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AI-Based Clinical Handover Assistant: Enhancing Patient Safety through Intelligent Clinical Communication

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Abstract: *Shift-to-shift handover is one of the most error-prone moments in hospital care. In most hospitals it is still performed through verbal briefings, handwritten notes or free-text electronic health record (EHR) entries, which is time-consuming, inconsistent and rarely restricted to the nurse who actually receives the patient. This paper presents the AI-Based Clinical Handover Assistant, a secure hybrid web and mobile system that automates nurse-to-nurse handover documentation, with escalation to a doctor when the receiving nurse cannot manage a case. An outgoing nurse records a voice or text handover addressed to specific incoming nurses; the audio is normalised with FFmpeg, transcribed by a speech-to-text service and summarised by the Gemini API into a structured SBAR/ISBAR report from which medications, vital observations and pending tasks are extracted. Every record is encrypted before storage and can be decrypted only by its addressed recipients; on escalation it is re-encrypted for the chosen doctor. A retrieval-augmented generation (RAG) chatbot lets authorised users query their own handovers. The system is built with Django, MySQL and Flutter. We present the literature survey, system architecture and data flow design of the proposed system.*

Keywords: Clinical handover, SBAR/ISBAR, speech recognition, large language models, retrieval-augmented generation, recipient-bound encryption, patient safety.

I. INTRODUCTION

Clinical handover is the transfer of professional responsibility and accountability for some or all aspects of a patient's care from one clinician or team to another. In hospitals it happens several times a day, most visibly at nursing shift changes, when the outgoing nurse briefs the incoming nurse on each patient's condition, medications, recent observations and outstanding tasks. Because the incoming nurse acts on this information immediately, the completeness and accuracy of a handover directly influence continuity of care and patient safety. Structured handoff programmes have been associated with a reduction in medical errors [4], and a systematic review has examined the evidence for structured handoff protocols during within-hospital transitions [3].

In practice, nursing handover is still carried out largely through verbal briefings, handwritten notes or free-text EHR entries. Verbal information that is not written down is easily forgotten or misheard, and the same information is often communicated twice, once verbally and once in the nursing notes [5]. Frameworks such as SBAR (Situation, Background, Assessment, Recommendation) and its ISBAR variant, which adds an initial Identify step, give handovers a predictable structure [2], but they still depend on the nurse to compose and type each report by hand.

Advances in speech recognition and large language models (LLMs) now make it feasible to capture a spoken handover and convert it into structured documentation automatically. Early work showed that speech recognition combined with information extraction could draft nursing handover documents [6], and a recent hospital deployment combined domain-adapted speech recognition with an LLM to produce structured nursing records that nurses verify before filing

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[11]. Adapted LLMs can produce clinical summaries comparable to those of medical experts [14], although errors and fabricated content remain a safety concern that calls for human review [15], [16].

Handover records contain highly sensitive patient information, so any digital solution must protect confidentiality in transit and at rest. Attribute-based encryption of health records shows that data can be encrypted before storage so that only authorised parties can read it [19], [20]. Retrieval-Augmented Generation (RAG) lets a language model answer questions from passages retrieved from a document store [17], which suits a chatbot that answers from the handovers a nurse has actually received [18].

The proposed AI-Based Clinical Handover Assistant brings these ideas together in one workflow. The main objectives are: (i) to convert voice or text handovers into structured SBAR/ISBAR summaries and extract medications, vitals, pending tasks and care instructions; (ii) to encrypt each record so only the named recipient nurse(s) can decrypt it, and to re-encrypt it for a doctor on escalation; (iii) to secure communication with HTTPS/TLS and role-based access control (RBAC); and (iv) to provide a RAG chatbot for natural-language queries over received handovers. The system supports clinical staff and does not replace clinical judgement; AI-generated summaries must be reviewed by the nurse, and direct EHR integration is outside the scope of this version.

II. LITERATURE SURVEY

Twenty related works were reviewed and are grouped by theme: handover practice, speech recognition for clinical documentation, LLMs for clinical text, RAG, and encryption of health records.

A. Clinical Handover Practice

Galli et al. [1] studied nursing handover in an emergency department and treat handover quality as something that can be observed, measured and improved. Alizadeh-Risani et al. [2] compared SBAR with a modified handover model and measured both handover quality and nurse perception, supporting SBAR as the baseline structure and showing that nurse acceptance matters. McCarthy et al. [3] reviewed structured handoff protocols for within-hospital transitions, supporting a fixed SBAR/ISBAR layout over free text. Starmer et al. [4] reported a reduction in medical errors after the I-PASS handoff programme, linking structured handoff to a measurable safety outcome.

B. Speech Recognition for Clinical Documentation

Johnson et al. [5] analysed 162 recorded handovers alongside written nursing notes and found comparable content (2109 items versus 1902), suggesting one spoken handover could generate the written record. Suominen et al. [6] combined speech recognition with information extraction; the best recorder–microphone setup reached 79% correctness and accented speech was harder to recognise, which motivates audio normalisation before transcription. Xu et al. [7] support speech as a hands-free input channel. Hou et al. [8] developed a code-switching ASR system for nursing records with a reported word error rate of 12.3% in intensive care. Lee et al. [9] observed mean accuracy rising from 87.06% to 95.07% across four sessions with 21 nurses. Ng et al. [10] systematically reviewed AI speech recognition for clinical documentation and support keeping a human review step.

C. Large Language Models for Clinical Text

Su et al. [11] combined a fine-tuned Whisper model with an LLM to generate structured nursing notes; the mixed error rate fell from 44.79% to 6.67%, the hallucination rate was 2.51%, and 75.8% of surveyed nurses reported a favourable experience. This is the work closest to our voice-to-structured-note pipeline. Hartman et al. [12] generated emergency-medicine handoff notes with LLMs: the notes were more detailed but rated lower in overall quality and carried more potential safety risk. Cao et al. [13] used a structured template and prompt framework to generate nursing diagnoses and care plans. Van Veen et al. [14] found that adapted LLMs produced summaries judged equivalent (45%) or superior (36%) to those of medical experts. Tang et al. [15] showed that zero-shot summaries can be factually inconsistent, and Asgari et al. [16] proposed the CREOLA framework to assess hallucination and omission in LLM-generated clinical notes.

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D. *Retrieval-Augmented Generation*

Lewis et al. [17] introduced RAG, pairing a generative model with a retrievable document memory. Xiong et al. [18] proposed the MIRAGE benchmark and MedRAG toolkit and showed that RAG raised the accuracy of six models by up to 18% over chain-of-thought prompting, demonstrating the value of retrieval grounding in medicine.

E. *Encryption of Health Records*

Li et al. [19] proposed patient-centric attribute-based encryption (ABE) of personal health records on semi-trusted servers, with revocation and break-glass access. Walid et al. [20] compared CP-ABE, KP-ABE and multi-authority ABE for EHR systems on MIMIC-III data, guiding the choice of encryption approach for recipient-bound records.

TABLE I: SUMMARY OF THE SURVEYED LITERATURE

Theme	Refs.	Contribution to this work
Handover practice	[1]–[4]	Handover is a vulnerable, improvable step; SBAR/ISBAR and structured protocols reduce errors
Speech recognition	[5]–[10]	Voice can yield documentation; audio quality matters; human review kept
LLMs for clinical text	[11]–[16]	Voice-to-note is feasible; hallucination risk requires nurse verification
RAG	[17], [18]	Retrieval grounding improves medical answers; basis of chatbot
Health-record encryption	[19], [20]	Encrypt before storage; only authorised parties decrypt

The survey shows that structured handover formats, speech recognition, LLM summarisation, RAG and attribute-based encryption have each been studied and applied in healthcare, but generally in isolation. None of the surveyed papers combines, in a single nurse-to-nurse handover workflow, AI-generated SBAR/ISBAR summaries, encryption bound to the named recipient nurses, escalation of the re-encrypted record to a doctor, and a RAG chatbot restricted to each recipient's own decrypted handovers. This is the gap addressed by the proposed system. The work on hallucination and safety [12], [15], [16] also confirms that AI-generated summaries should be presented to nurses for review rather than filed unchecked.

III. SYSTEM DESIGN

A. *Existing System and Its Limitations*

Handover today relies on verbal briefings, handwritten notes or free-text EHR entries. The incoming nurse must listen, transcribe and cross-check manually. The limitations are: the process is slow and error-prone; documentation style is inconsistent; SBAR/ISBAR is followed on paper with no AI assistance; past handovers are hard to retrieve; there is no conversational way to query them; encryption is limited; and handover data is typically visible to any staff member with system access rather than only the intended recipient.

B. *System Architecture*

The system follows the layered architecture of Fig. 1. The Presentation Layer has two clients: a web application (HTML5, CSS3, Bootstrap, JavaScript) for the Administrator and Hospital roles, and a Flutter mobile application for the Nurse and Doctor roles. Both exchange JSON with the backend over HTTPS/TLS. The Application Layer is a Django backend whose REST API applies authentication and RBAC to every request and routes it to the Hospital and User Management, Handover Management, AI Handover Generation, Recipient-Bound Encryption and RAG Chatbot modules. The Data Layer comprises a MySQL database holding users, hospitals, patients and encrypted handover records, and a vector store (FAISS or Chroma) holding chatbot embeddings. External AI Processing Services provide audio normalisation (FFmpeg), speech-to-text, the Gemini API for SBAR summaries and chatbot answers, and an embedding model. Because each handover is encrypted before storage, the database holds only encrypted records.

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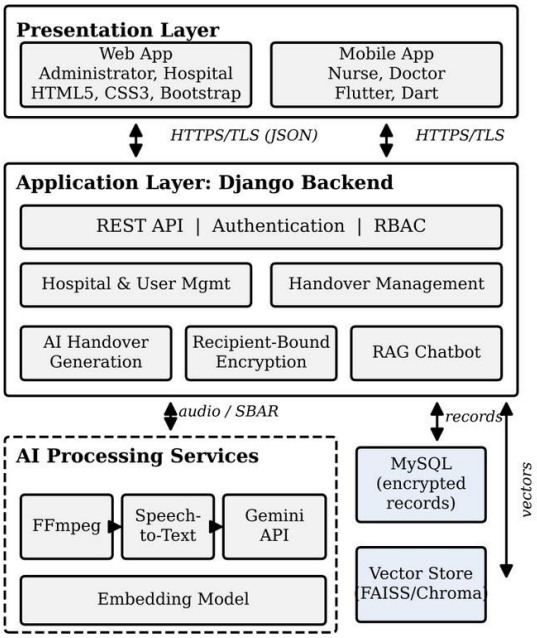


Fig. 1. System architecture of the proposed system.

C. *Handover Workflow*

The workflow of the proposed system is as follows.

- A hospital registers and is approved by the Administrator; it then adds and manages nurses and doctors, and registers and admits patients to wards.
- At shift change, the outgoing nurse records a voice or text handover and selects the incoming nurse(s).
- The audio is normalised with FFmpeg, transcribed by the speech-to-text API and summarised by the Gemini API into an SBAR/ISBAR report; medications, vitals and pending tasks are extracted and saved as separate records.
- The nurse reviews the generated summary before it is sent, in line with the need for human verification of AI output [11], [16].
- The record is encrypted and bound to the addressed recipient(s); the summary is chunked and indexed for the recipient's chatbot.
- The recipient decrypts and reviews the handover or queries the chatbot. If the case cannot be handled, it is escalated to a doctor, re-encrypted for that doctor, and an email notification is sent.

D. *Recipient-Bound Encryption*

Every handover record is encrypted before storage and bound to the named recipient nurse(s), so a handover sent to one nurse cannot be opened by any other nurse or doctor, even on the same ward. When the receiving nurse cannot handle the case, the handover is escalated with an escalation reason and re-encrypted so that only the chosen doctor can open it. Client–server traffic uses HTTPS/TLS and passwords are stored in encrypted form. All access is checked against RBAC and recipient binding and logged for audit.

E. *RAG-Based Handover Chatbot*

Decrypted summaries are split into chunks, converted to embeddings and stored in the vector store [21]. When a nurse or doctor asks a question, the most relevant chunks from that user's own authorised handovers are retrieved and passed with the question to the Gemini API [22] to produce a grounded answer [17], [18]. Each question and answer is logged for traceability. Email notifications via SMTP inform recipients of new or escalated handovers.

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F. Modules and Data Entities

The system has four role-based modules and four supporting modules. The Administrator module (web) approves hospital registrations, views nurses, doctors and patients, and generates system reports. The Hospital module (web) manages its nurses, doctors, wards and patient admissions and reviews shift audit history. The Nurse module (mobile) records handovers, reviews AI summaries, views received handovers, escalates to a doctor, uses the chatbot, and views vitals, medications and pending tasks. The Doctor module (mobile) views escalated handovers with vitals, medications and escalation reason, views pending tasks and history, and uses the chatbot. The supporting modules are AI Handover Generation, Recipient-Bound Encryption, RAG Chatbot and Email Notification. The main data entities are Hospital, Nurse, Doctor, Patient, Wards, HandoverReport, HandoverRecipient, VitalObservation, MedicationRecord, PendingTask, HandoverEmbedding and ChatQueryLog.

G. Data Flow Design

Data flow diagrams (DFDs) describe how data moves between the external users, the processes of the system and its data stores. The Level 0 diagram shows the system as a single process, and the Level 1 diagrams break it into the processes available to each role.

The Level 0 diagram (Fig. 2) is the context diagram. The external entities (Administrator, Hospital, Nurse and Doctor) send requests to the AI Clinical Handover System and receive responses. The system in turn reads from and writes to the MySQL database in the same request–response manner.

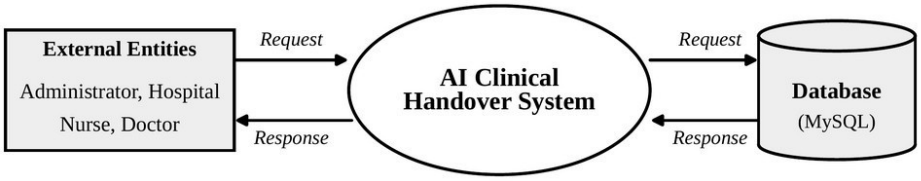


Fig. 2. Level 0 data flow diagram (context diagram) of the AI Clinical Handover System.

The Level 1 diagrams expand the system into the processes available to each role and the data stores they use. Table II lists the data stores that appear in the Level 1 diagram of each module.

TABLE II: DATA STORES IN THE LEVEL 1 DFDS

Module	Data stores
Administrator	D1 Auth User; D2 Hospital; D3 Nurse; D4 Doctor; D5 Report
Hospital	D1 Hospital; D2 Auth User; D3 Nurse; D4 Doctor; D5 Wards; D6 Patient; D7 Handover Report
Nurse	D1 Auth User; D2 Nurse; D3 Handover Report; D4 Handover Recipient; D5 Chat Query Log; D6 Vital Observation; D7 Medication Record; D8 Patient
Doctor	D1 Auth User; D2 Handover Report; D3 Pending Task; D4 Chat Query Log

1) Administrator Module: The Administrator logs in against the Auth User store (D1), manages hospitals (D2), views the profile, views nurses (D3) and doctors (D4), and generates system reports (D5), as shown in Fig. 3. Login verifies the Administrator against the Auth User store. Manage Hospitals approves or manages the hospital registrations held in the Hospital store. View Nurses and View Doctors read the approved nurse and doctor profiles. System Reports reads the Report store to give a system-wide view of handover activity.

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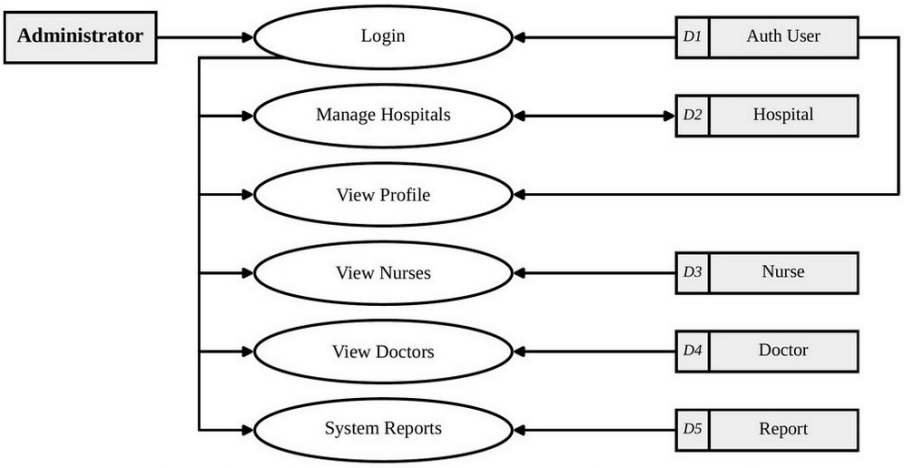


Fig. 3. Level 1 data flow diagram of the Administrator module.

2) Hospital Module: The Hospital registers and logs in (D1, D2), views its profile, manages its nurses (D3) and doctors (D4), manages wards and departments (D5) and patient admissions (D6), and reviews shift audit history from the handover reports (D7), as shown in Fig. 4. Register and Login create and authenticate the hospital account, and the registration is approved by the Administrator. Manage Nurses and Doctors under Hospital adds and manages the staff of the hospital. Manage Wards/Departments and Manage Patient Admissions maintain ward capacity and admit patients to wards. Shift Audit History reads the handover reports so that the hospital can audit shift handovers.

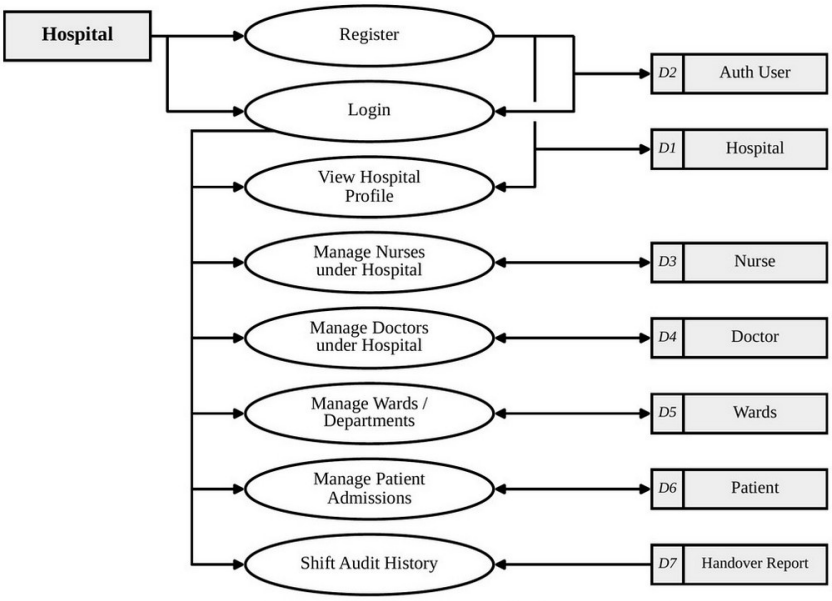


Fig. 4. Level 1 data flow diagram of the Hospital module.

3) Nurse Module: The Nurse logs in (D1), updates the profile (D2), records and sends a handover to a specific nurse, reviews the AI-generated summary and sends it through encrypted transmission (D3), views received handover reports (D4), escalates a received handover to a doctor, uses the RAG-based chatbot (D5), views patient vitals and medications (D6, D7), searches previous handover reports and updates patient status (D8), as shown in Fig. 5. Record/Send Handover captures the voice or text handover and the chosen recipient(s); the AI pipeline creates the SBAR/ISBAR summary and stores the encrypted report. Review AI-Generated Summary and Encrypted Handover Transmission let

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the nurse check the summary before the encrypted handover is sent. View Received Handover Report decrypts a handover for the addressed recipient only, using the Handover Recipient store. Escalate Received Handover to a Doctor re-encrypts the record for the chosen doctor with an escalation reason. The RAG-Based Chatbot answers questions from the nurse's own handovers and logs each query. The remaining processes read the extracted vitals and medications, search past reports and update the Patient store.

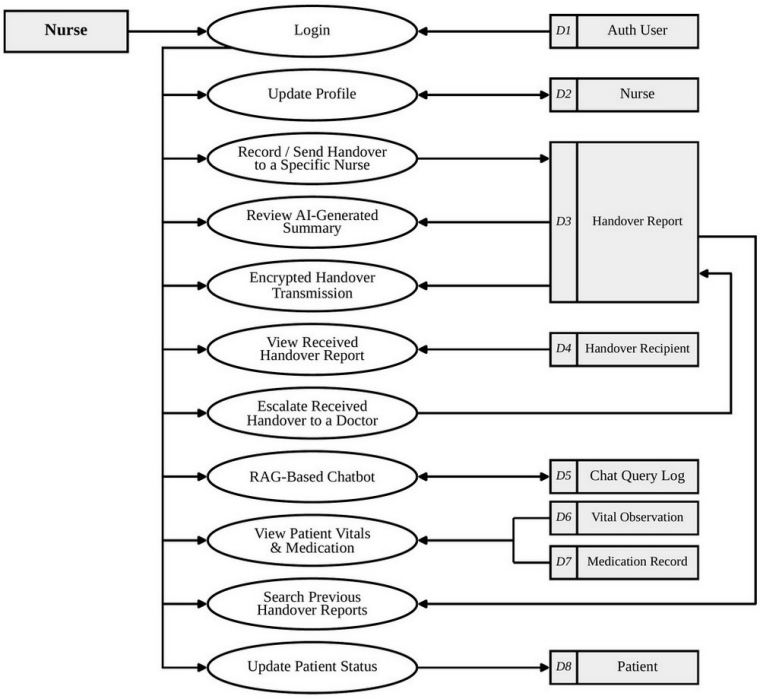


Fig. 5. Level 1 data flow diagram of the Nurse module.

4) Doctor Module: The Doctor logs in (D1), views handover reports escalated by nurses (D2) and the handover history, views pending tasks (D3) and uses the RAG-based handover chatbot over the handovers escalated to the doctor (D4), as shown in Fig. 6. View Handover Report Sent by Nurse shows the escalated report with its SBAR/ISBAR summary, vitals, medications and escalation reason. View Handover History lists previously escalated handovers, searchable by patient and date. View Pending Tasks shows the pending clinical tasks extracted from escalated handovers. The RAG-Based Handover Chatbot answers questions about the handovers escalated to the doctor and logs each query.

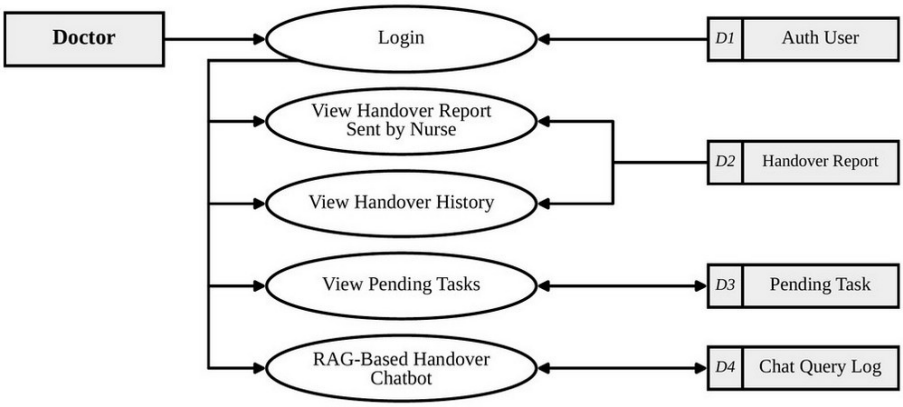


Fig. 6. Level 1 data flow diagram of the Doctor module.

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IV. CONCLUSION AND FUTURE WORK

This paper presented the AI-Based Clinical Handover Assistant, a secure hybrid web and mobile system for nurse-to-nurse shift handover. A survey of twenty papers showed that structured handover, speech recognition, LLM summarisation, RAG and attribute-based encryption have each proved useful in healthcare but are rarely combined in a single workflow. The proposed design converts voice or text handovers into SBAR/ISBAR summaries, encrypts each record so that only the addressed recipient nurse(s) can read it, supports escalation to a doctor through re-encryption, and gives recipients a RAG chatbot grounded in their own authorised handovers. The system is expected to reduce documentation time, minimise communication gaps between shifts, and strengthen patient safety and confidentiality. This phase covers requirements and design; implementation and evaluation of summary accuracy, transcription quality and chatbot answers remain for later phases.

Future work includes: AI-based clinical completeness checks that flag missing or unusual details in a summary; multi-language support for regional languages; stronger voice or biometric authentication for shared devices; deeper EHR integration; trend summaries across a patient's handover history; QR-code bedside access and offline-capable mobile recording; and cloud deployment (e.g., AWS or Azure) for multi-hospital scale.

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REFERENCES

[1]. A. Galli, E. Andreoli, F. Y. Pallua, I. Silvestri, A. Manenti, L. Dignani, S. Contucci, et al., "Improvement of nursing handover in emergency department: a prospective observational cohort study," 2025, doi: 10.1007/s44250-025-00180-3.

[2]. A. Alizadeh-Risani, F. Mohammadkhah, A. Pourhabib, Z. Fotokian, et al., "Comparison of the SBAR method and modified handover model on handover quality and nurse perception in the emergency department: a quasi-experimental study," 2024, doi: 10.1186/s12912-024-02266-4.

[3]. S. McCarthy, A. Motala, E. Lawson, and P. G. Shekelle, "Use of structured handoff protocols for within-hospital unit transitions: a systematic review from Making Healthcare Safer IV," BMJ Qual. Saf., vol. 34, no. 10, pp. 680–690, 2025, doi: 10.1136/bmjqs-2024-018385.

[4]. A. J. Starmer et al., "Changes in medical errors after implementation of a handoff program," N. Engl. J. Med., vol. 371, no. 19, pp. 1803–1812, 2014.

[5]. M. Johnson et al., "Comparing nursing handover and documentation: forming one set of patient information," Int. Nurs. Rev., vol. 61, no. 1, pp. 73–81, 2014.

[6]. H. Suominen et al., "Capturing patient information at nursing shift changes: methodological evaluation of speech recognition and information extraction," J. Am. Med. Inform. Assoc., vol. 22, no. e1, pp. e48–e66, 2015, doi: 10.1136/amiajnl-2014-002868.

[7]. W. Xu et al., "Application and research of intelligent speech recognition technology in barrier-free human–computer interaction," 2025, doi: 10.1109/CSNT64827.2025.10968167.

[8]. S. Y. Hou, Y. L. Wu, K. C. Chen, et al., "Code-switching automatic speech recognition for nursing record documentation: system development and evaluation," JMIR Nursing, vol. 5, no. 1, e37562, 2022, doi: 10.2196/37562.

[9]. T. Y. Lee, C. C. Li, K. R. Chou, et al., "Machine learning-based speech recognition system for nursing documentation – a pilot study," Int. J. Med. Inform., vol. 178, 105213, 2023, doi: 10.1016/j.ijmedinf.2023.105213.

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[10]. J. J. Ng, E. Wang, X. Zhou, et al., "Evaluating the performance of artificial intelligence-based speech recognition for clinical documentation: a systematic review," BMC Med. Inform. Decis. Mak., vol. 25, no. 1, p. 236, 2025, doi: 10.1186/s12911-025-03061-0.

[11]. M.-H. Su, W.-C. Wang, Y.-M. Hsu, S.-Y. Hou, S.-J. Chuang, and S.-S. Chang, "Voice-based structured nursing documentation using automatic speech recognition and large language models: development and evaluation study," JMIR Nursing, vol. 9, e88567, 2026, doi: 10.2196/88567.

[12]. V. Hartman et al., "Developing and evaluating large language model–generated emergency medicine handoff notes," JAMA Netw. Open, 2024.

[13]. Y. Cao, L. Hu, X. Cao, and J. Peng, "Can large language models facilitate the effective implementation of nursing processes in clinical settings?," BMC Nursing, vol. 24, art. 394, 2025, doi: 10.1186/s12912-025-03010-2.

[14]. D. Van Veen et al., "Adapted large language models can outperform medical experts in clinical text summarization," Nat. Med., vol. 30, pp. 1134–1142, 2024, doi: 10.1038/s41591-024-02855-5.

[15]. L. Tang et al., "Evaluating large language models on medical evidence summarization," npj Digit. Med., vol. 6, 2023, doi: 10.1038/s41746-023-00896-7.

[16]. E. Asgari et al., "A framework to assess clinical safety and hallucination rates of LLMs for medical text summarisation," npj Digit. Med., vol. 8, art. 274, 2025.

[17]. P. Lewis et al., "Retrieval-augmented generation for knowledge-intensive NLP tasks," in Advances in Neural Information Processing Systems (NeurIPS), vol. 33, 2020.

[18]. G. Xiong, Q. Jin, Z. Lu, and A. Zhang, "Benchmarking retrieval-augmented generation for medicine," in Findings of the Association for Computational Linguistics: ACL 2024, 2024.

[19]. M. Li, S. Yu, Y. Zheng, K. Ren, and W. Lou, "Scalable and secure sharing of personal health records in cloud computing using attribute-based encryption," IEEE Trans. Parallel Distrib. Syst., vol. 24, no. 1, pp. 131–143, 2013.

[20]. R. Walid, K. P. Joshi, and S. G. Choi, "Comparison of attribute-based encryption schemes in securing healthcare systems," Sci. Rep., vol. 14, 2024, doi: 10.1038/s41598-024-57692-w.

[21]. J. Johnson, M. Douze, and H. Jégou, "Billion-scale similarity search with GPUs," IEEE Trans. Big Data, vol. 7, no. 3, pp. 535–547, 2021.

[22]. Gemini Team, Google, "Gemini: a family of highly capable multimodal models," arXiv:2312.11805, 2023