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Awareness, Perceptions and Readiness for Generative AI Adoption in Recruitment at Healthcare Sectors in Kerala: A Qualitative Study of Hospitals in Kerala

Arjun Hari [1] and Dr. Annapurna Nagoji [2]

[1] M.B.A. student (Human Resource Management), Department of Management Studies,

Faculty of Management and Commerce, M. S. Ramaiah University of Applied Sciences, Bengaluru 560 054, India

[2] Faculty of Management and Commerce, M. S. Ramaiah University of Applied Sciences, Bengaluru 560 054, India

Corresponding author: arjunhari100@gmail.com and annapurnaprakash.ms.mc@msruas.ac.in

Abstract. Generative Artificial Intelligence (GenAI) tools such as ChatGPT, Gemini and Copilot have entered everyday office work quickly, but little is known about what the professionals that run hospital recruitment have to say about them. This study evaluates the awareness, perception and readiness of human resource (HR) professionals towards GenAI adoption in healthcare recruitment. A qualitative, descriptive and exploratory design was followed. Open-ended questionnaire and interview responses were collected from one HR or recruitment professional, per each of 30 hospitals in Kerala, India and were analysed in NVivo using a four-parent, seventeen-child codebook, word frequency queries, word clouds and objective-wise thematic interpretations. The respondents were generally aware of GenAI and familiar with the common tools, although awareness had not yet become an organisational adoption. The potential utility of GenAI were seen to be in organisation of applications, preparation of candidate summaries, qualification matching and reduction of repetitive administrative work, although gains in hiring time had not been consistently reported. Concerns were raised around accuracy, privacy, biases, ethics, trust and organisational barriers. The respondents expect adoption to be a gradual and human-led process, contingent upon AI-literacy, training and governance. The study contributes context-specific qualitative evidence on this topic that has mostly been explored in clinical settings and in other industries, and proposes a phased, governance-first approach to adoption. Keywords: Generative AI; healthcare recruitment; HR professionals; awareness; perceptions; readiness; NVivo; thematic analysis; Kerala

1. Introduction

Every hospital starts with a hiring decision. Ward, theatre and laboratory functions can begin only after doctors, nurses, technicians and administrators have been found, screened and recruited, and the quality of care a hospital delivers depends greatly on the people it manages to find. In Kerala, recruitment is a continuous activity: the state has a dense mix of government, private and charitable hospitals, a long tradition of training healthcare professionals and a labour market in which skilled workers are drawn towards other Indian cities and overseas destinations.

In this setting has arrived Generative AI, the family of systems that produce text, summaries and other content in response to plain language instructions. Since the public release of ChatGPT in late 2022, such tools have moved rapidly from curiosity to routine use in many offices (Dwivedi et al., 2023). Recruiters can use them to draft job advertisements, summarise résumés or rewrite candidate communications. Whether this convenience translates into better and fairer hiring in hospitals, and whether hospital HR teams are ready to rely on it, are separate questions.

The research problem begins with a distinction that is easy to blur. AI is already present in healthcare in clinical decision support, imaging and digital records, and hospitals also use applicant tracking systems and job portals. None of this means that Generative AI is being used for recruitment. A hospital can be clinically AI-enabled and still hire in a conventional way. Existing studies mostly examine clinicians' views of AI or the use of AI in HR in other industries;

studies that bring together Generative AI, healthcare recruitment and HR professionals are scarce, and evidence from Indian hospitals is thinner still.

This paper reports a qualitative study of HR and recruitment professionals in 30 hospitals in Kerala. Its aim is to assess their awareness, perceptions and readiness towards Generative AI adoption in healthcare recruitment. Four objectives follow from the aim:

To explore the awareness and familiarity of HR professionals with Generative AI in healthcare recruitment;

To examine their perceptions of the potential benefits of Generative AI in recruitment; To identify the barriers, challenges and concerns affecting adoption; and
To assess the future readiness and expectations of healthcare organisations towards adopting Generative AI in recruitment.

The paper makes three contributions. It provides qualitative evidence on a combination of Generative AI, hospital recruitment and HR professionals that earlier work has addressed only in part; it documents an NVivo codebook that other researchers can reuse; and it translates the findings into a phased, governance-first approach for hospital HR leaders.

2. Literature Review and Theoretical Lens

2.1 AI in HR and recruitment

Studies on AI in human resource management have been accumulating steadily. Tambe et al. (2019) concluded that HR is a challenging domain for AI due to "poorly defined outcome measures, smaller sample sizes, and questions about ethics and legality." Black and van Esch (2020) examined how recruiters could benefit from AI-enabled solutions, particularly by accelerating sourcing and screening, but warned managers about the importance of data quality, candidate reactions, and other factors; Budhwar et al. (2023) proposed a research agenda on ChatGPT and other generative AI in HRM, including recruitment, ethical issues, and the evolving competence needs of HR professionals. Indeed, the risk of discrimination is not unfounded, as illustrated by the well-documented case of an experimental software that penalized job applicants who identified as women (Dastin, 2018). On the other hand, vendors' claims about the ability of their technology to reduce bias in hiring decisions were challenged by Raghavan et al. (2020).

2.2 Healthcare professionals' perceptions of AI

There were ten studies that examined the perceptions of healthcare professionals in relation to at least one of the four facets investigated in this paper. Ayorinde et al. (2024) conducted a systematic review of 25 studies across nine countries and produced a list of seven themes, including understanding, trust, perceived value, governance, and collaboration. Yousif et al. (2024) interviewed 25 clinicians and identified themes of awareness, acceptance/training, merits/demerits, and challenges. Qiu et al. (2026) analysed the transcripts of 23 healthcare workers' interviews and grouped the barriers to AI adoption in healthcare around themes of technology, organization, cognition, and governance. Zhou et al. (2026) Interviewed 25 physicians to explore the drivers and barriers to AI utilization in hospital management. Another study used a qualitative design to examine the perceptions of 24 health professionals about conversational agents, one of the technologies conceptually related to generative AI ("MacNeill et al., 2024"). Physical therapists expressed concerns regarding privacy, ethics, and the need for education about such technologies"(Shawli et al., 2024)". Nazir et al. (2026) implemented a mixed-methods study, namely, a survey and interviews, to explore the attitudes of Australian healthcare professionals towards generative AI, focusing on their needs for guidance and organizational support. Finally, a systematic review of 26 qualitative studies produced insights on benefits, workforce-related considerations, communication, technical aspects, and ethical issues related to AI in healthcare ("Huotari et al., 2026"). Two of the included articles specifically examined recruitment-related aspects. Pandey et al. (2025) interviewed 21 HR professionals working in the IT industry to elicit their views on the utilization of generative AI in recruitment. Participants highlighted the efficiency gains but also voiced ethical concerns and worries about the loss of personal touch. Similarly, Kyambade and Namatovu (2026) interviewed 12 Ugandan hospital HR officers about generative AI in recruitment and identified themes of learning/training, trust/algorithms, efficiency versus human

judgment, and transparency.

2.3 Policy context

There are two significant policy considerations in India. First, the National Strategy for AI, developed by NITI Aayog (2018), includes healthcare as one of the priority domains for AI investments. Second, the Digital Personal Data Protection Act, 2023, concerns appropriate processing of personal data by organizations (Government of India, 2023). In particular, a candidate's resume contains personal data; thus, its analysis by an external agency, as proposed by some of the interviewees, would fall under the responsibilities outlined in this Act.

2.4 Theoretical lens and research gap

There are four conceptual frameworks that have informed this study as theoretical lenses but were not explicitly tested as hypotheses. First is the Technology Acceptance Model (Davis, 1989), which highlights the role of perceived usefulness and ease of use in technology adoption. The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) is consistent with the Technology Acceptance Model but also includes the constructs of social influence and perceived usefulness. Another relevant framework is the Technology–Organization–Environment (Tornatzky & Fleischer, 1990) framework that informs technology implementation. Finally, the theory of diffusion of innovations (Rogers, 2003) applies to the processes through which new solutions, in this case, generative AI, are adopted.

Five areas of gaps in the literature have been addressed by this study. First, there is a dearth of literature on the application of Generative AI to healthcare recruitment. Second, most studies utilized students as participants, whereas healthcare professionals are the actual users of such technology. Third, there is limited literature on the application of generative AI in India in general and Kerala in particular. Fourth, the readiness of healthcare organizations to adopt such technologies and their expectations are poorly understood. Finally, the extant literature lacks systematic qualitative thematics.

3. Methodology

3.1 Research design

The paper employed an interpretive stance and used an inductive approach with qualitative designs. The objectives of the study were descriptive and exploratory whereby the main aim was to describe what HR professionals know, expect and fear in a business practice area that has received limited attention in the past. The timeframe used was cross-sectional. Table 1 below shows the different design choices that were made.

Table 1. Summary of research design

Design element	Choice made in this study
Approach and design	Qualitative; descriptive and exploratory; interpretivist, largely inductive
Data collection	Open-ended questionnaire / interview responses, structured by objective
Study population	HR / recruitment professionals in selected hospitals in Kerala
Sample	30 hospitals; one respondent per hospital (30 responses); purposive
Analysis	NVivo coding, word frequency analysis, word clouds; objective-wise thematic interpretation
Time horizon	Cross-sectional

3.2 Conceptual framework

The framework (Figure 1) includes four overarching dimensions that together capture the healthcare organisation's general preparedness to embrace Generative AI in recruitment: awareness and familiarity, perceived benefits, barriers, challenges, and concerns, and future readiness and expectations. Each of these areas is the focus of one objective and, thus, one parent code in the analysis. The arrows should be read in the direction of reasoning, and not as influences, with awareness enabling consideration of benefits, which in turn provide the motivation for action; barriers dictate the extent to which motivation will be actualised; and finally, readiness governs whether action will take place responsibly.

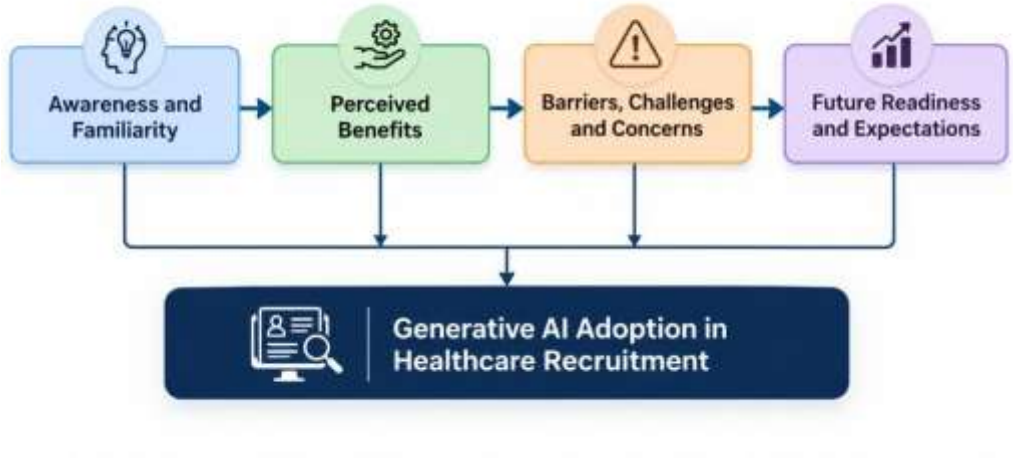


Figure 1. Conceptual framework of the study

3.3 Sample and respondents

The unit of analysis was the hospital, represented by its HR or recruitment professional. Thirty hospitals in Kerala were included, representing one respondent, one data file. The respondents were selected purposefully (Patton, 2002). Sample-size formulae such as Cochran's or Slovin's are intended to generalize numerical estimates and were not used; the relevant criterion in qualitative work is whether the sample has enough information to answer the research questions, the notion of information power (Malterud et al., 2016). The aim is narrow, respondents hold exactly the position of interest, questions were asked in the same structured way to everyone, and the sample of 30 is larger than the 12 to 25 participants in comparable studies and well above the point at which themes were found to stabilise in a widely cited analysis (Guest et al., 2006). Because the sample is purposive, the findings are not statistically generalisable.

The respondents were experienced (Table 2, Figure 2): 63.3% had six to seven years of HR experience, 20.0% had four to five years and 16.7% had eight to nine years. The hospitals ranged from 25 to more than 500 employees, with 63.4% employing between 101 and 500 people.

Table 2. Respondent and hospital profile (N = 30)

Parameter	Category	Percentage	Number
HR experience	4–5 years	20.0%	6
	6–7 years	63.3%	19

Parameter	Category	Percentage	Number

	8–9 years	16.7%	5
Hospital workforce	25–100 employees	23.3%	7
	101–250 employees	36.7%	11
	251–500 employees	26.7%	8
	501+ employees	13.3%	4

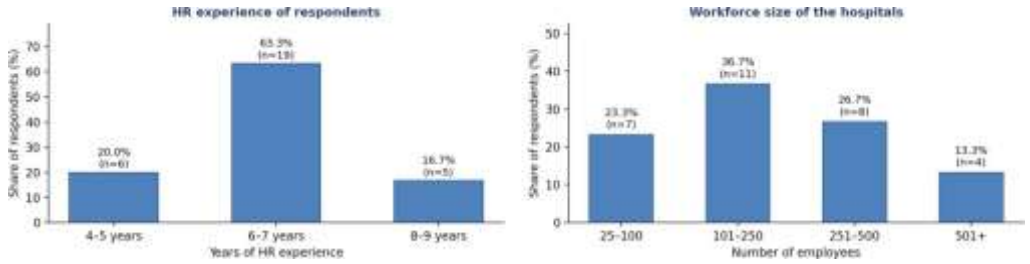


Figure 2. Respondents by years of HR experience (left) and hospitals by workforce size (right)

3.4 Instrument

The instrument was a set of open-ended questions arranged into four sections according to the objectives, with a short profile preceding them. Open-ended questions were selected because respondents could answer them in their own words, and the answers could be subjected to coding and thematic analysis. The first section contained one composite question about the understanding of GenAI, knowledge of tools, and sources of awareness and confidence. The second section had three questions about the changes in recruitment brought by AI, the most beneficial activities, and a practical example. The third section comprised five questions about challenges, ethical concerns, candidate privacy, trust in recommendations, and organisational barriers. Finally, the fourth section asked four questions regarding the future perspective of GenAI, training and skills, human–AI collaboration, and additional insights.

3.5 Data analysis

The analysis followed the process of thematic analysis (Braun & Clarke, 2006) and was conducted using NVivo. The 30 responses were uploaded as 30 files and read for familiarisation. Then, a codebook with four parent codes, corresponding to the objectives, and seventeen child codes (Table 3, Figure 3) was created. Each child code was linked to all 30 files and 30 references in the final project. Then, the word frequency query for each objective's coded content was performed to record the ten most frequent words, and the same frequency was visualised as word clouds. The findings and interpretations were written for each objective separately and compared between the objectives. The raw counts were read with caution because the connective words such as "however" and "because" reflected sentence construction rather than thematic content, and the frequent occurrence of "clinical" did not imply the use of GenAI in clinical settings.

Table 3. NVivo codebook (each child code linked to 30 files and 30 references)

Parent code (objective)	Child codes
O1: Awareness and Use of Generative AI	AI Conceptual Understanding; Generative AI Tool Familiarity; Confidence and HR Digital Literacy; Sources of AI Awareness
O2: Perceived Benefits of Generative AI	Experienced Benefits of Generative AI; Improved Recruitment Efficiency; Improved Candidate Quality; Improved Candidate Experience
O3: Challenges of Generative AI	Challenges Encountered; Ethical Concerns; Candidate Privacy Concerns; Trust in AI Recommendations; Organizational Barriers
O4: Future Outlook of Generative AI	Future Influence of Generative AI; HR Skills Development; Recommendations for AI Adoption; Additional Insights

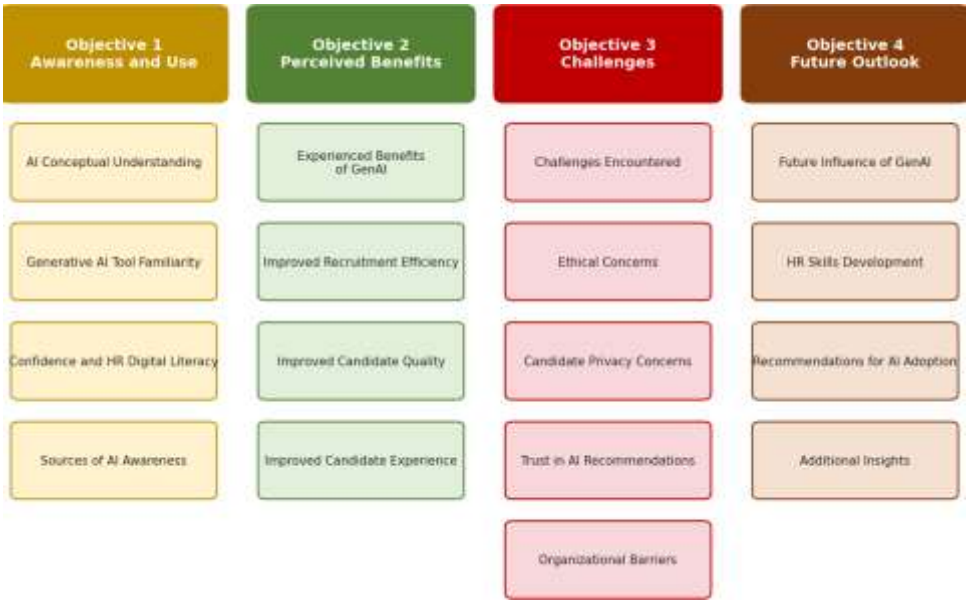


Figure 3. Thematic structure of parent and child codes

3.6 Trustworthiness and ethics

Trustworthiness was evaluated using the criteria of Lincoln and Guba (1985) applied to the thematic analysis of Nowell et al. (2017). Credibility was enhanced by the purposeful sampling of respondents who occupied the relevant role, asking all participants the same questions, requesting exemplifying statements and adhering to their verbatim when possible. Transferability was achieved by describing the sample and the hospitals as well as the limitation of this study. Dependability was established by using a single dated NVivo project and having a codebook that was developed. Confirmability was reached by distinguishing between findings and interpretations and using word count statistics as another independent verification. Triangulation was achieved by using coded material, word frequencies and word clouds as three facets of a methodological triangulation. The hospitals or respondents are not identified, the results are reported aggregately and there were no candidate data collected.

4. Results

Because each child code was linked to all 30 hospital files, each theme was present in the overall sample. However, the data do not provide information about the number of respondents that held each view to a certain extent and therefore the following results refrain from using terms such as "most respondents". Figure 4 displays the ten most frequent words for each objective and Figure 5 the corresponding word clouds.

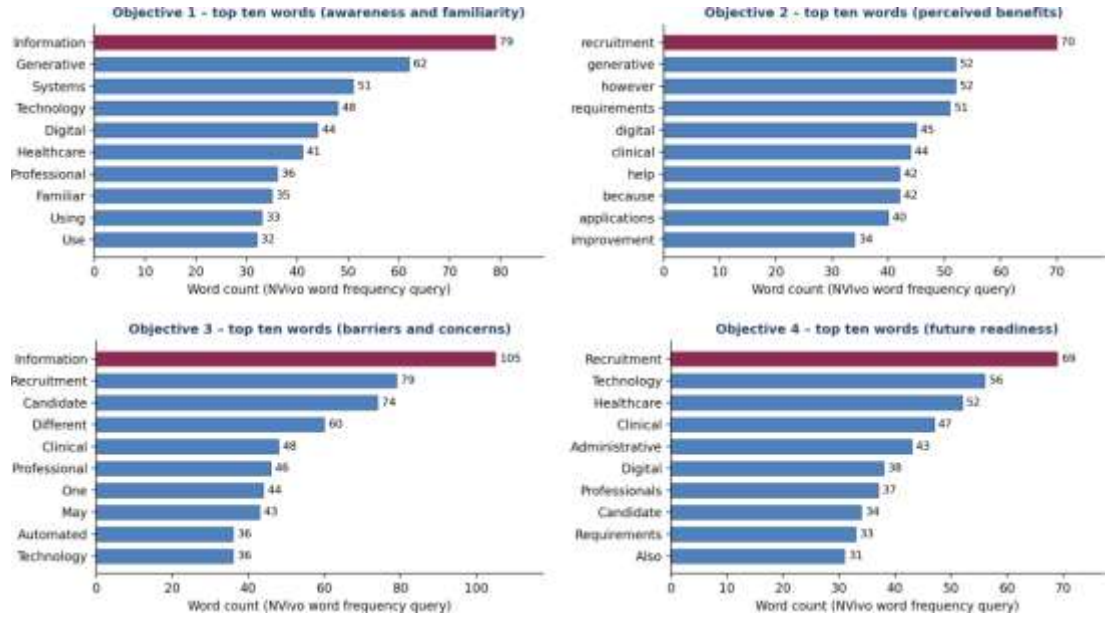


Figure 4. Ten most frequent words by objective (NVivo word frequency query)



Figure 5. Word clouds by objective (top left: O1; top right: O2; bottom left: O3; bottom right: O4)

4.1 Awareness and familiarity (O1)

"Information" (79), "generative" (62), "systems" (51), "technology" (48) and "digital" (44) dominated the vocabulary, and "familiar", "using" and "use" were also among the top ten. Respondents described GenAI in terms of how it manipulates information and spoke from their own experience, not only from hearsay.

Respondents demonstrated general awareness and familiarity with Generative AI. ChatGPT, Gemini and Copilot were

the most commonly named tools. Awareness came through their professional and workplace exposure, online and digital sources and healthcare technology exposure. Confidence varied, and respondents stressed the need to verify AI-generated information before it is used in HR decisions. Awareness and familiarity were demonstrated, but organisational adoption in recruitment was not formal.

4.2 Perceived benefits (O2)

"Recruitment" (70) led the list, followed by "generative" and "however" (52 each) and "requirements" (51). The prominence of "requirements" fits the context of healthcare hiring, where each vacancy has qualification, registration and departmental conditions, and "however" indicates that benefits were stated with a qualification attached.

GenAI was perceived as a beneficial tool for organisation of applications, preparation of candidate summaries and recruitment information, and supporting qualification and competency matching, and reducing repetitive administrative work. However, measurable improvement in hiring time was limited or inconsistently reported, so efficiency benefits are currently potential rather than demonstrated. Respondents also indicated that digital recruitment systems such as job portals and applicant tracking show more visible current impact than formal GenAI use, and human involvement remained important throughout.

4.3 Barriers, challenges and concerns (O3)

"Information" (105) was the most frequent word in the whole analysis, followed by "recruitment" (79) and "candidate" (74), with "professional", "clinical" and "automated" also present. In the context of privacy and trust questions, candidate information is the raw material of recruitment, and handling it safely was a central concern.

Five groups of concern emerged. The first was accuracy, reliability, context and role-specific requirements. The second was privacy and data security, as CVs and personal and professional information require safe handling. The third was ethical, including bias, fairness, transparency and automated screening. The fourth was trust and human oversight, because AI recommendations were felt to need human review and professional judgement. The fifth was organisational: training, policies, cost, resistance to change and system integration.

4.4 Future readiness and expectations (O4)

"Recruitment" (69), "technology" (56) and "healthcare" (52) led the list, and "administrative"

(43) was distinctive, suggesting that respondents who looked ahead pictured GenAI taking on administrative work in recruitment and not the core of selecting people.

Respondents said that future adoption depends on HR readiness and AI literacy, and highlighted the need for training and upskilling. They expect greater use of AI in recruitment, particularly for administrative and technology-supported activities, with human judgement and professional expertise remaining important. They stressed the need for clear policies, governance, privacy and data-security safeguards for responsible adoption. Table 4 summarises the results by objective.

Table 4. Summary of results by objective

Objective	Key results	Interpretation
O1 Awareness and familiarity	General awareness; ChatGPT, Gemini and Copilot commonly known; awareness via workplace, online and healthcare technology exposure; confidence varied; verification before important decisions	Awareness does not mean formal adoption; GenAI to be distinguished from clinical AI and digital recruitment systems
O2 Perceived benefits	Organising applications, candidate summaries, qualification and competency matching, less repetitive administrative work; hiring-time gains not consistently reported	Efficiency more potential than demonstrated; digital systems show more visible impact; human involvement remains important
O3 Barriers and concerns	Accuracy and context; privacy and data security; bias, fairness and transparency; trust and human oversight; training, policy, cost, resistance, integration	Healthcare roles make human judgement important; AI seen as support, not replacement
O4 Future readiness	Depends on AI literacy, training and upskilling; more administrative use expected; human judgement to remain; policies and safeguards needed	Gradual, capability-and-governance-led adoption

5. Discussion

5.1 Awareness is not adoption

The most valuable aspect of the first set of results is what they don't say; one could know ChatGPT, have used it to polish an email and still be in a hospital where no recruitment process uses it. This aligns with Yousif et al.'s (2024) finding that awareness is a distinct stage that precedes acceptability and training, and with Rogers' (2003) view of knowledge as only the first stage of diffusion. This also aligns with the case for distinguishing Generative AI from clinical AI and from conventional digital recruitment systems, a distinction lost in discussions of AI in healthcare. The variance in confidence is in keeping with Ayorinde et al.'s (2024) finding that many health professionals were unsure of their own understanding of AI. The respondents' practical response, verifying before relying, is also prudent and also indicates that HR digital literacy has not kept pace with the availability of the tools.

5.2 Benefits are expected more than demonstrated

Benefits cluster around information handling, that is, what a language-based tool does best, and not around decisions about people. This corresponds with Nazir et al.'s (2026) respondents' reports of efficiency and workload benefits and with Pandey et al.'s (2025) HR participants' seeing gains in recruitment efficiency. The gap between potential and demonstrated benefit is a caution for managers in both directions: improvements that come from digitalisation more broadly should not be credited to GenAI and GenAI should not be discarded because its effect on time to hire has not yet been measured.

5.3 Concerns are specific and cluster around trust and information

The five groups of concern align closely with earlier work: trust, understanding and governance in Ayorinde et al. (2024); technology, organisation, cognition and governance in Qiu et al. (2026); and trust, algorithmic bias and transparency in Kyambade and Namatovu (2026). What is distinctive in recruitment is the importance of role-specific

requirements. A system that summarises a CV without recognising that a certain registration is mandatory, or that an intensive care role needs a certain type of experience, misleading. Privacy is also a compliance issue: a hospital that uploads a CV to an external tool is handling personal data covered by the Digital Personal Data Protection Act, 2023, so privacy cannot be left to individual vigilance. Bias requires particular attention as its harms are less visible; a biased shortlist does not advertise itself (Dastin, 2018; Raghavan et al., 2020), which supports human review of any AI-assisted screening.

5.4 The future is gradual and about capability and governance

Respondents neither see GenAI as a threat to be resisted nor a solution to be rushed, but as a capability to be built. This is in keeping with the call for education, training and attention to ethical concerns in the 2026 systematic review and the emphasis on organisational support and guidelines in Nazir et al. (2026). Two implications follow. Readiness is mainly a human issue, as the tools are already accessible to anyone with an internet connection. And governance needs to take place before scale, as it is much easier to create the rules for a small pilot than to bring a widespread, unmanaged habit under control.

5.5 Reading the results through theory

Through the Technology Acceptance Model (Davis, 1989), the respondents' recognition of the usefulness, mostly in information handling, but their hesitancy to rely on the results without double-checking suggests that perceived usefulness is not sufficient in high-stakes and uncertain accuracy. Through UTAUT (Venkatesh et al., 2003), the emphasis on training, policy and support corresponds to facilitating conditions. Through the TOE framework (Tornatzky & Fleischer, 1990), technology concerns (accuracy, context), organisation concerns (training,policy, cost, resistance, integration) and environment concerns (data-protection expectations) are all visible. And through diffusion of innovations (Rogers, 2003), most respondents fall between knowledge and persuasion: they know the innovation and form opinions of it, but a formal adoption decision has mostly not yet been taken. This is not a test of the theories; it indicates that their categories transfer reasonably well to a new setting. Table 5 lists the status of the four guiding propositions that framed the study.

Table 5. Status of the guiding propositions

No.	Proposition	Evidence	Status
P1	General awareness and familiarity, but not yet formal organisational adoption	Section 4.1	Supported
P2	Benefits lie in administrative and information tasks; no consistent measurable gains yet	Section 4.2	Supported
P3	Concerns about accuracy, privacy, bias, ethics, trust and organisational barriers; human review expected	Section 4.3	Supported
P4	Gradual adoption led by training, literacy, governance and human–AI collaboration	Section 4.4	Supported

6. Implications

6.1 For hospital HR leaders

Four directions emerge from the results. First, invest in AI literacy: training should cover what tools can and cannot do, how to write clear instructions, how to evaluate outputs and how to recognize bias and errors. Second, keep humans accountable: AI-produced summaries and shortlists should be regarded as drafts to be double-checked against the

original application, and no candidate should be rejected solely on the basis of a generated output. Third, adopt a written responsible-use policy encompassing approved tools, what candidate information may be entered into them, who checks the results and how concerns are raised. Fourth, introduce GenAI gradually. Table 6 sets out a four-phase approach, which represents the authors' synthesis of the findings and the literature; it is a starting point and has not been tested.

Table 6. A phased approach to GenAI in hospital recruitment (authors' synthesis)

Phase	Focus	Safeguards	What to track
1. Prepare	AI literacy training; list of approved tools; short written policy	Rules on candidate data entered into external tools; named accountable person	Staff trained; policy issued
2. Pilot	Low-risk administrative tasks: notices, standard messages, application summaries	Human check of every output; originals kept; no decisions on AI output alone	Time saved; errors found
3. Extend	Support for qualification and competency matching in selected roles	Documented human review of shortlists; periodic bias checks	Shortlist quality; complaints
4. Review and embed	Review evidence from phases 2 and 3; decide on wider use	Update policy; refresh training; re-check data protection compliance	Time to hire; satisfaction

6.2 For policymakers, educators and professional bodies

Hospital associations and HR bodies could devise sector-level guidance so that smaller hospitals do not each formulate policy independently. Universities and training providers could develop short, practical AI-literacy courses for human resources professionals. Data-protection guidance in plain language on what candidate information may be fed into external AI tools would help hospitals comply with the 2023 Act.

7. Limitations and Future Research

The study includes selected hospitals in Kerala only, which limits the generality of conclusions for other states and organisations with different ownership and size. Since each hospital provided only one HR respondent, senior managers, clinical heads and candidates were not involved in the study. The evidence was based on perception, not measured outcomes. The study used a purposive sample and a qualitative design, and thus, the findings are not statistically informative but provide an in-depth description and basis for developing research questions. The word frequencies reflect how often respondents mentioned something specific when talking about one of the topics, which might say more about their intention than what they actually meant, and thus, it should be complemented with the coded content. Finally, the data represent a point-in-time assessment, and the field of study evolves at a very rapid pace.

Future research can build upon this study by including clinics, diagnostic chains, teaching and public hospitals and other states; using a larger sample representative of all hospitals in terms of seniority and multiple respondents; following up on the qualitative findings with a quantitative survey to establish the extent of these patterns across the board; collecting evidence on actual outcomes, such as the time to hire, cost per hire, quality of hire and candidate satisfaction; returning after one or two years in a longitudinal study; and adding the candidates' perspective on AI-assisted screening and communication.

8. Conclusion

HR professionals in the hospitals studied are aware of Generative AI and familiar with common tools, but this awareness has not yet become formal adoption by recruitment. They see its value primarily in administrative and information-handling work, and they regard its benefits as more potential than shown. Their concerns are specific and consistent in their nature: accuracy and context, privacy and data security, bias and ethics, trust and the need for human review, and organisational barriers. They expect adoption to be gradual and conditional on training, governance and human oversight. The central message is neither enthusiasm nor resistance: hospitals that build AI literacy, set out clear rules and keep humans accountable for decisions about people will be best positioned to benefit from Generative AI in recruitment.

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