Research Project Proposal

Immersive AI-Driven Nursing Education: A Multimodal Integration of VR Simulations and Conversational Language Models For Advanced Wound Care Training

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Abstract

Nursing education requires immersive, hands-on training to develop critical clinical skills, particularly in advanced wound care. Traditional teaching methods, such as lecture-based instruction and task-oriented training, often fail to provide the level of interactivity and realism necessary for mastering these complex procedures. This research explores the integration of Virtual Reality (VR) simulations and Artificial Intelligence (AI) driven conversational models to enhance nursing education. By leveraging VR, students can engage in realistic, interactive scenarios that simulate clinical environments, while AI driven conversational agents provide real-time feedback and personalized guidance.

The proposed approach involves a five step VR based simulation framework, including scenario introduction, patient history gathering, wound assessment, wound cleaning, and final evaluation. The system integrates AI models for speech-to-text (STT) and text-to-speech (TTS) processing, enabling seamless voice-based interactions. Fine tuned Large Language Models (LLMs) are used for virtual patient and the evaluator, guiding students through the simulation and providing performance assessments. Haptic feedback devices further enhance the realism of the experience by simulating tactile sensations during wound care procedures.

This study aims to bridge the gap between theoretical knowledge and practical competence in nursing education by offering an immersive, cost-effective, and scalable training solution. The findings will contribute to the advancement of AI-driven VR applications in medical training, improving the competency and preparedness of future healthcare professionals.

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1. Introduction

Nursing education plays a pivotal role in preparing healthcare professionals to deliver high-quality, patient-centered care. However, traditional teaching methods, such as lecture-based instruction and task-oriented clinical training, often fall short in providing the immersive, hands-on experiences necessary for mastering complex clinical procedures, including advanced wound care. This limitation has prompted the exploration of innovative technologies, such as Virtual Reality (VR) and Artificial Intelligence (AI), to elevate nursing education to new standards of effectiveness and engagement.

Advanced wound care training presents unique challenges, as it demands a blend of technical proficiency, critical thinking, and practical experience. Immersive technologies, including VR simulations and AI-driven conversational models, offer a transformative solution by creating realistic, interactive, and scalable training environments. These tools not only enhance clinical decision support and e-learning platforms but also provide students with opportunities to practice complex procedures in safe, controlled settings. For example, VR platforms like vSim for Nursing and Shadow Health's Digital Clinical Experience enable students to hone their clinical skills through immersive simulations. Similarly, AI-powered tools facilitate personalized feedback, adaptive learning, and the generation of tailored educational content, such as quizzes and wound images, to support diagnosis and treatment planning.

Furthermore, the integration of metaverse technologies combining VR, Augmented Reality (AR), and machine learning offers real-time diagnostics and immersive experiences, making wound care training more engaging, personalized, and efficient. These advancements hold significant promise for bridging the gap between theoretical knowledge and practical application in nursing education. This research project seeks to address the limitations of traditional nursing education by integrating VR simulations and AI-driven conversational models, with a specific focus on advanced wound care training. The study will explore the theoretical foundations, methodologies, and practical applications of these technologies, emphasizing their potential to enhance student engagement, competence, and confidence in clinical practice. By leveraging cutting-edge tools, this research aims to create a more immersive, interactive, and effective learning environment for nursing students.

The remainder of this proposal outlines the motivation behind this research, identifies key objectives, reviews relevant literature, and details the proposed methodology, including implementation strategies, expected outcomes, and the technologies to be utilized. Through this exploration, the study aims to contribute to the ongoing evolution of nursing education, ensuring that future healthcare professionals are better equipped to meet the demands of modern patient care.

2. Problem Statement

Traditional approaches to nursing education, including lecture-based teaching and task-focused clinical training, often fall short in delivering the realism and interactivity necessary to adequately prepare students for intricate procedures such as advanced wound care. These conventional methods lack the immersive, hands-on experiences essential for developing technical proficiency, critical thinking, and the ability to apply knowledge in real-world clinical settings. Consequently, a significant disconnect exists between theoretical understanding and practical skills, potentially compromising the quality of patient care and the effectiveness of wound care training.

Figure 1: Bleeding thigh wound and evisceration on mannequin

Currently, nursing education relies heavily on manikin-based training like showed in *Figure 1*, which presents several critical limitations. Manikins are costly, require extensive preparation, and allow only one student to practice at a time, making it difficult for instructors to assess every student individually. Additionally, the preparation and maintenance of manikins are time-consuming and expensive, further restricting their scalability and accessibility in nursing programs. These challenges hinder the efficiency of training and limit opportunities for students to gain hands-on experience.

To bridge this gap, emerging technologies such as Virtual Reality (VR) and Artificial Intelligence (AI) have been identified as promising solutions. A VR-based training system integrated with Conversational AI offers the potential to create an immersive, interactive, and cost-effective learning environment where students can practice wound care techniques without the constraints of physical equipment. However, the integration of VR with AI-driven conversational models presents several challenges:

- Technical Complexity: Developing a fine-tuned Large Language Model (LLM) for guiding students through wound care procedures within a VR environment requires advanced expertise in AI, natural language processing, and medical simulation.

- Voice Recognition Accuracy: Ensuring that the AI model accurately interprets and responds to voice commands in real time is critical for effective training but remains a technical hurdle.

- Realism and Effectiveness: The VR simulation must offer a high-fidelity and realistic experience to properly replicate wound care procedures, requiring sophisticated graphical and haptic feedback mechanisms.

- Performance Assessment Reliability: The AI-driven system must provide accurate, objective, and meaningful feedback to students, necessitating the development of reliable assessment criteria and robust datasets.

- High Initial Investment: While VR training can be more cost-effective in the long run, the initial costs of VR hardware, software development, and AI model training can be substantial for educational institutions.

- Adoption and Learning Curve: Faculty and students may require significant training to effectively utilize VR-based wound care training, which could impact adoption rates.

- Infrastructure and Resource Demands: The successful deployment of a VR-based training system requires VR-ready computers, headsets, and sufficient institutional support, which may pose logistical and financial challenges.

Despite these challenges, integrating VR simulations with Conversational AI represents a transformative approach to nursing education. By enhancing accessibility, reducing training costs, and providing automated performance assessments, this approach has the potential to overcome the limitations of traditional methods and significantly improve the competency and preparedness of nursing students in advanced wound care. However, further research is necessary to optimize this integration, validate its effectiveness, and address the technical and practical challenges associated with its implementation.

3. Aim and Objectives

3.1. Aim

The aim of this research is to investigate the integration of Virtual Reality (VR) simulations and Artificial Intelligence (AI)-driven conversational models in nursing education, with a specific focus on advanced wound care training. It seeks to evaluate how these innovative technologies can address the limitations of traditional nursing education methods and enhance the preparation of nursing students for complex clinical procedures. The research will explore the effectiveness of VR and AI in improving technical skills, critical thinking, and hands-on practice, ultimately aiming to bridge the gap between theoretical knowledge and practical competence in nursing education.

3.2. Objectives

3.2.1 General Objective

The aim of this research is to investigate the integration of Virtual Reality (VR) simulations and Artificial Intelligence (AI)-driven conversational models in nursing education, with a specific focus on advanced wound care training. It seeks to evaluate how these innovative technologies can address the limitations of traditional nursing education methods and enhance the preparation of nursing students for complex clinical procedures. The research will explore the effectiveness of VR and AI in improving technical skills, critical thinking, and hands-on practice, ultimately aiming to bridge the gap between theoretical knowledge and practical competence in nursing education.

3.2.2 Specific Objectives

1. Immersive VR Environment

   Develop a realistic, interactive, and user-friendly virtual environment tailored to nursing education scenarios.

2. Conversational AI Integration

   Implement a robust, context-aware AI capable of natural, real-time interactions to simulate patient communication and provide feedback.

3. System Efficiency

   Ensure the VR system and AI operate seamlessly with minimal latency, high responsiveness, and scalability.

4. Educational Effectiveness

   Enhance learning outcomes by providing realistic, scenario-based training that bridges theoretical knowledge and practical skills.

5. Learning Objectives:

   - Identifying different types of wounds (e.g., surgical, pressure ulcers, burns).

- Understanding wound assessment techniques (e.g., measuring size, depth, and infection signs).
- Practicing proper wound cleaning, dressing, and bandaging techniques.
- Recognizing signs of complications (e.g., infection, necrosis).
- Developing communication skills.

4. Literature Review

The literature review explores the integration of Virtual Reality (VR) simulations and AI-driven conversational models in nursing education, particularly for advanced wound care training [1]. Traditional nursing education often lacks immersive, hands-on experiences needed for mastering complex procedures, making VR and AI promising solutions [1]. The review examines the theoretical underpinnings, methodologies, and applications of these technologies, emphasizing their potential to bridge the gap between theory and practice.

4.1. The Role of VR in Nursing Education

Virtual Reality (VR) is an immersive technology that simulates a computer-generated environment, allowing users to interact with digital spaces in a realistic manner. The health-care industry has increasingly focused on VR, Augmented Reality (AR), Mixed Reality (MR), and Extended Reality (XR) technologies, as they enhance the efficacy and efficiency of nursing and medical healthcare services while addressing the limitations of traditional medical practices and education [2]. VR improves knowledge retention, skill acquisition, and learner satisfaction compared to other methods [3]. Interactive virtual simulation provides nursing students with an engaging learning experience, allowing them to cultivate the competencies necessary to deliver high-quality patient care [3]. VR enhances learning experiences, improves engagement and retention, ensures standardized training procedures, offers long-term cost savings, and builds empathy through realistic patient simulations [4].VR is often considered superior to AR and XR for certain types of research due to its immersive nature and controlled environment [3]. VR enables students to visualize complex phenomena, understand dynamic relation- ships between variables, and explore abstract concepts in a 3D format [2]. It also provides opportunities for experiential learning that may not be feasible due to time, cost, safety, or availability constraints [2]. VR platforms like vSim for Nursing and Shadow Health's Digital Clinical Experience allow students to practice clinical skills in safe, controlled environments [5]–[9].

One methodology for using VR is aimed at systematically developing 3D nursing simulation content based on Han's VR educational design model and the National League for Nursing (NLN) Jeffries Simulation Theory [10]–[12]. Another methodology involves gaining an understanding of wound care and the procedures for changing a wound dressing by referring to relevant texts and instructional videos, as well as consulting clinical experts regarding the procedures, techniques, and training approaches used in real practice [12], [13]. A key feature in dementia care involves conversations with Non-Player Characters (NPCs) [14].

4.2. Limitations and challenges of VR in Nursing Education

VR provides safe training environments but struggles to replicate complex real-world scenarios [15]. Practical experience gained through VR may be limited compared to actual clinical exposure [15]. Virtual simulations and models present idealized solutions but encounter difficulties when applied to real-world scenarios [15]. Translating virtual representations into real-world medical practice requires consideration of additional variables and unforeseen factors [15]. One potential improvement for VR-based learning could include AI-driven conversational interactions or error detection systems to enhance engagement and learning outcomes [4]. A study with nursing experts indicated difficulties with voice recognition, as the system did not always accurately recognize spoken keywords [12]. Some participants also found the virtual interactive experiences fascinating and were pleased to apply what they learned in practice [12]. Some feedback described the experience as feeling like "playing with air" [13]. The hardware adopted in this study was the HTC VIVE VR system, which provides a pair of controllers capable of producing vibrotactile haptic feedback, but a gap is evident in the hand detection system [13]. A summary of the Different VR methodologies for nursing education can be found in Table 01.

Table 1: Summary table - Different VR methodologies for Nursing education

Method	Limitations	Benefits of using the method
Han's VR Educational Design Model & NLN Jeffries Simulation Theory	• Voice recognition inaccuracies • Technical issues with virtual object manipulation • Disruptions in virtual spaces	• NLP using keyword detection
Iterative Development Cycle with Clinical Expert Feedback	• Lack of realistic haptic feedback • Limited fine motor skill simulation • Feels like "playing with air"	• Responsive method with good feedback from the users
Head-Mounted VR System for Dementia Care with NPCs	• Requires a second person for roleplaying • Limited conversational AI integration	• Introducing a non-character-based roleplay scenario for conversation.

4.3. Conversational AI

Conversational AI is a sub-domain in artificial intelligence that deals with text-based or speech-based AI agents designed to simulate human-like conversations in natural language. Conversational AIs can be used to personalize, make accessible, and keep up-to-date educational content for healthcare professionals. [16] It consists of three major components: natural language understanding, dialogue management system, and natural language generation. [17] Voice-Based Conversational Agents in Virtual Reality (VR) use 3D human-like avatars that interact with users through both text and speech, enhancing engagement compared to traditional text-based conversational AI. In below paragraphs, how different methodologies are utilized in the previous studies are explored.

4.3.1. RASA Open-Source Conversational AI Framework

RASA is an open-source conversational AI framework that separates natural language [18] understanding (NLU) and dialogue management, enabling task-oriented chatbots. Its modularity makes it suitable for specific tasks like customer service or FAQ bots, but it requires manual work for handling complex contexts and new inputs. The key limitation is that RASA doesn't support end-to-end learning, which can cause difficulties in adapting to dynamic conversational scenarios. Enhancements could include integrating end-to-end models or combining RASA with more advanced NLU components to handle more dynamic, multi-turn conversations and complex contexts. [19]

4.3.2. Generative Pretrained-Based Recurrent Neural Networks

GPbRNN integrates Recurrent Neural Networks (RNNs) with Generative Pretrained Transformers (GPTs) [20] to enhance emotional prediction, response relevance, and conversational fluency. It showed strong performance on the MIMIC-III dataset [21] with high accuracy and F1 scores. However, real world applications are still limited, and further validation is needed. The model's structure, which includes input, hidden, tokenization, lemmatization, and output layers, could be enhanced by integrating more sophisticated emotion recognition and contextual understanding features to improve its dynamic performance in healthcare environments.

4.3.3. Dialogflow-Based Approach

DialogFlow uses an intent- and entity-based method for natural language understanding (NLU), ideal for structured interactions like those in nursing education. [22] However, it struggles with deviations from predefined conversation paths, leading to a lack of conversational fluidity. A major limitation is its retrieval-based nature, which limits the flexibility of responses. Future enhancements could involve hybrid models that combine retrieval-based methods with generative capabilities, allowing the system to handle unexpected conversational turns and provide more dynamic, context-aware responses.

4.3.4. Retrieval-Augmented Generation (RAG)

RAG combines retrieval and generation [23], where a retriever fetches relevant context or information from external sources, and a generative model (like GPT or BART) uses that context to generate answers. This approach enables the AI to respond dynamically to new queries without relying solely on static training data. The limitations include the potential for inaccurate responses if the retrieval mechanism fails. Enhancements could involve improving the accuracy of the retrieval mechanism and integrating real-time knowledge sources for even more up-to-date information.

4.3.5. Fine Tuning LLM

Fine-tuning [23] adapts pre-trained models (like GPT or LLaMA) to a specific domain, such as healthcare or wound care, by training the model on a specialized dataset. This improves the model's relevance and accuracy for domain specific tasks. The key limitation is that it requires a large, well-annotated dataset, and computational resources can be high. Enhancements could involve using Low-Rank Adaptation (LoRA) to make the fine-tuning process more efficient, reducing computational costs while maintaining high performance, and periodically updating the fine-tuned model with new data.

When the solution is developed, we can use one of above methodologies in *Table 2* below or go with a completely newer method for implementing conversational AI. In the proposed approach section the selected methodology is explained in detail.

Table 2: Summary Table – Methodologies for Creating Convocational AI

Method	Limitations	Benefits of using the method
RASA (Rule-based & ML-based NLU)	Doesn't support end-to-end learning. Struggles with complex context.	Ideal for task-oriented chat bots Easy to implement

GPbRNN (Generative Pretrained RNNs)	Limited real-world implementation.	Strong sentiment understanding
Google Dialog Flow (Intent-based NLU)	Limited flexibility Struggles with unstructured or small talk.	Well-structured for predefined workflows Can be integrate with fine-tuned LLMs
Fine tuning	Computationally expensive. Needs retraining for new information.	More flexible More accuracy for seen and unseen data More resources to learn
Retrieval Augmented Generation (RAG)	May generate inaccurate responses if retrieval fails.	Better for frequently changing dataset.

4.4. Text-To-Speech (TTS) and Speech-To-Text (STT) Systems

In the development of immersive virtual reality (VR) applications with conversational AI (CA) for training scenarios like wound care for nurses, the integration of text-to-speech (TTS) and speech-to-text (STT) systems plays a crucial role in enhancing the interactivity and realism of the experience. Traditionally, many CAs have been limited to text-based interactions. However, with advancements in technology, it is now possible for CAs to engage in voice-based conversations with users in a virtual environment (VE) [18]. A study explored avatar-based communication in VR [18] using TTS and STT modules. A voice-to-voice sub- module facilitates audio exchange between users and the TTS module. There is a central server managing input transcription and response synthesis. The system employs Wav2Vec2.0 for STT (0.8s on CPU) and SpeechT5 for TTS (1.7s on CPU). To maintain conversational flow, long responses are divided into smaller chunks, strategically incorporating natural pauses to reduce delays. However, response time discrepancies persist, making real-time interactions feel less natural, especially in dynamic training scenarios.

Another study on a ChatGPT-powered immersive virtual reality experience [24] uses OpenAI's Whisper for STT. The transcribed text is then processed by the GPT-4 Turbo model, which generates contextually relevant responses. For verbal output, the system employs OpenAI's TTS model to convert text-based responses into realistic speech. To mitigate latency, responses are streamed in smaller chunks. However, challenges persist, particularly with text response streaming delays fromGPT-4 Turbo via OpenAI's API. While an edge server helps reduce communication lag, the overall response generation time remains a bottleneck, especially for complex queries.

A study conducted to enable voice commands in a virtual environment [25] (example - arranging a given number of cubes in a row based on voice commands), has utilized the fine-tuned OpenAI Whisper model for this purpose. It was fine-tuned with 29,237 audio files to enhance accent robustness. A limitation of the system is the slow response time, even with a powerful edge server (GPU: Nvidia RTX 3070).

As a conclusion, each methodology has limitations and special benefits of using it based on the research previously done in Table 3.

Table 3: Summary table TTS modules

Method	Limitations	Benefits of using the method
Wav2Vec2.0	• Slower response time • Must have to fine-tuned for domain specific data	• Open source
OpenAI Whisper	• Slower response time for low performance server	• Open source • Highly customizable
Google's Speech-to-Text API	• Poor recognition of non-native accents.	• Ideal for real Time conversations • Medical SST model available for trained for healthcare sector data

Shorey et al. [22] highlight another possible limitation in the STT model. They used Google's Speech-to-Text API, which is optimized for American and British English, leading to poor recognition rates for non-native accents. A study conducted with Singaporean nursing students revealed this issue, as the STT system struggled to accurately transcribe speech influenced by local linguistic patterns. The system also failed to recognize culturally specific pronunciations and complex medical terminology, resulting in translation errors. To mitigate this limitation, researchers implemented a pre-test phase where participants read predefined words to calibrate the STT model. But this problem is not fully resolved by the that approach

4.5. Integration of AI with VR

The convergence of Artificial Intelligence (AI) and Virtual/Augmented Reality (VR/AR) is an area of increasing interest [26]. Vision Language Models (VLMs) are among the most promising AI technologies because they combine computer vision (CV) and natural language processing (NLP) capabilities [27]. VR-GPT enhances VR experiences by leveraging visual language models (VLMs) to enable natural language interactions [27]. GPT-VR Nexus focuses on improving user interaction by incorporating generative AI (like ChatGPT) [24]. There are more Gen AI applications combined with VR, such as sMoRe a mixed reality (MR) application that integrates Generative AI and Large Language Models (LLMs) to help users create, place and manage virtual objects in physical spaces using voice or text commands. [28]

The Virtual Operative Assistant is an explainable AI tool designed for simulation-based training in surgery and medicine serving as an automated educational feedback platform [29]. The platform uses a support vector machine (SVM) to classify skilled and novice participants based on performance in a virtual reality brain tumor resection task and gives two-step feedback [24]. There is also a VR and AI framework to revolutionize advanced manufacturing education and nearshoring in Mexico, aiming to bridge training gaps and empower stakeholders [15].

4.6. Challenges and Future Directions for Integrated VR and AI

A key challenge in VR-based nursing education is the lack of real-time guidance, which can make users feel isolated during training. Integrating conversational AI with VR could address this issue by providing interactive feedback and guidance, thereby enhancing the learning experience. A major limitation of current VR-based systems is the absence of conversational interaction, leaving users without dynamic responses to their actions. Researchers suggest that a conversational AI model, specifically trained for nursing wound care strategies, could improve engagement by responding to the user’s environment and actions within the VR simulation. There are major drawbacks in costly hardware expectations and latency in generating objects and responses. Studies emphasize the significance of evaluating surgical performance in VR based on professional practices, which leads to effective self-learning and self-evaluations of the nursing students.

5. Proposed Approach

Our Proposed VR simulation has 5 major steps

1. Introduction to the accident scenario
2. History taking
3. Wound Assessment
4. Wound Cleaning
5. Evaluation

5.1. Introduction to the accident scenario

The simulation environment is designed to replicate a specific medical scenario, which is pre-defined and provided as a prompt to the Conversational AI model. This fixed scenario ensures consistency and allows for the evaluation of the project's feasibility.

The student, acting as the healthcare provider, will wear a VR headset and activate the virtual environment. Upon initialization, the VR system will display the contextual details of the scenario, which are generated and communicated by the Conversational AI model. These details include:

- Time: The temporal context of the scenario.
- Location: The physical setting where the scenario takes place.
- Patient's Situation: The medical condition or symptoms presented by the virtual patient.
- Environment: The surrounding context relevant to the scenario

The Conversational AI model will first establish a normalized scenario to ensure the student is fully immersed in the virtual environment. Following this, the VR system will render a detailed scene of the patient within a medically relevant setting (e.g., a hospital room or clinic). The student is expected to carefully analyze the displayed scenario, including the patient's condition and the environmental context, to prepare for the subsequent steps of patient interaction and treatment.

Once the scenario is set, the Conversational AI will assume the role of the virtual patient. It will engage the student in a simulated conversation, focusing on the history-taking phase of the medical consultation. This interaction will allow the student to practice diagnostic and communication skills in a controlled, immersive environment.

5.2. History Gathering

The history-taking phase is a critical component of the simulation, designed to enable students to gather essential information about the patient's condition before initiating treatment. The student, acting as the nurse, will communicate directly with the virtual patient, played by a fine-tuned and prompt-engineered Conversational AI model. The details the student is expected to obtain include the patient's health status, age, allergies, emotional state, and pain levels. These elements are aligned with the standard procedures followed in nursing education, particularly in wound care treatment, ensuring that the simulation adheres to established methodologies for training nursing students.

The Conversational AI model, acting as the patient, will be fine-tuned using data sourced from the allied health science department. This data will include comprehensive patient details such as medical history, current illnesses, and the circumstances of the accident or incident leading to the patient's condition. These details will be provided to the Large Language Model (LLM) as contextual input, enabling it to respond accurately and realistically to the student's questions during the history-taking process. The fine-tuning of the Conversational AI will be completed during the initial phase of project development to ensure its readiness for the simulation.

During the interaction, all questions posed by the student will be logged and analyzed by an Evaluator AI. This Evaluator AI, which will also be a fine-tuned or prompt-engineered LLM, will compare the student's question lineup with the expected lineup of questions a skilled nurse would ask in a real-world scenario. Based on this comparison, the Evaluator AI will generate detailed feedback, highlighting areas where the student performed well and identifying specific points for improvement. This feedback will be delivered at the end of the history-taking phase to provide the student with a clear understanding of their performance. The High level Structure of the History gathering is shown in *figure 2*.

The feedback will be presented through a virtual display within the VR environment, accompanied by a voice narration that reads the feedback aloud. Key points will be visually highlighted on the display to reinforce the evaluator's comments. This multimodal feedback mechanism ensures that students receive comprehensive and actionable insights, enabling them to refine their communication and diagnostic skills effectively.

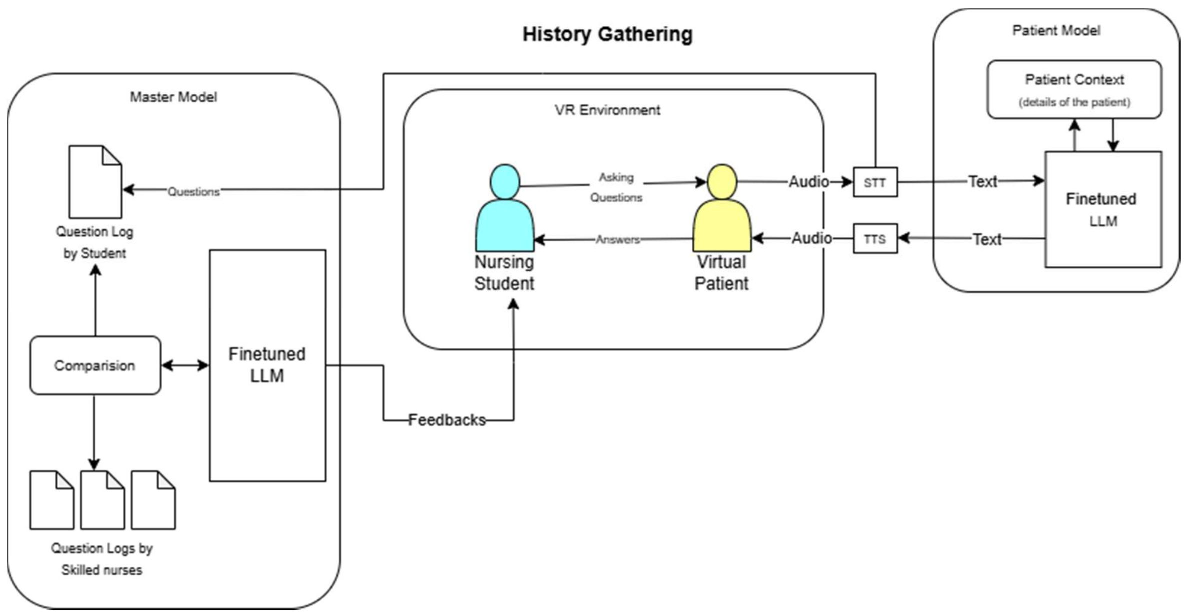

Figure 2: High Level Architecture of the history gathering

5.3. Wound Assessment

Following the completion of the history-taking phase and the receipt of feedback, the student will proceed to the wound assessment stage. In this phase, the student is required to examine the wound area in detail and assess it based on specific criteria, including the wound's location, type, tissue characteristics, measurements, exudate levels, and the condition of the periwound area. To facilitate this process, the 3D virtual environment will provide a digital clipboard for the student to record the patient's status and wound details systematically.

During the assessment, the student will interact with the VR environment to identify and classify the wound type. For instance, the student will be prompted to select the correct wound type from a predefined list, which includes options such as normal, incision, laceration, abrasion, puncture, pressure ulcer, contusion, and hematoma as given in the *Figure 3*. The Evaluator AI, a fine-tuned model specialized in wound assessment, will provide real-time feedback based on the student's selections. If the student chooses the correct answer, the Evaluator AI will offer positive reinforcement and share additional insights to enhance the student's understanding. If the student selects an incorrect answer, the Evaluator AI will provide constructive feedback and guide the student toward the correct classification based on the wound type presented in the simulation.

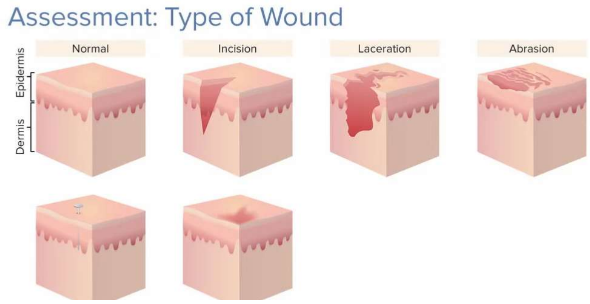

Figure 3: Wound Types Assessment

The Evaluator AI used in this phase will be fine-tuned using specialized data on wound types and assessment criteria, sourced from the Allied Health Science department. This data will include detailed information on wound characteristics, classification, and best practices for wound care, ensuring the AI's responses are accurate and aligned with real-world medical standards. The feedback generated by the Evaluator AI will be directly integrated into the simulation, providing the student with immediate, actionable insights to improve their diagnostic skills.

All responses and actions taken by the student during the wound assessment phase will be logged and stored in a comprehensive response log. This log will track the student's performance and serve as a record that is carried forward to subsequent steps in the simulation. By maintaining a detailed log, the system ensures continuity and allows for a holistic evaluation of the student's progress throughout the training exercise like in the Diagram given in the *Figure 4*.

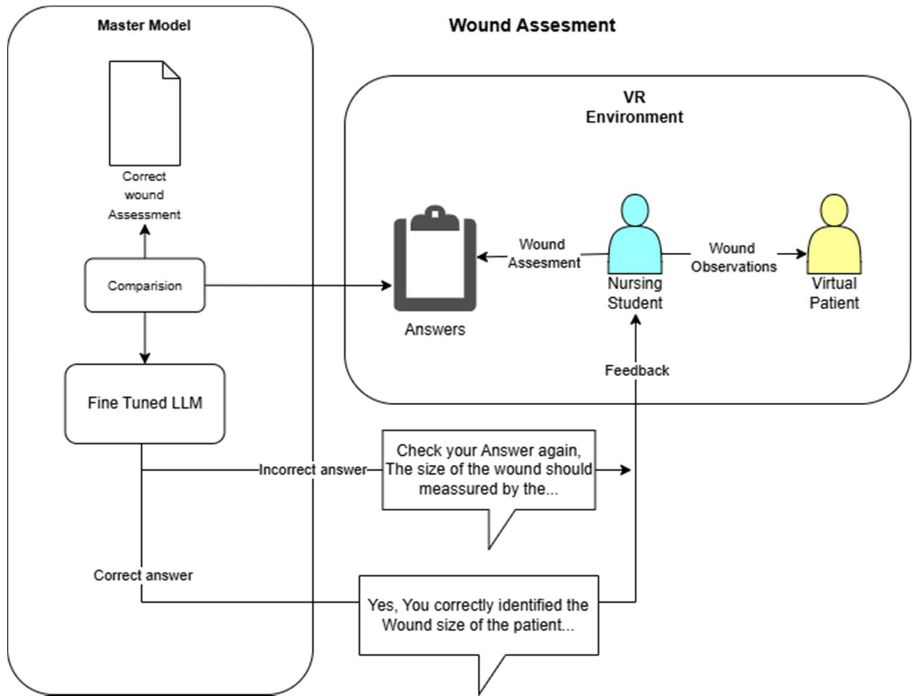

Figure 4: Wound Assessment Flow Diagram

5.4. Wound Cleaning

In this step, the student will perform the practical procedure of cleaning and dressing the wound, adhering to all necessary safety protocols and guidelines. The student is expected to demonstrate a thorough understanding of the materials, tools, and techniques required for effective wound care. This includes selecting appropriate instruments, handling equipment correctly, applying the correct volume of medications, and following the proper sequence of steps for wound cleaning and dressing. All actions taken by the student, such as tool selection, tool movements, medication application, and procedural sequence, will be meticulously logged and recorded as part of the performance me trics in the backend system.

The Evaluator AI (Master model) will actively supervise the student's actions throughout the procedure, comparing their performance against predefined matrices that reflect the standards of a skilled nurse. Based on this comparison, the Evaluator AI will provide real-time feedback on the student's performance, highlighting areas of excellence and identifying aspects that require improvement. When necessary, the Evaluator AI will offer guidance and supervision to help the student correct mistakes and perform the wound cleaning and dressing procedure effectively. The correct procedural steps and tool selections are pre-programmed into the Evaluator AI, ensuring that the feedback is accurate and aligned with best practices in wound care.

To further support the student, a Conversational AI will remain accessible throughout the procedure to provide live feedback, answer questions, and offer assistance as needed. This Conversational AI is the same model used earlier during the history-taking phase, ensuring consistency and continuity in the student's learning experience. The AI will assist with any clarifications or guidance required during the wound cleaning process, enhancing the student's confidence and competence.

The wound and cleaning equipment are rendered as interactive 3D models within the virtual environment, allowing the student to manipulate instruments and perform the procedure as they would in a real-world setting. The environment mirrors the patient's surroundings, with all necessary instruments and materials pre-prepared according to the guidelines provided by the Allied Health Science department for wound care treatment. This ensures that the simulation is both realistic and aligned with established medical standards.

During the procedure, detailed raw data is collected, including metrics such as the time a wool swab is kept on the wound, the number of swabs used, the number of soaks applied, the area cleaned, the instruments utilized, and the manner in which they are handled. This raw data is then processed and filtered to extract relevant performance metrics, which are subsequently sent to the Evaluator AI for comparison with the ideal procedural standards. The filtered data enables the Evaluator AI to generate precise and actionable feedback, ensuring that the student's performance is evaluated comprehensively and constructively like the Diagram given below in the *Figure 5*.

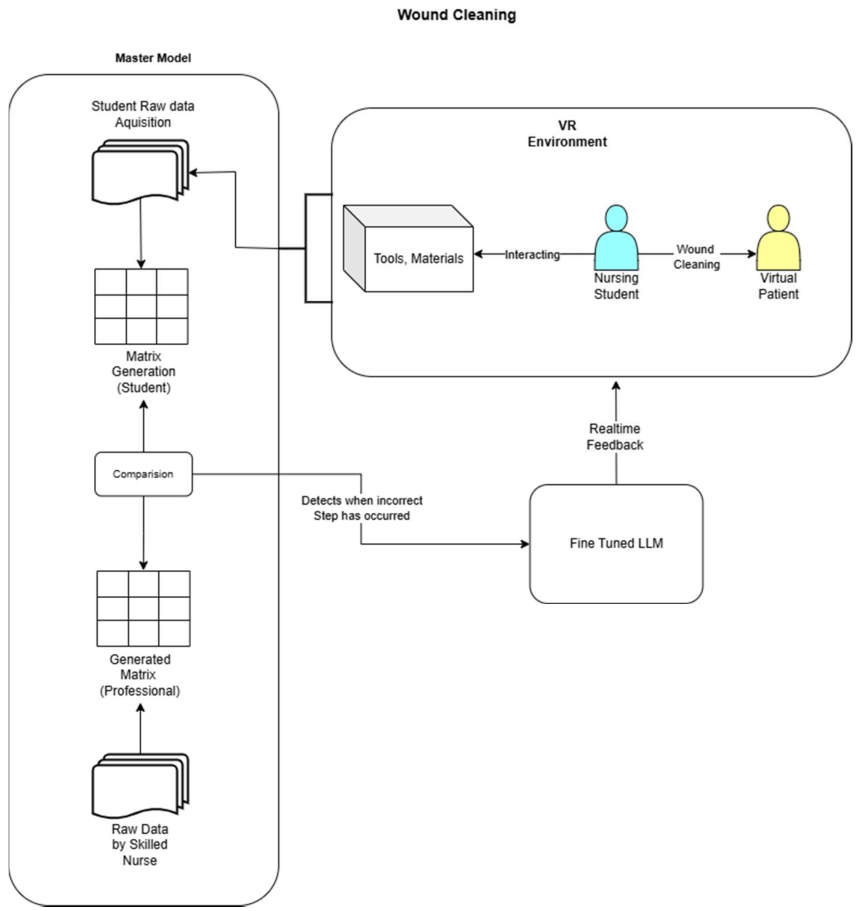

Figure 5: Wound cleaning phase Flow diagram

5.5. Evaluation

The evaluation phase represents the final step in the simulation, where the Evaluator AI conducts a comprehensive assessment of the student's overall performance. Utilizing the detailed log report generated throughout the simulation, which includes all responses, actions, and decisions made by the student, the Evaluator AI calculates an overall performance score. This score is accompanied by detailed feedback, highlighting areas for improvement, theoretical knowledge gaps, and best practices or techniques that can enhance the student's proficiency in wound care procedures. The feedback is designed to facilitate self-evaluation, enabling students to reflect on their performance and identify specific ways to refine their skills.

The Evaluator AI analyzes the log data to generate a structured report, which is then compared against predefined performance benchmarks. This analysis provides a clear and objective evaluation of the student's strengths and weaknesses. The results, along with actionable recommendations, are presented to the student in a clear and concise manner. To further support the student's learning, a Conversational AI is integrated into this phase, acting as a virtual instructor. This AI allows the student to ask questions or seek clarification on any aspect of the feedback, ensuring a thorough understanding of the evaluation results and the steps needed for improvement (High Level Structure is given in the *Figure 6*).

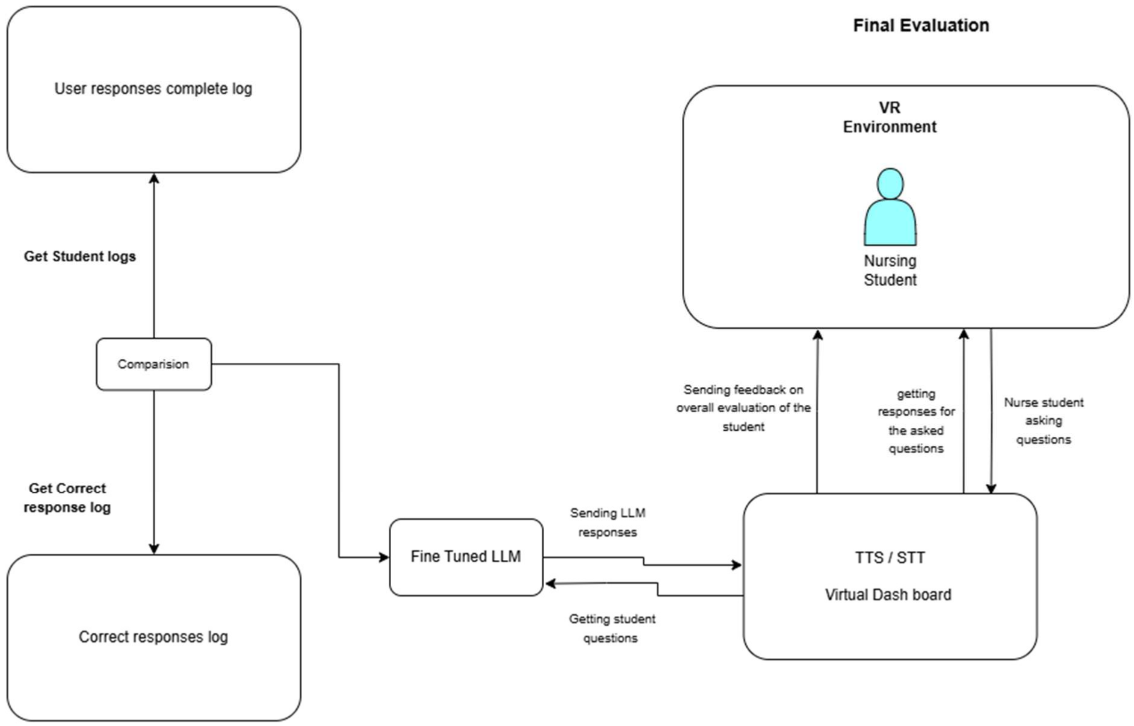

Figure 6: Flow Diagram for the Evaluation phase

The evaluation process not only assesses the student's performance but also empowers them to practice and refine their skills independently. By leveraging the insights provided, students can engage in self-directed practice at any time and in any setting, without the need for mock wounds, physical equipment, or a skills lab. This flexibility promotes continuous learning and skill development, ensuring that students can achieve mastery in wound care procedures through repeated practice and application of the feedback provided.

6. Technologies to be used

6.1. Patient Model

The patient model is developed using a prompt engineering-based approach. For this task, GPT-4 will be utilized due to its accessible API, which allows easy integration and setup. GPT-4 provides flexibility in defining behaviors for the patient models. No need for setting up servers for running the model. The UnityWebRequest library will be used to send API calls to the GPT-4 API.

6.2. Master Model

The master model involves fine-tuning LLaMA using relevant documents, articles, and provided rules by the wound assessment theory. This model will be hosted on an online server (AWS EC2 or department server). It will be exposed to the web using FastAPI in Python. It offers greater customizability and is open-source, with multiple parameter models to choose from. The model's weight precision can be reduced through quantization, allowing it to run on resource-constrained systems. While still meeting the functional requirements of the project. LLaMA has strong community support. Based on research done it has more precision and recall compared to fine-tuned GPT models. HuggingFace Transformers and PyTorch libraries will be used for fine-tuning. The UnityWebRequest library will handle API calls.

6.3. Speech-to-Text Model (STT)

There are two options for the speech-to-text model suggested.

Paid Speech-to-Text V2 API - This option is faster, more reliable, and supports real-time conversations, including a special medical model for STT. It does not require a server to run. The UnityWebRequest library will be used to send API calls.

Whisper - Whisper is a general-purpose open-source model. It can be fine-tuned for domain-specific data if needed. Initially, it will be tested without fine-tuning; however, if errors are detected in speech recognition, fine-tuning will be considered. The transformer and PyTorch libraries will be used to run the model on the server. This is also exposed to the web using fastApi python api.

An experiment will be conducted to determine which option delivers better results. If Whisper performs better, no need to proceed with the paid Speech-to-Text API.

6.4. Text-to-Speech Model (TTS)

For the text-to-speech model, the options are Amazon Polly and Google Cloud (WaveNet). Both tools will be compared to determine which one generates a more human-like voice. While both are paid services, they offer free trials, which should be sufficient for the research. The UnityWebRequest library will be used to send API calls.

6.5. 3D modeling

Realistic wound modeling is essential for helping students accurately identify wound types and perform assessments. Blender, a free and open-source 3D software, is ideal for this due to its powerful sculpting and texturing tools.

Key Sculpting Techniques:

- Dynamic Topology: For detailed wound edges and irregular skin tears.
- Multiresolution Sculpting: Helps refine wound depth and structure.
- Alpha Textures & Stencils: Adds realistic skin details and wound patterns.
- Boolean Operations: Creates deep cuts and puncture wounds.
- Texture Painting: Enhances realism with color variations for bruising and infection.

Blender enables educators to create detailed, interactive wound models, improving students' understanding and assessment skills in medical training

6.6. VR development

Most research studies have predominantly utilized the Unity game engine for developing simulation environments. Unity offers a dedicated VR development library, a vast collection of assets, and specialized tools designed for immersive VR applications. Given these advantages, Unity will be the chosen platform for this project, ensuring a robust and efficient VR simulation experience.

6.7. Haptic Feedback Devices

Haptic feedback devices serve as controllers in the VR simulation, providing realistic tactile sensations to enhance immersion. These devices allow users to feel textures, pressure, and resistance, making wound care training more interactive and lifelike for nursing students.

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