provides an evidence base for identifying and addressing unintended fairness effects as the system scales.	Organisational justice (P1)
Avoid assuming that a single system configuration or set of prompts will work identically across business units, geographies or role families.	Reduces the risk that efficiency gains in one context come at the cost of fit or fairness in another.	Contingency theory (P3)

7. Limitations and Future Research Agenda

This study has several limitations that future research should address. First, the implementation observations in Section 5 come from a single enterprise and a relatively short period of early use, and the author was directly involved in the system's design and implementation, which raises the possibility of social-desirability and confirmation effects in how early feedback was interpreted. Second, the study does not yet include a controlled pre-post quantitative evaluation of recruiter attitudes (for example, using established organisational justice or role-identity scales), nor objective HR metrics such as time-to-hire, quality-of-hire or shortlist diversity collected over a defined evaluation window. Third, the candidate-side perspective, how applicants perceive a recruitment process supported by a GenAI assistant, is not addressed at all.

Building on these limitations, and on the conceptual model in Figure 1, future research should pursue the following agenda:

- A longitudinal, mixed-methods evaluation across one or more organisations, combining pre- and post-implementation surveys of procedural justice (e.g., based on Colquitt's, 2001, dimensions) and professional role identity, with objective HR metrics such as time-to-screen, time-to-hire, quality-of-hire and shortlist diversity.
- Semi-structured interviews and thematic analysis of recruiters' experiences of the shift from 'screener' to 'curator/verifier' roles, including the new skills (such as prompt formulation and critical evaluation of AI outputs) that this shift appears to require.
- Comparative analysis of system use and outcomes across role families that differ in complexity and hiring volume, to test the contingency proposition (P3) that efficiency benefits are greatest for high-volume, lower-complexity roles.
- Investigation of candidate-side fairness perceptions where GenAI assistants are used in screening, and of any disclosure obligations to candidates.
- Cross-cultural and cross-sectoral replication, given that the present case is drawn from a single enterprise context, to examine the generalisability of the conceptual model in Figure 1.

8. Conclusion

This paper has presented the design, technical implementation and early enterprise experience of a Generative AI-powered HR Assistant for intelligent CV analysis, and placed this practitioner-led system within an HRM-relevant theoretical framework drawing on organisational justice, role identity and contingency theory. The system's layered, cloud-native architecture shows that GenAI-based CV parsing, indexing and conversational interaction can be implemented securely and at enterprise scale. Early implementation observations suggest such systems can meaningfully cut the time recruiters spend on manual CV screening and standardise how key candidate attributes are identified, while reshaping recruiters' day-to-day work towards verifying and interpreting AI-generated outputs. Whether these changes translate into improved fairness perceptions, positive professional-identity adjustment, and strategic talent-acquisition value, and under what organisational conditions, remains an empirical question that this paper frames but does not answer. The conceptual model and propositions developed here, together with the design principles and practical recommendations summarised in Tables 1 to 3, are offered as a starting point for the kind of theory-led, longitudinal empirical research on GenAI in recruitment that the HRM field is well placed to carry out.

Declarations

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Disclosure Statement

The author reports no conflicts of interest.

Declaration of Generative AI Use

Generative AI tools (large language models) were used to assist with literature retrieval, language editing and document formatting during the preparation of this manuscript. The system design, implementation and conceptual contribution described in the paper are the author's own work, and the author has reviewed and takes full responsibility for the content of the final manuscript.

Data Availability Statement

The architecture documentation and configuration artefacts underlying the system description in Section 4 are available from the corresponding author upon reasonable request. Candidate CV data are not available for sharing due to data-protection and confidentiality obligations.

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I. List of Tables and Figures