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

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***Abstract*—This paper reviews research on the integration of Virtual Reality (VR) simulations and AI-driven conversational models in nursing education, particularly for advanced wound care training. Traditional nursing education often lacks the immersive, hands-on experiences needed for mastering complex procedures, making VR and AI promising solutions. The review explores the use of VR to create realistic, interactive training environments and AI-driven conversational agents to provide personalized feedback and guidance. While VR enhances learning experiences, engagement, and skill development, it also faces limitations in replicating real-world scenarios and providing real-time guidance. The integration of conversational AI can address these limitations by offering interactive feedback and responding to user actions within the VR simulation. The review highlights the need for lightweight, efficient AI systems that can seamlessly integrate with VR without requiring high-performance hardware. By examining existing techniques and research gaps, this review aims to enhance nursing education in wound care treatment using VR and conversational AI.**

***Index Terms*—Immersive Learning, Augmented Reality (AR), Virtual Reality (VR), AI-Driven Education, Nursing Simulation, Wound Care Training, Conversational AI, Healthcare, Nursing Education**

I. Introduction

Nursing education plays a pivotal role in preparing healthcare professionals to deliver high-quality patient care [1], [2]. However, traditional methods like lecture-based instruction and task-oriented clinical training often fail to provide the immersive, hands-on experiences needed for mastering complex procedures such as advanced wound care [1]. This gap has led to the exploration of innovative technologies, including Virtual Reality (VR) and Artificial Intelligence (AI), to transform nursing education to even better [3].

Advanced wound care training presents unique challenges, as it requires a combination of technical skills, critical thinking, and hands-on practice [4]. Traditional methods often lack the realism and interactivity needed to prepare nursing students for these complex procedures [1], [4]. Immersive technologies like VR simulations and AI-driven conversational models offer a promising solution by providing realistic, interactive, and scalable training environments [5]. These technologies enhance clinical decision support and e-learning platforms by creating complex, hands-on simulations that improve student engagement and competence.

For Instance, VR platforms like vSim for Nursing [6] and Shadow Health's Digital Clinical Experience [7] allow students to practice clinical skills in safe, controlled environments, Additionally AI-powered tools enhance personalized feedback and adaptive learning through simulation-based training with explainable AI [8], virtual communication skill applications [9], and AI-integrated pain education [10].

Generative AI further supports learning by creating personalized quizzes and wound images, helping students diagnose conditions and plan treatments while allowing educators to tailor content [11].

Additionally, metaverse technologies (VR / AR) and machine learning provide real time diagnostics and immersive experiences, making wound care training more engaging, personalized, and efficient [12].

This literature review explores the integration of VR simulations and AI-driven conversational models in nursing education, with a focus on advanced wound care training. It examines the theoretical foundations, methodologies, and applications of these technologies, highlighting their potential to bridge the gap between theory and practice. The review is structured as follows: First, it discusses the role of VR in nursing education, followed by an analysis of AI-driven conversational models. Finally, it examines the integration of these technologies and their implications for advanced wound care training.

II. VR (Virtual Reality)

Virtual Reality (VR) is an immersive technology that simulates a computer-generated environment, allowing users to interact with digital spaces in a realistic manner. It is becoming increasingly popular in the modern era with advancements in technology. VR in education is another vital area where extensive feasibility analyses and research on novel ideas are being conducted [13]. There are four key sections to consider:

Augmented Reality (AR)

AR enhances the real world by overlaying digital content, such as images, text, and 3D objects, onto the physical environment through devices like smartphones or AR glasses [14].

Virtual Reality (VR)

VR immerses users in a fully digital environment, replacing the real world with a computer-generated space, typically experienced through a VR headset and motion-tracking devices [15].

Mixed Reality (MR)

MR blends real and virtual elements, allowing users to interact with both physical and digital objects in real time, creating an interactive environment that responds to user actions [16].

Extended Reality (XR)

XR is an umbrella term that encompasses AR, VR, and MR, referring to all immersive technologies that merge the physical and digital worlds to enhance user experiences [16].

AR, VR, MR, and XR are technological trends that enable 3D effects in research. The healthcare industry has increasingly focused on these technologies as they enhance the efficacy and efficiency of nursing and medical healthcare services while addressing the limitations of traditional medical practices and education [17]. These are expected to become widely used in the nursing and medical fields. By offering educational benefits beyond those of conventional simulated learning media, the technology can help prepare graduates for the workforce. The integration of these techniques in nursing education allows students to visualize complex phenomena, understand dynamic relationships between variables, and explore abstract concepts in a 3D format. Additionally, it provides opportunities for experiential learning that may not be feasible due to time, cost, safety, or availability constraints [17].

Training in medicine is undergoing a significant transformation due to the adoption of immersive technologies. These facilitate more effective learning, innovative patient treatment approaches, and new medical insights. Although challenges remain, the benefits of immersive technologies in healthcare are evident. Educational institutions and healthcare professionals should explore and implement these technologies to enhance medical education and patient care quality. As these technologies continue to develop, their seamless and meaningful integration into medical practices is expected to usher in a new era in healthcare [17].

A. Why VR Is Often Preferred Over AR and XR for Research

Virtual Reality (VR), Augmented Reality (AR), Mixed Reality (MR), and Extended Reality (XR) each have unique strengths and applications in research. However, VR is often considered superior for certain types of research due to its immersive nature and controlled environment. VR significantly improves knowledge retention, skill acquisition, and learner satisfaction compared to other methods [18]. Interactive virtual simulation provides nursing students with a partially immersive and engaging learning experience, allowing them to cultivate the competencies necessary to deliver high-quality patient care. This simulation format enables dynamic, bidirectional communication between participants and digital devices or content, enriching the learning environment [18].

A research done has analyzed the decision-making processes of 119 nursing students who resolved a clinical case on a web platform, focusing on success rates across different knowledge categories (theoretical knowledge, data interpretation, and clinical management) and resolution time. The findings suggest that virtual simulation is a valuable tool for fostering applied knowledge and critical thinking in a realistic context, although students showed lower success rates in clinical management decisions compared to data interpretation [19]. .

Furthermore, VR has been shown to enhance nursing students' theoretical knowledge, practical skills, skill retention, and satisfaction compared to traditional methods. However, studies indicate that VR does not significantly enhance critical thinking skills [13], [19]. A systematic review and meta-analysis evaluating the effectiveness of VR in nursing education identified it as a valuable tool for immersive and interactive learning, realistic clinical scenario creation, and enhanced engagement [19]. The study systematically reviewed 12 randomized controlled trials involving 1,167 participants, comparing VR-based learning with traditional teaching methods.

B. Limitations and Challenges of VR in Nursing Education

Limitations of VR Simulations:

- VR provides safe training environments but struggles to replicate complex real-world scenarios.
- Practical experience gained through VR may be limited compared to actual clinical exposure [20].

Real-World Implementation Challenges:

- Virtual simulations and models present idealized solutions but encounter difficulties when applied to real-world scenarios.
- Translating virtual representations into real-world medical practice requires consideration of additional variables and unforeseen factors [20].

Addressing these challenges, a potential improvement for VR-based learning could include AI-driven conversational interactions or error detection systems to enhance engagement and learning outcomes.

C. The Importance of VR in Wound Care Nursing Education

Focusing on the advantages of VR in wound care nursing education is essential, as it:

- Enhances learning experiences
- Improves engagement and retention
- Ensures standardized training procedures
- Offers long-term cost savings
- Builds empathy through realistic patient simulations

These factors ultimately contribute to better skill development and improved patient care outcomes [19]. The following sections will discuss the different methodologies used in VR for wound care nursing education.

D. Different VR methodologies for Nursing education

There are different methodologies followed to achieve optimal results in the education field through VR usage.

One methodology for using VR is aimed at systematically developing 3D nursing simulation content based on Han's VR educational design model [21] and the National League for Nursing (NLN) Jeffries Simulation Theory [22]. This method has proposed a multidisciplinary VRS content development model [23]. The selection of these two theories as a framework for this methodology was a strategic approach to systematically consider the characteristics of VR media and educational elements to maximize learning effectiveness.

A research study has developed a scenario to test the above methodology with nursing experts. The researchers have developed a prototype that provides an immersive and interactive VR experience for enhancing nursing competencies through hands-on practice and voice communication with virtual objects. Specifically, the research tested the prototype content based on feedback from nursing experts. The experts indicated difficulties with voice recognition, as the system did not always accurately recognize spoken keywords. To address this, they incorporated a synonym learning algorithm using Google's synonym crawling technology to enhance the system's ability to understand and respond to varied inputs. Some participants also found the virtual interactive experiences fascinating and were pleased to apply what they learned in practice. However, participants reported difficulties with voice recognition because communication was centered on specific keywords, as well as issues with technical aspects of virtual object manipulation. Additionally, some participants experienced disruptions during the nursing procedure due to instability in certain virtual spaces. Hence, there is a gap in this methodology in terms of improving communication accuracy, reducing disruptions, and enhancing the overall VR learning experience [23].

Another methodology involves first 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. Next, the scope of the simulation, level of detail, and complexity are determined based on available resources and the technical limitations of VR technology. An iterative development cycle then proceeds, where feedback from clinical experts is continuously sought to improve the design and system [24].

This method of using VR for nursing education has certain limitations. Researchers who followed this methodology pointed out that while feedback indicates the system is engaging and useful for training cognitive and procedural skills, it lacks realistic haptic feedback and fine motor skill simulation. The VR system has potential as a cost-saving, self-paced alternative to traditional methods. Some feedback also described the experience as feeling like "playing with air" [24].

Although respondents highlighted the lack of haptic feedback, the hardware adopted in this study was the HTC VIVE VR system, which provides a pair of controllers capable of producing vibrotactile haptic feedback. Each controller is equipped with a multifunction trackpad, grip buttons, dual-stage trigger, system button, and menu button. Hence, a gap is evident in the hand detection system, as using only the hands negatively affected participants' experience, and there was a lack of fine motor skill simulation.

A study by E. Akchelov and E. Galanin focuses on a head-mounted VR system within a virtual patient space designed for dementia care. The simulation is structured as a game, emphasizing its significance for student education and future areas of development. A key feature of this study is the creation of Non-Player Characters (NPCs). A Virtual Environment (VE) was constructed using reference images and videos of hospital wards, facilities, and equipment [25].

The research methodology followed in this study is as follows: The main task in the project involves a conversation with a patient suffering from dementia. A script was written by an expert practitioner in dementia care to ensure its accuracy and validity as a learning tool and to promote greater transferability. The study utilizes multiple VR headsets, with one participant acting as an agent for responses and maintaining communication. The software supports two VR headsets: Oculus Rift and Google Cardboard. The latter is a system that utilizes smartphone technology to display VEs in conjunction with an inexpensive hardware mount. In this setup, a second person is required to role-play the scenario for the conversational experience [25].

One area for improvement is eliminating the need for a second person to role-play by integrating conversational AI into the VR environment. Adding conversational AI to NPCs and implementing AI-driven responses would enhance the system's functionality and realism. A summary of the Different VR methodologies for Nursing education can be found in TABLE I.

TABLE I
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 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.

III. CONVERSATIONAL AI

Conversational AI is a sub-domain in artificial intelligence that deals with text based or speech-based AI agents. These are designed to simulate human like conversations in natural language. Conversational AIs can be used to personalized, accessible, and up-to-date educational content for healthcare professionals [26].

This consist of 3 major components namely

- natural language understanding
- dialogue management system
- natural language generation [27].

How these components are used to create conversational AIs is explored in Fig. 1.

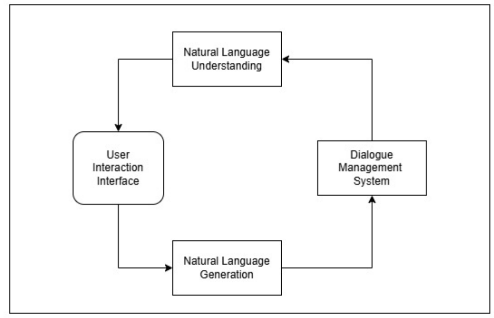

Fig. 1. Conversational AI Architecture

A. *Voice-Based Conversational Agents in Virtual Reality*

A recent study [28] explored the integration of Embodied Conversational Agents (ECAs) in Virtual Reality (VR). These 3D human-like avatars interact with users through both text and speech, enhancing engagement compared to traditional text-based conversational AI. One key advantage of this system is its ability to manage multiple agents dynamically, selecting the most appropriate one based on interaction context.

The study implemented the system using the RASA open-source framework, a widely adopted tool for developing conversational AI applications. RASA facilitates machine-learning-based dialogue management and natural language understanding (NLU), making it accessible to developers. However, RASA does not support end-to-end learning, meaning that NLU and dialogue management are decoupled. This design choice introduces several limitations:

- Increased Manual Effort: The system requires extensive manual configuration and training to improve accuracy.
- Limited Adaptability: The model struggles to handle new inputs dynamically and lacks adaptability to complex conversational contexts.
- Lack of Gesture Recognition: The conversational AI does not interpret or respond to users' body gestures, limiting the naturalness of interactions.

Despite these limitations, RASA remains well-suited for task-oriented chatbots, such as customer service agents and FAQ-based assistants [29]. To address the lack of body gesture recognition, researchers propose contextual grounding, linking conversations to elements within the virtual environment. This approach aims to improve situational awareness and enhance the realism of AI-driven interactions in VR.

B. *Conversational AI in Healthcare using GPbRNN*

A recent study explored the development of Conversational AI for healthcare using Generative Pretrained-based Recurrent Neural Networks (GPbRNN) [30]. This approach integrates Recurrent Neural Networks (RNNs) and Generative Pretrained Transformers (GPTs) to enhance emotional prediction, response relevance, and conversational fluency. The methodology involved several key steps, including data preprocessing, feature extraction, sentiment analysis, and chatbot integration.

The GPbRNN model architecture consisted of five layers:

- Input Layer – Processes raw text data.
- Hidden Layer – Captures contextual dependencies.
- Tokenization Layer – Converts text into structured tokens.
- Lemmatization Layer – Reduces words to their base forms.

- Output Layer – Generates the final AI response.

The model was evaluated using the MIMIC-III dataset [31], achieving 98% accuracy, 97% precision, 96% recall, and an 88% F1-score, indicating strong performance in medical dialogue processing. However, real-world implementation remains limited, and further research is required to validate the model's effectiveness in dynamic healthcare environments.

C. Virtual counseling application for Nursing Education

Shorey et al. developed a Virtual Counseling Application for Nursing Education at the National University of Singapore [32]. The system utilized Google's Dialog Flow, which employs an intent- and entity-based approach for Natural Language Understanding (NLU). The Conversational AI was structured around standardized nursing communication frameworks, including MIRS, COLDSPA, SBAR, NURS, and IFE, ensuring a consistent and structured dialogue flow.

However, a key challenge of this approach was its inability to anticipate all possible conversational intents. Nursing students often deviated from structured guidelines, engaging in small talk, which caused Dialog Flow to struggle with maintaining dialogue coherence. Its retrieval-based architecture limited responses to predefined intent permutations, thereby reducing conversational fluidity.

To address these limitations, future work should explore hybrid AI models [33] that combine retrieval-based and generative approaches, integrating Large Language Models (LLMs) fine-tuned for nursing contexts. This would enhance the system's ability to generate dynamic and contextually relevant responses, improving the overall educational experience.

D. Conversational AI for Medicare using fine-tuning and Retrieval Augmented Generation

A study on Conversational AI Dialog for Medicare, powered by Fine-Tuning and Retrieval-Augmented Generation (RAG) [34], evaluated the performance of Large Language Models (LLMs) in healthcare applications. The research implemented fine-tuning and RAG techniques using GPT and LLaMA-2, leveraging a combination of three datasets [35]–[37].

Fine-tuning was conducted on a predefined dataset, with GPT models requiring proprietary APIs, limiting customization. In contrast, LLaMA-2, being open-source, allowed complete architectural modifications. To optimize computational efficiency, Low-Rank Adaptation (LoRA) was employed, significantly reducing resource consumption while maintaining model performance.

RAG consists of two key processes: retrieval and generation. The retriever extracts relevant information from external sources, leveraging embeddings, while the generator—a pre-trained language model such as GPT or BART—formulates responses. By dynamically incorporating retrieved knowledge, RAG reduces dependency on static training data. However, it may produce inaccurate or unexpected outputs when retrieval mechanisms fail.

To assess model performance, BLEU, BERT, and ROUGE scores were used, evaluating fluency, semantic similarity, and response relevance. These metrics provided a comprehensive assessment of conversational AI effectiveness in Medicare applications. Performance comparison of different models are given in TABLE II.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS

	BLEU	ROGUE	F1	Precision	Recall
GPT (FT)	0.372	0.294	0.584	0.616	0.571
GPT (RAG)	0.243	0.235	0.529	0.506	0.551
Llama (FT)	0.241	0.186	0.810	0.829	0.838
Llama (RAG)	0.288	0.259	0.861	0.851	0.875

IV. TTS AND SST

Traditionally, many Conversational AIs have been limited to text-based interactions. Scenarios like wound care training for nurses, the integration of text-to-speech (TTS) and speech-to-text (STT) systems plays a crucial role in enhancing the interactivity. [28]

Research conducted by Michele et al. uses avatars to communicate like humans with TTS and STT modules. Before sending data to the TTS module, two sub-modules—LipSync and Voice-to-Voice—are employed. LipSync synchronizes the avatar's facial movements with the spoken words. The Voice-to-Voice sub-module facilitates the exchange of audio files between the TTS module and the user. A central server processes the user's input and sends it to the TTS module, which transcribes it to conversational AI. The resulting text is then sent back to the TTS module, which synthesizes the response into speech. In human conversations, the response time between individuals is typically around 500 milliseconds. To achieve a similar level of responsiveness, the architecture uses the Wav2Vec2.0 model for STT, which has an average processing time of 0.8 seconds on a CPU, and SpeechT5 for TTS, which is slower at 1.7 seconds on a CPU. To address this delay, the system strategically masks the TTS delay by incorporating natural pauses in the dialogue and dividing long sentences into chunks. One limitation is the response time discrepancy, which remains a challenge for real-time interaction, making it feel unnatural, especially in more complex or dynamic training scenarios.

Another study on a ChatGPT-powered immersive virtual reality experience [38] 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 from GPT-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 [39] (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).

Shorey et al. [32] 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. A summary of the TTS modules is given in TABLE III.

TABLE III
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

V. INTEGRATION OF AI WITH VR

The convergence of Artificial Intelligence (AI) and Virtual/Augmented Reality (VR/AR) is an area of increasing interest, with researchers and developers eager to explore the potential synergies between these technologies.

A. Vision Language Models

Because it combines computer vision (CV) and natural language processing (NLP) capabilities, Vision Language Models (VLMs) are among the most promising AI technologies. These models bridge the gap between natural language descriptions and visual information by comprehending and producing text about images. It has been demonstrated that the state-of-the-art (SOTA) models are accurate and effective enough to be used in a variety of domains, such as autonomous driving [40], robotics [41], and healthcare [42].

VR-GPT [43] enhances VR experiences by leveraging visual language models (VLMs) to enable natural language interactions. It processes user inputs to provide real-time assistance and guidance within VR environments. System Architecture of VR-GPT can be seen in Fig. 2. By bridging the gap between visual data and language, VLMs allow for more intuitive and context-aware interactions. The system integrates key technologies such as Unity, speech-to-text (STT), text-to-speech (TTS), and Quen-VL for visual question answering. It runs on a high-performance RTX 4090 GPU for VLM processing, while the Unity game operates on a GTX 1080 GPU, with the Meta Quest 2 used as the VR headset.

Despite its advancements, VR-GPT faces challenges, particularly in real-time optimization and computational demands. Running complex VLMs requires significant GPU memory, leading to high costs and technical difficulties in maintaining smooth interactions.

B. VR with GenAI

GPT-VR Nexus [38], another project integrating AI with VR, focuses on improving user interaction by incorporating generative AI (like ChatGPT). It aims to overcome three key issues: AI's limited VR context comprehension, hallucination problems, and the lack of tools to translate AI-generated responses into VR environments. To address these, the system employs a two-step prompt strategy, in which user requests are first categorized before being refined for better accuracy. Additionally, a post-processing layer ensures that AI-generated content aligns with VR constraints, preventing object misplacement and logical inconsistencies.

There are more Gen AI applications combined with VR, such as sMoRe [44] 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.

Although GPT-VR Nexus significantly improves AI-VR integration, it still faces challenges, including **unreliable AI responses, hallucinations, and the need for extensive computational resources**. Both VR-GPT and GPT-VR Nexus contribute to developing immersive AI-driven VR experiences but require further optimization to address real-time processing and reliability concerns.

C. Virtual Operative Assistants

The Virtual Operative Assistant is an explainable AI tool designed for simulation-based training in surgery and medicine. It serves as an automated educational feedback platform.

Moving into the medical domain, there is a paper that introduces an explainable AI tool designed for simulation-based training in surgery and medicine [45]. T They've created

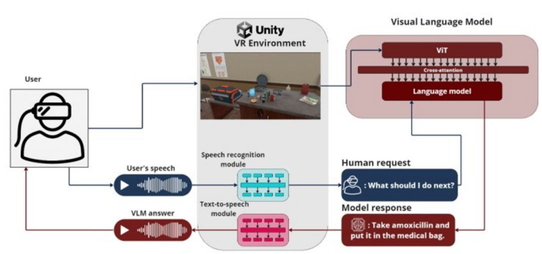

Fig. 2. System Architecture of VR-GPT

and validated the Virtual Operative Assistant, an automated educational feedback platform. 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. Limitations of this framework include the following:

- The framework was developed with a Support Vector Machines (SVM) algorithm distinguishing between two groups of expertise .
- The bias in the machine learning model is left out of metric-wise assessment.
- A very high positive score in one metric may overcompensate for other smaller negative metrics, impacting the classification.
- Creating video feedback is challenging because there may be multiple ways expertise in a metric could be achieved.
- Social and ethical impacts of AI-based teaching, including concerns about updating algorithms, the ability of the algorithm for users to train to become more skilled, the affective component of feedback, and human-to-human connection.

And they state some further directions to explore such as real-world validations, and improved feedback mechanisms. The development of systems that can record the entire simulation and extract time points and events led the algorithm to classify the user performance as novice for a particular metric.

There are also some works related to education with AI and VR in Different fields. One paper introduces a VR and AI framework to revolutionize advanced manufacturing education and nearshoring in Mexico, aiming to bridge training gaps and empower stakeholders [20]. The framework employs a step-by-step methodology, integrating virtual product design, manufacturing company development, and product evaluation. The effectiveness is demonstrated through immersive VR training and AI-driven process optimization. However, challenges remain in implementing virtual simulations in real-world settings, managing the level of automation, and the high financial resources required for VR and AI integration.

VI. Discussion

This study reviewed 45 research papers exploring the role of Virtual Reality (VR) and conversational AI in nursing education, specifically in wound care training. The findings indicate that most studies focused on integrating VR or conversational AI individually, highlighting a research gap in the combined use of both technologies, specifically in nursing education. 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. Another 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. However, the reviewed studies also highlight practical challenges in implementing conversational AI, particularly the need for lightweight, efficient systems that can integrate seamlessly with VR without requiring high-performance hardware. The significance of evaluating surgical performance in VR based on professional practices is emphasized in several studies, which leads to effective self-learning and self-evaluations of the nursing students.

Several conversational techniques have been explored, including Natural Language Processing (NLP) models based on keyword detection. However, studies indicate that these methods often fail due to inaccurate word recognition. Other approaches, such as using another human to interact with the user as a role play, have also been reported as ineffective.

Additionally, existing systems that are tried to bridge the gap between VR and AI realm, such as VLMs, GenAI applications with VR, and Virtual operative assistants, play a huge role, but there are major drawbacks in costly hardware expectations and latency in generating objects and responses. However, that integrate both VR and conversational AI are not specifically designed for nursing education and wound care training, further emphasizing the need for targeted research in this area.

Conclusion

The integration of immersive technologies in education has significantly enhanced learning in the medical domain. Virtual Reality (VR) and conversational AI systems have demonstrated substantial improvements in nursing education, particularly in wound care training, by making the learning process more effective and practical. Various studies have proposed enhancements for both VR and AI applications in nursing education.

This article presents a systematic review focusing on the role of VR and conversational AI in nursing education and wound care treatment. It examines the techniques employed, identifies key findings, and highlights areas for improvement. A common theme among the reviewed studies is the inclusion of either VR or AI in wound care training, with detailed explanations of their impact. Additionally, this review discusses effective methodologies and existing research gaps that can be leveraged to further enhance nursing education in wound care treatment using VR and conversational AI.

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