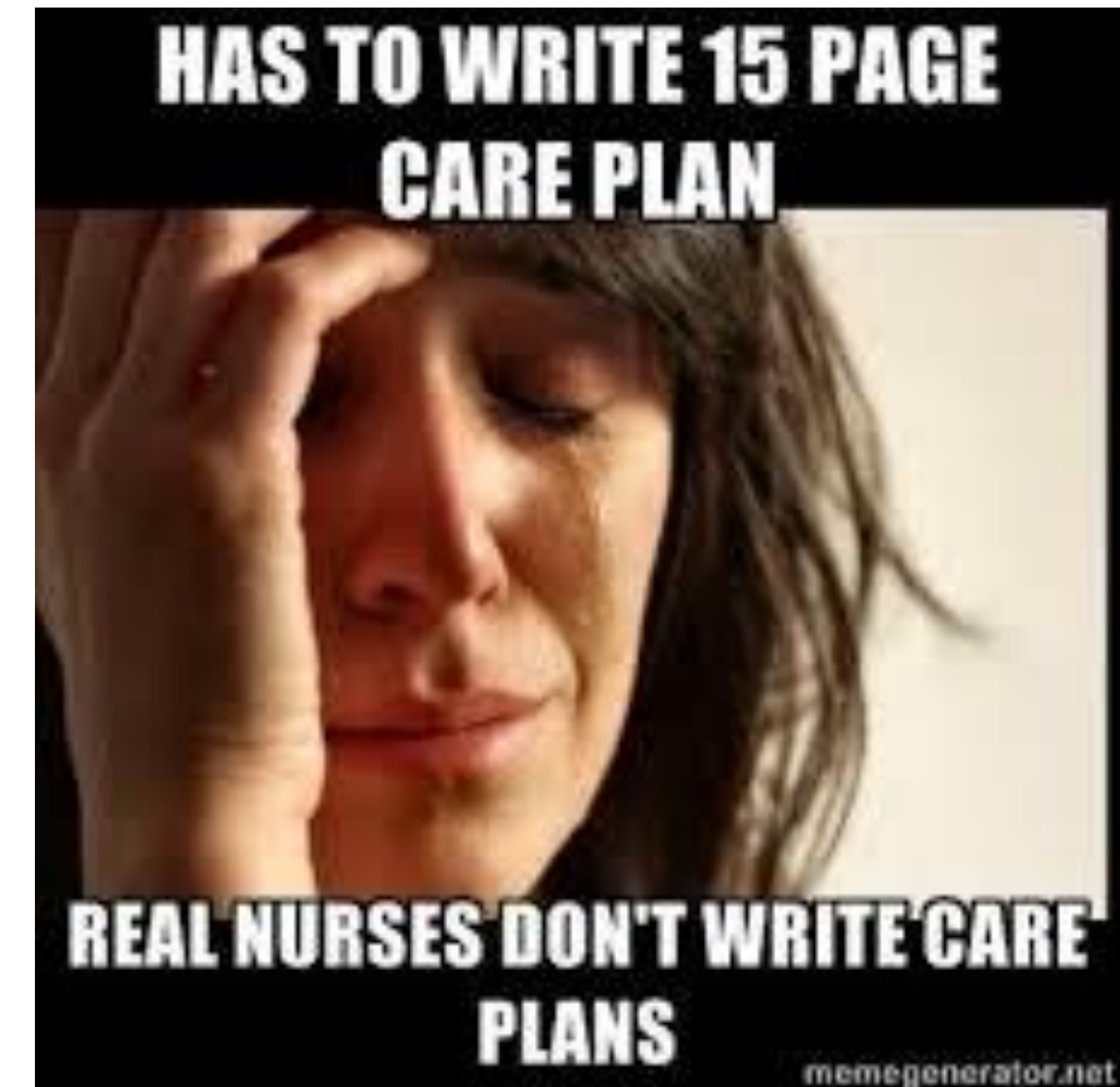
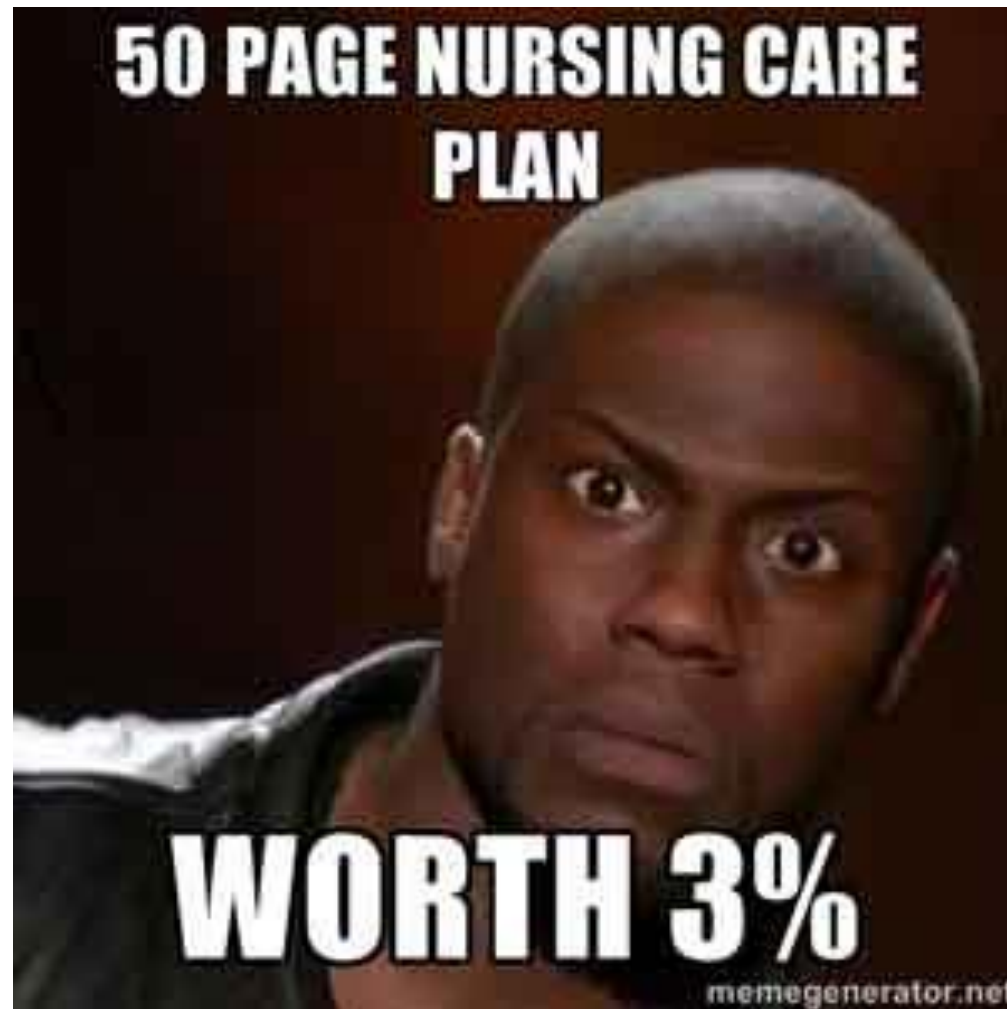




# **Using AI to assist in the creation and documentation of nursing care plans in EHR**

TAMARA G.R. MACIEIRA, PHD, RN

# I love care plans!





# Care plans in nursing school

Suffolk County Community College-School of Nursing  
**EXEMPLAR: NURSING CARE PLAN GUIDE**

## Student Nursing Care Plans

Client: Jon Stark  
Care Plan by: W. Smith, RN  
Date initiated: 12-29-2018

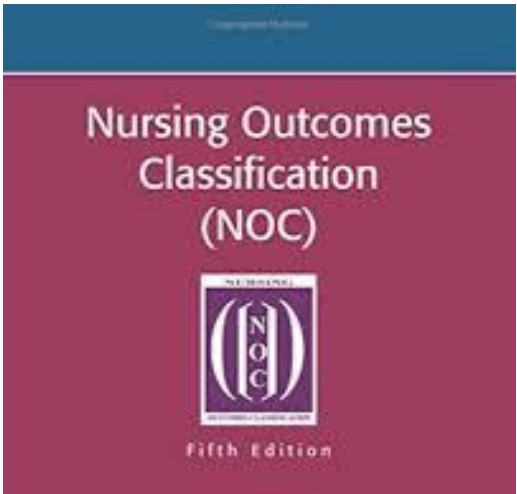
ASSESSMENT	DIAGNOSIS	OUTCOMES	INTERVENTIONS	RATIONALE	EVALUATION
(+) Dyspnea (+) Abnormal breath sounds Heart rate = 128bpm Restlessness (+) Productive cough	Impaired gas exchange RT collection of mucus in airways	Patient will maintain optimal gas exchange.	1. Assess respirations: note quality, rate, rhythm, depth, use of accessory muscles, ease, and position assumed for easy breathing. 2. Elevate head and encourage frequent position changes, deep breathing, and effective coughing.	1. Manifestations of respiratory distress are dependent on/and indicative of the degree of lung involvement and underlying general health status as patients will adapt their breathing patterns to facilitate effective gas exchange. 2. These measures promote maximum chest expansion, mobilize secretions and improve ventilation.	Patient maintained optimal gas exchange AEB normal respiratory rate. (-) dyspnea, effective coughing techniques.

### ASSESSMENT DATA FOR NURSING DIAGNOSIS:

<ol style="list-style-type: none"><li>Review and cluster patient information from a data base – DNPP or Comprehensive Assessment Form.</li><li>List only PERTINENT data for <u>each</u> individual problem i.e., skin breakdown, immobility, anxiety, etc.</li><li>The data cluster for each problem is listed on its own separate page and will be the supporting data in the development of a relevant Nursing Diagnosis for each problem.</li></ol>	
Subjective: Patient states, “_____” Reports symptoms of _____ (location, intensity, etc) Reports history of _____ Denies _____ Reports Pain Scale: 2/10 Past diagnostic test results	Objective: List the following findings only if applicable to this problem:  VS / General Survey Inspection    Palpation Percussion    Auscultation Lab Data
<b>EXAMPLE:</b> Subjective Data: <i>Patient reports “I hurt my head in a car accident and they said I was knocked out for 10 minutes” “I can’t remember what happened, but I just want to go to sleep.” Patient presents alert but disoriented to time and place; denies nausea, vomiting; no history of past neurologic injury;</i>	Objective Data: <i>Client presents with 4 cm clean laceration on left side forehead; no bleeding, bruising, swelling or redness noted; Pupils are sluggish to light stimulus and are unequal L =5mm R=2mm; Moves all extremities to command and without difficulty. Posture is upright and gait is steady; Behaviors are appropriate.</i>

### NURSING DIAGNOSIS / COLLABORATIVE PROBLEM:

<ol style="list-style-type: none"><li>Choose an applicable Nursing Diagnostic label from a NANDA source (NUR 101 student list, NANDA text)</li><li>Formulate a Nursing Diagnosis in PES format: Problem/Etiology/Signs &amp; Symptoms (state assessment data) OR P+RF format: Potential Problem/AEB/Risk Factors</li></ol>
<i>Impaired Cerebral Tissue Perfusion related to effects of recent head injury AEB report of loss of consciousness lasting 10 minutes, memory impairment and unequal pupils L&gt;R.</i>



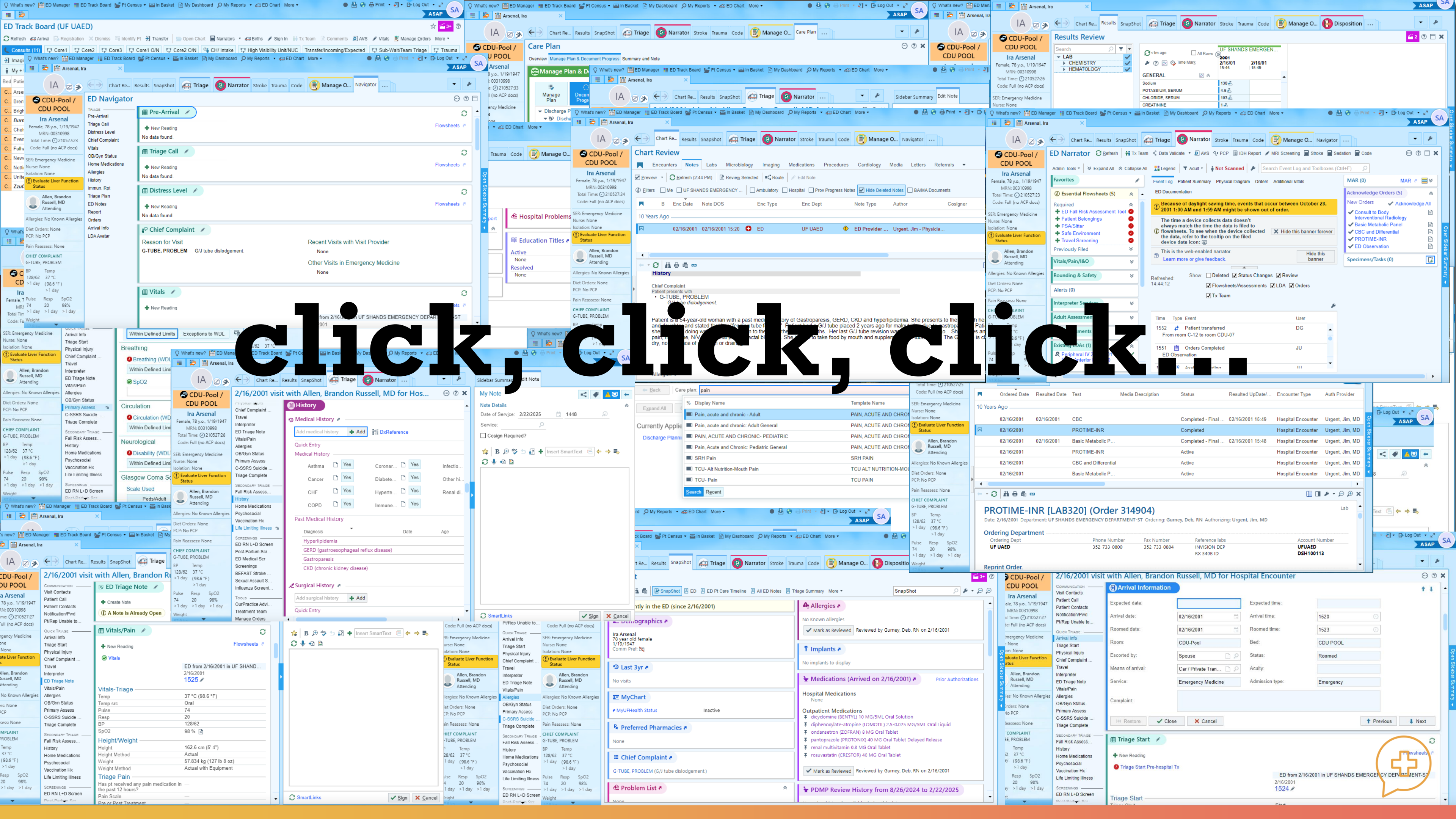
Nursing Care Plan						
Is a written guide that organizes information about client's care into a meaningful whole						
Cues	Nursing Diagnosis	Analysis	Goals and Objective	Intervention	Rationale	Evaluation
Subjective cues: Objective cues: (Includes relevant data such as vital signs, laboratory tests, observations)	ONANDA based: The condition upon based on cues (as stated in NANDA) Related to — the immediate cause of the client's condition	Explains the nursing diagnosis. Include references. May also present the underlying pathophysiology of the patient's condition.	Short-term and long-term  Specific, Measurable, Reasonable, Realistic and time bounded	Nursing interventions to be performed by the student during her duty to include Evidence-based nursing practice	Reason why a particular intervention will be performed. To include evidence why this intervention may be done. Include references	Actual result <del>result</del> on each intervention given.  Appropriate Appropriate Appropriate Appropriate Appropriate
			1- 2- 3- 4- 5-	1- 2- 3- 4- 5-	1- 2- 3- 4- 5-	





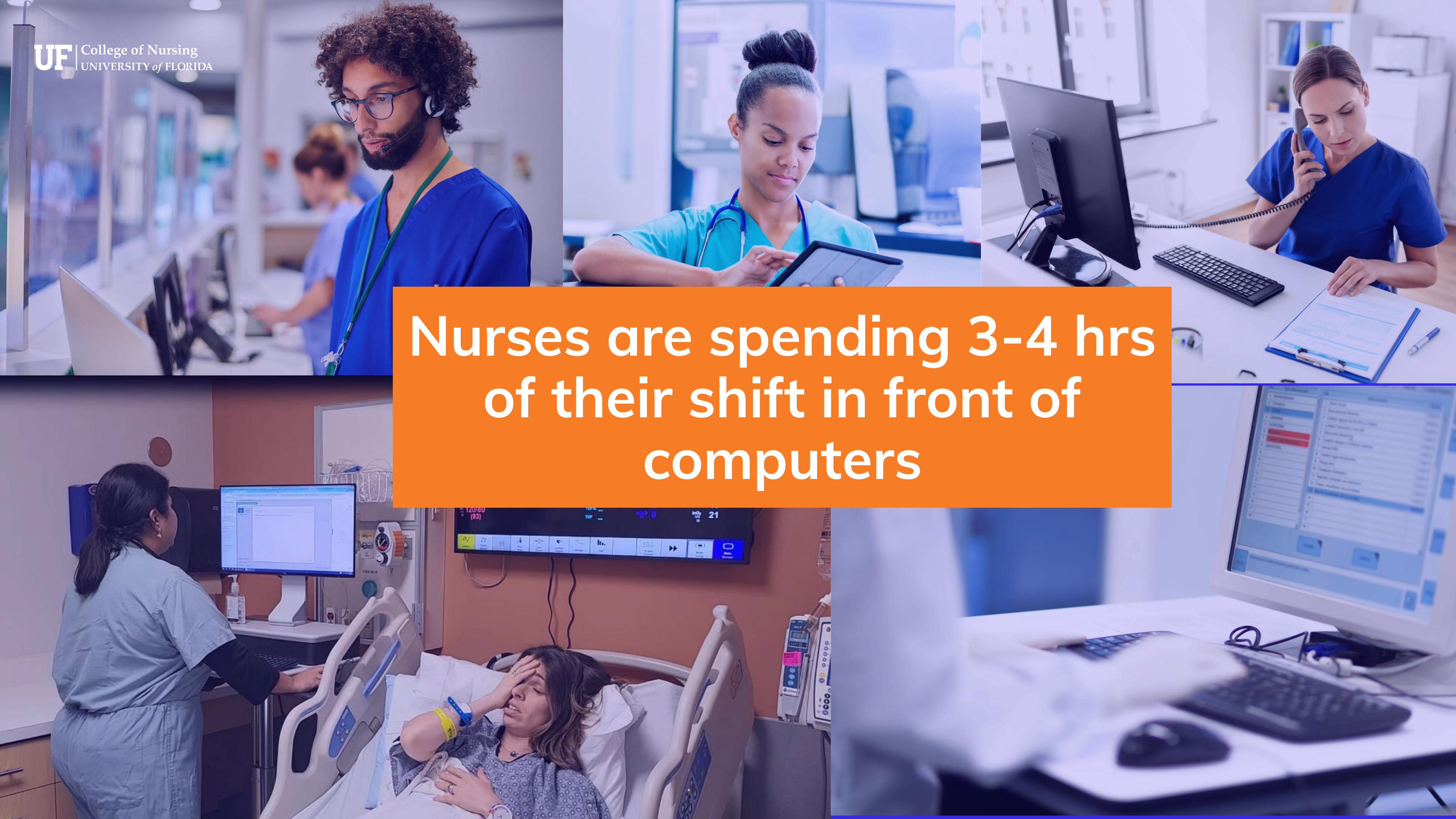
**WHAT HAPPENS BETWEEN  
NURSING SCHOOL AND PRACTICE?**







Nurses are spending 3-4 hrs  
of their shift in front of  
computers





My EHR does not  
support “good” nursing  
documentation!







We all create mental  
care plans!





# Care plans have value

**Table 3.** Summary of predictors and outcomes for included studies that measured impact of nursing care

First author	Predictors	Outcomes
Monsen <sup>64</sup>	Nurses, nursing diagnoses (ie, problems), nursing interventions	Maternal risk index score
Monsen <sup>54</sup>	Patient’s characteristics, nurses, nursing interventions	Health literacy score
Olsen <sup>65</sup>	Patient’s age, gender and body mass index, nursing diagnoses, number of physical activity-related nursing interventions	Physical activity-related outcomes scores
Gao <sup>62</sup>	Nursing diagnoses used to determine social and behavioral determinants of health index, and frailty	Knowledge, behavior, and status outcomes scores
Lodhi <sup>38</sup>	Patient’s age, nurse experience, length of stay, time of admission, time of discharge, outcome ratings	Hospital readmissions
Lodhi <sup>41</sup>	Patient’s age, nurse experience, length of stay, nursing diagnoses and interventions domains	Meeting or not expected comfortable death outcome score
Lodhi <sup>43</sup>	Patient’s age, nurse experience, length of stay, nursing diagnoses and interventions domains, outcomes scores	Meeting or not expected pain-related outcome score
Stifter <sup>47</sup>	Nurse continuity, nurse-staffing variables	Pressure ulcer-related outcomes
Yao <sup>44</sup>	Patient’s age, length of stay, pain-related outcomes, number of nursing diagnoses in a care plan	Nursing diagnoses, interventions, and outcomes related to palliative care
Lodhi <sup>37</sup>	Patient’s age, nurse experience, length of stay, nursing diagnosis of death anxiety	Meeting or not expected comfortable death outcome score
Almasalha <sup>40</sup>	Nursing interventions, length of stay	Meeting or not expected pain-related outcome score
Yao <sup>39</sup>	Nursing diagnoses, pain-related outcome scores, length of stay	Meeting or not expected pain-related outcome score
Escalada-Hernandez <sup>46</sup>	Health of the Nation Outcome Scale scores	Number of nursing diagnoses
Jenkins <sup>30</sup>	Patient characteristics, nurse characteristics	Nursing cost
Garcia <sup>59</sup>	Patient’s mental health conditions	Knowledge, behavior, and status outcomes scores
Monsen <sup>56</sup>	Nursing interventions	Patient’s hospitalization
Westra <sup>57</sup>	Nursing interventions, assessment data	Improvement on urinary or bowel incontinence
Shever <sup>33</sup>	Number of times the nursing intervention “surveillance” is delivered per day (more or less than 12 times)	Failure to rescue
Titler <sup>31</sup>	Patient characteristics, nursing unit characteristics, nursing interventions medical interventions, pharmacy interventions	Occurrence of falls
Shever <sup>32</sup>	Nursing staff variables, number of medical treatments, number of pharmacy treatments	Cost of the nursing intervention “surveillance”

Macieira TGR, Chianca TCM, Smith MB, et al. Secondary use of standardized nursing care data for advancing nursing science and practice: a systematic review. J Am Med Inform Assoc. 2019;26(11):1401-1411. doi:10.1093/jamia/ocz086

The impact of spiritual care delivered by nurses on patients’ comfort: A propensity score matched cohort utilizing electronic health record data

Fabiana Cristina Dos Santos<sup>a,\*</sup>, Tamara G.R. Macieira<sup>b</sup>, Yingwei Yao<sup>c</sup>, Monika Ardelt<sup>d</sup>, Gail M. Keenan<sup>b</sup>

<sup>a</sup> Columbia University, School of Nursing, New York, NY, United States  
<sup>b</sup> Department of Family, Community, and Health Systems Science, College of Nursing, University of Florida, Gainesville, FL, United States  
<sup>c</sup> Department of Biobehavioral Nursing Science, College of Nursing, University of Florida, Gainesville, FL, United States  
<sup>d</sup> Department of Sociology and Criminology & Law, University of Florida, Gainesville, FL, United States

## Nursing Care for Hospitalized Older Adults With and Without Cognitive Impairment

Tamara G. R. Macieira ▼ Yingwei Yao ▼ Madison B. Smith ▼ Jiang Bian ▼ Diana J. Wilkie ▼ Gail M. Keenan



CLINICAL SCHOLARSHIP | Full Access

### Determinants of Prolonged Hospitalization in Children and Adolescents: A Retrospective Observational Study

Manuele Cesare, Fabio D'Agostino, Mario Cesare Nurchis, Erasmo Magliozzi, Gianfranco Damiani, the Nursing and Public Health Group, Antonello Cocchieri✉

First published: 13 January 2025 | <https://doi.org/10.1111/jnu.13045>

— — — — —

### Deciphering the Link Between Diagnosis-Related Group Weight and Nursing Care Complexity in Hospitalized Children: An Observational Study

by Manuele Cesare<sup>1,\*</sup> ✉ , Fabio D’Agostino<sup>2</sup> ✉ , Emanuele Sebastiani<sup>3</sup> ✉ , Nursing and Public Health Group<sup>4</sup> ✉, Gianfranco Damiani<sup>5</sup> ✉ and Antonello Cocchieri<sup>5</sup> ✉

# How do we change this scenario?



Can AI help us?





# What are large language models (LLMs)?

LLMs are advanced types of artificial intelligence (AI) designed to understand, generate, and manipulate human language.

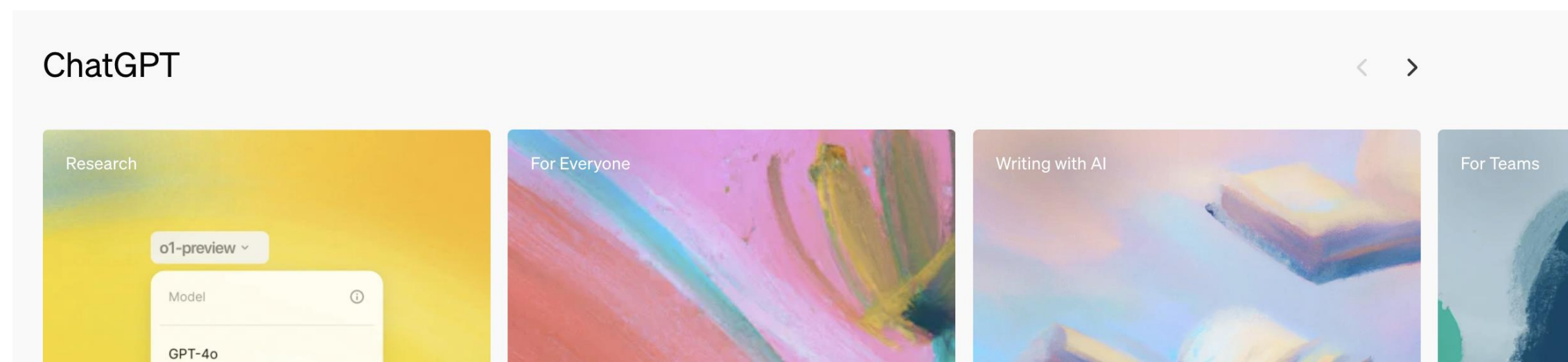
LLMs are trained on vast amounts of text data and can perform a wide range of natural language processing tasks, such as translation, summarization, answering questions, and generating human-like text.



# Types of LLMs

## Generative Pretrained Transformer (GPT)

- They generate text based on a given prompt
- GPT models are autoregressive, which means they predict the next word in a sequence based on the previous words
- They are used in applications like chatbots, content generation, summarization, and creative writing
- These models can generate highly coherent and contextually appropriate text, making them suitable for diverse healthcare applications, like generating patient summaries or aiding in clinical decision-making



# Types of LLMs

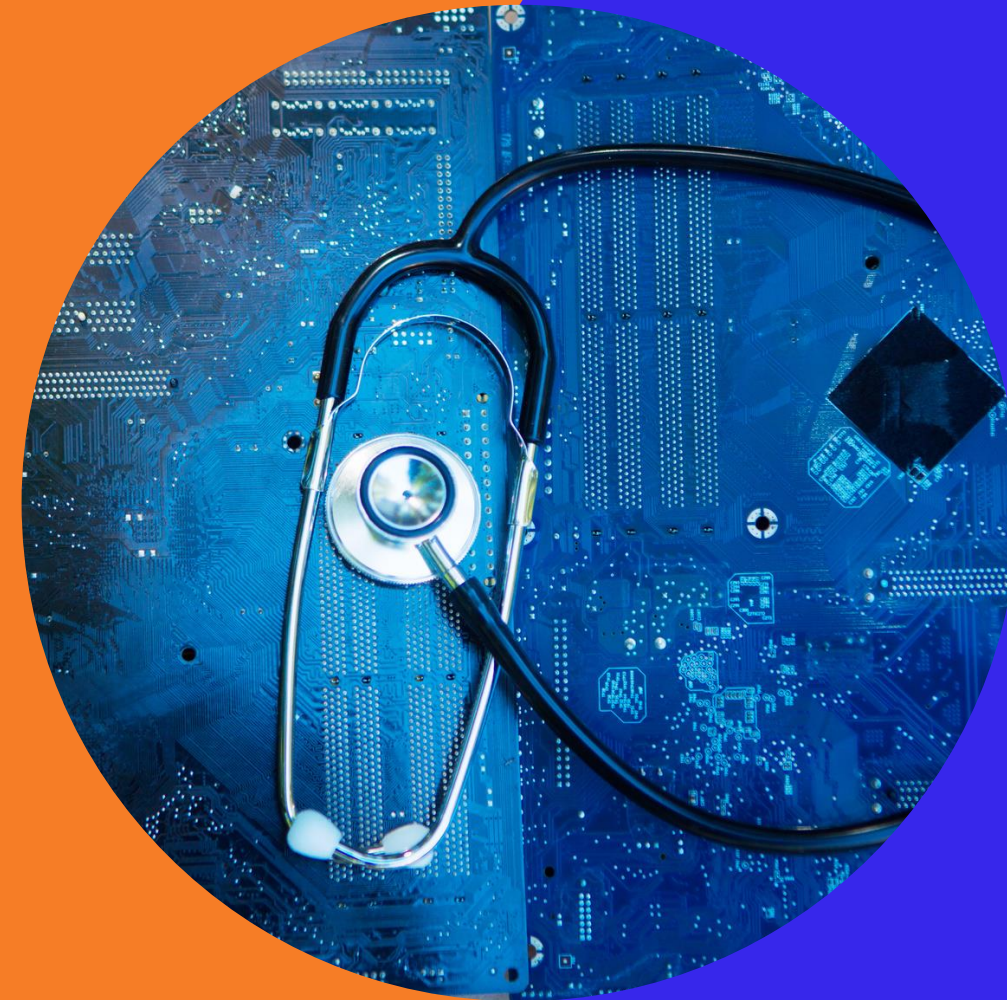
## **BERT (Bidirectional Encoder Representations from Transformers)**

- Bidirectional model, which means it understands the context of a word based on the words before and after it in a sentence
- BERT excels in tasks like answering questions, sentiment analysis, and understanding complex queries, which makes it valuable for retrieving clinical knowledge and understanding nuanced medical texts
- It's often used in applications like clinical text mining, document classification, and information retrieval in healthcare settings





# Why LLMs matter in healthcare today



## **Clinical Documentation Enhancement:**

- Auto-summarizing nursing notes and patient histories
- Streamlining nursing workflows with smart documentation tools

## **Clinical Decision Support:**

- LLMs in assisting with clinical guidelines and recommendations

## **Patient Education and Communication:**

- Generating patient-friendly educational material
- Enhancing nurse-patient communication through AI-driven interactions

## **Research and Data Analysis:**

- Supporting literature reviews and evidence synthesis
  - Patient engagement tools
  - Assisting with qualitative data analysis in nursing research
- 



# Challenges and ethical considerations

- Data privacy and security concerns
- Bias and fairness in LLMs
- Nurses' role in oversight and ethical use

***Nurses need to be more involved in AI development***

# Exemplars of LLM use in creation and documentation of care plans



# LLMs for care plans

## JOURNAL ARTICLE

### An example of leveraging AI for documentation: ChatGPT-generated nursing care plan for an older adult with lung cancer

Get access >

Fabiana C Dos Santos, PhD, MSN, RN ✉, Lisa G Johnson, MSN, RN, Olatunde O Madandola, MPH, RN, Karen J B Priola, MSCIS, Yingwei Yao, PhD, Tamara G R Macieira, PhD, RN, Gail M Keenan, PhD, RN, FAAN

*Journal of the American Medical Informatics Association*, Volume 31, Issue 9, September 2024, Pages 2089–2096, <https://doi.org/10.1093/jamia/ocae116>

**Published:** 17 May 2024    **Article history** ▼

## FEATURE ARTICLES

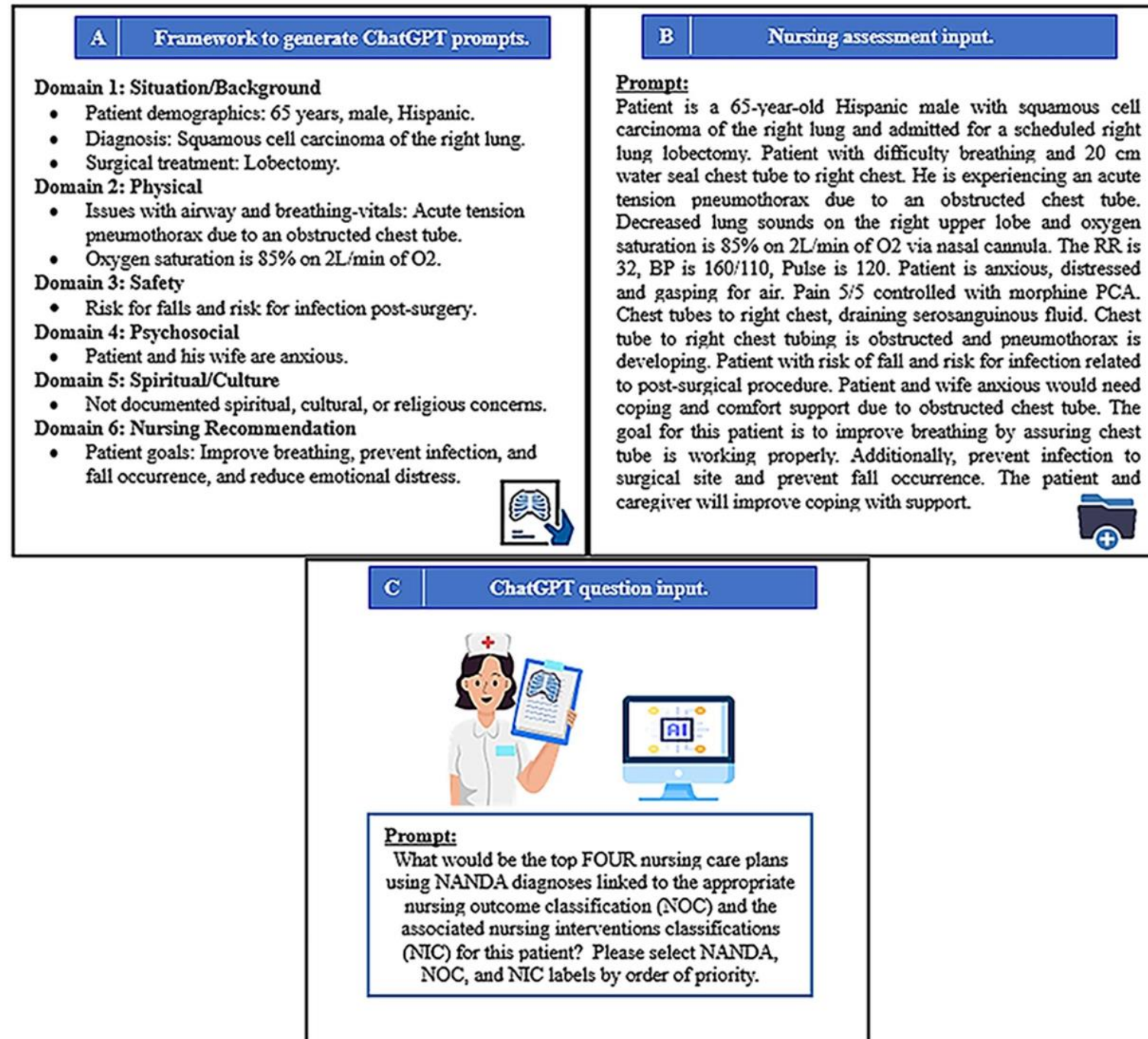
### Creating Perinatal Nursing Care Plans Using ChatGPT A Pathway to Improve Nursing Care Plans and Reduce Documentation Burden

Johnson, Lisa G. MSN, RN; Madandola, Olatunde O. MPH, RN; Dos Santos, Fabiana Cristina PhD, MSN, RN; Priola, Karen J. B. MSCIS; Yao, Yingwei PhD; Macieira, Tamara G. R. PhD, RN; Keenan, Gail M. PhD, RN, FAAN

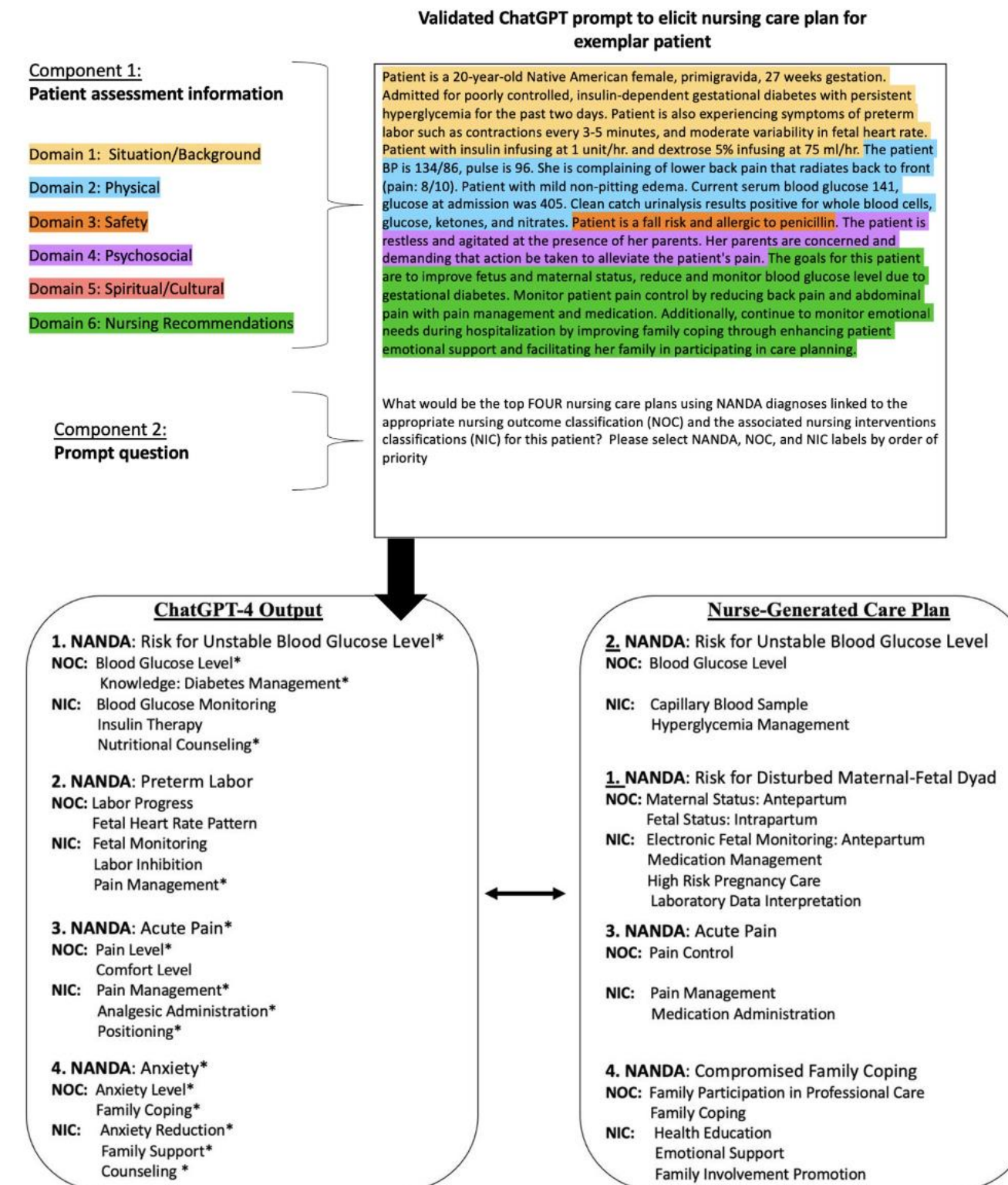
[Author Information](#) ☺

*The Journal of Perinatal & Neonatal Nursing* 39(1):p 10-19, January/March 2025. | DOI: 10.1097/JPN.0000000000000831

# LLMs for care plans



Dos Santos FC, Johnson LG, Madandola OO, et al. An example of leveraging AI for documentation: ChatGPT-generated nursing care plan for an older adult with lung cancer. *J Am Med Inform Assoc*. 2024;31(9):2089-2096. doi:10.1093/jamia/ocae116



Johnson LG, Madandola OO, Dos Santos FC, et al. Creating Perinatal Nursing Care Plans Using ChatGPT: A Pathway to Improve Nursing Care Plans and Reduce Documentation Burden. *J Perinat Neonatal Nurs*. 2025;39(1):10-19. doi:10.1097/JPN.0000000000000831



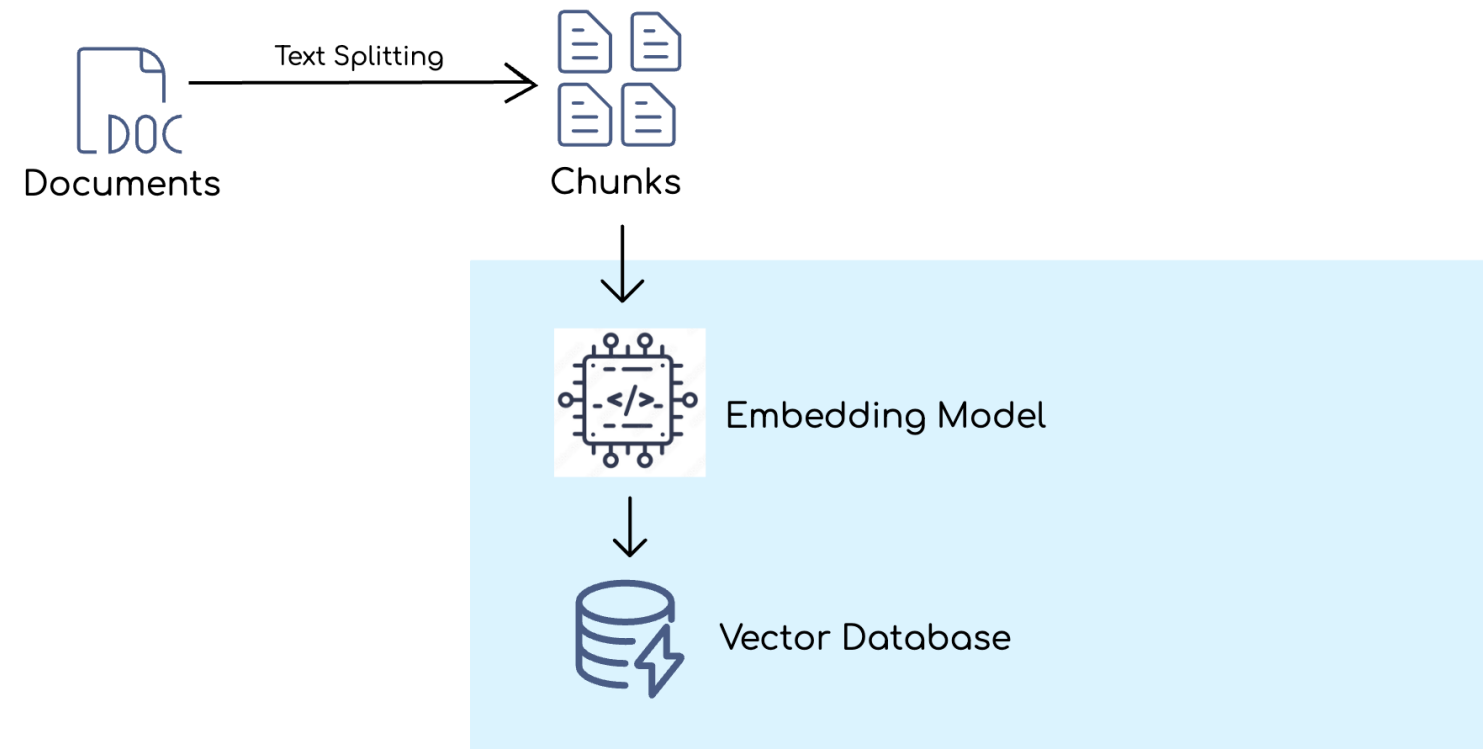
# Our findings:

- There is potential of using AI-based systems such as ChatGPT to generate nursing care plan documentation
- While the generated care plans show promise, nurses need to evaluate these plans critically in the context of the patient's unique needs
- LLM accessed through a chat interface does not generate standardized care plans – we *have hallucinations*
  - This is an **issue** for data interoperability, data exchange, and continuity of care



# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

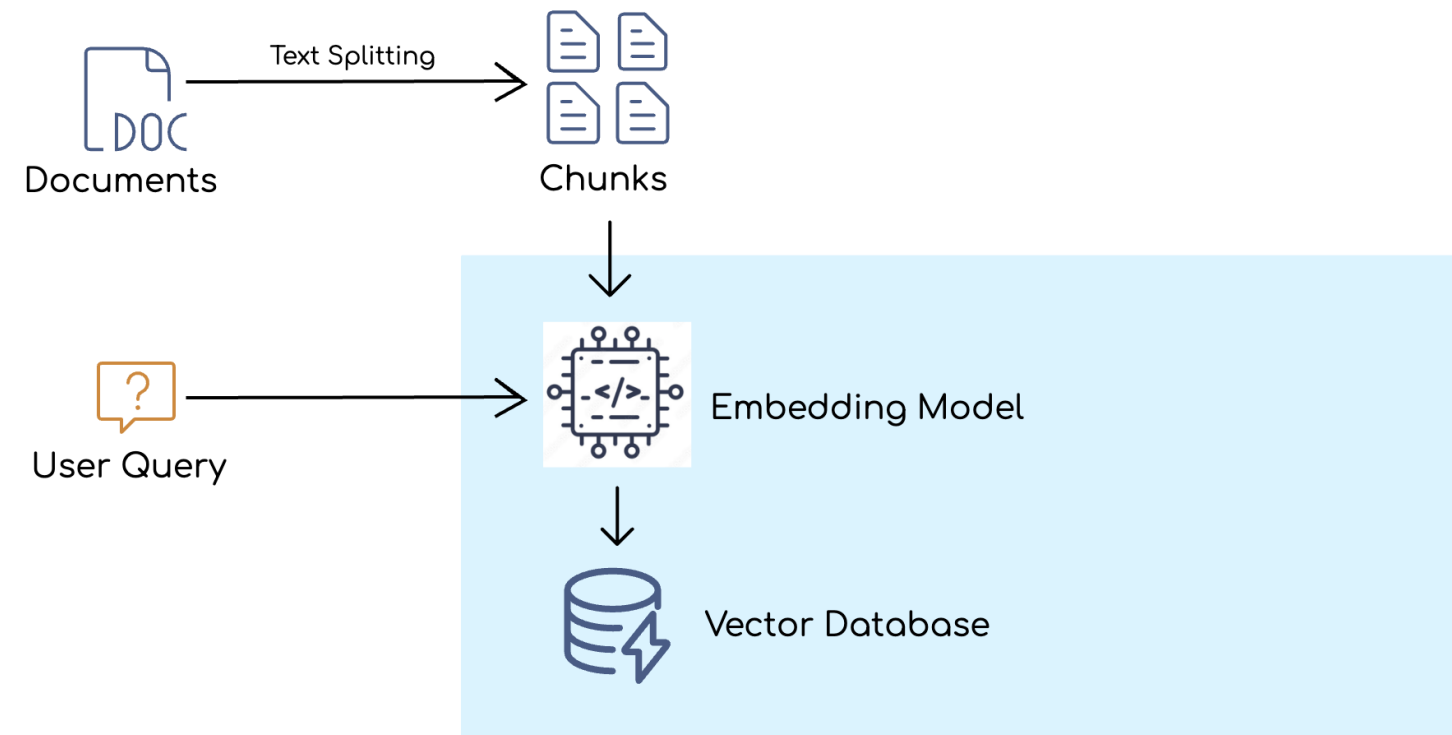
## Data Ingestion





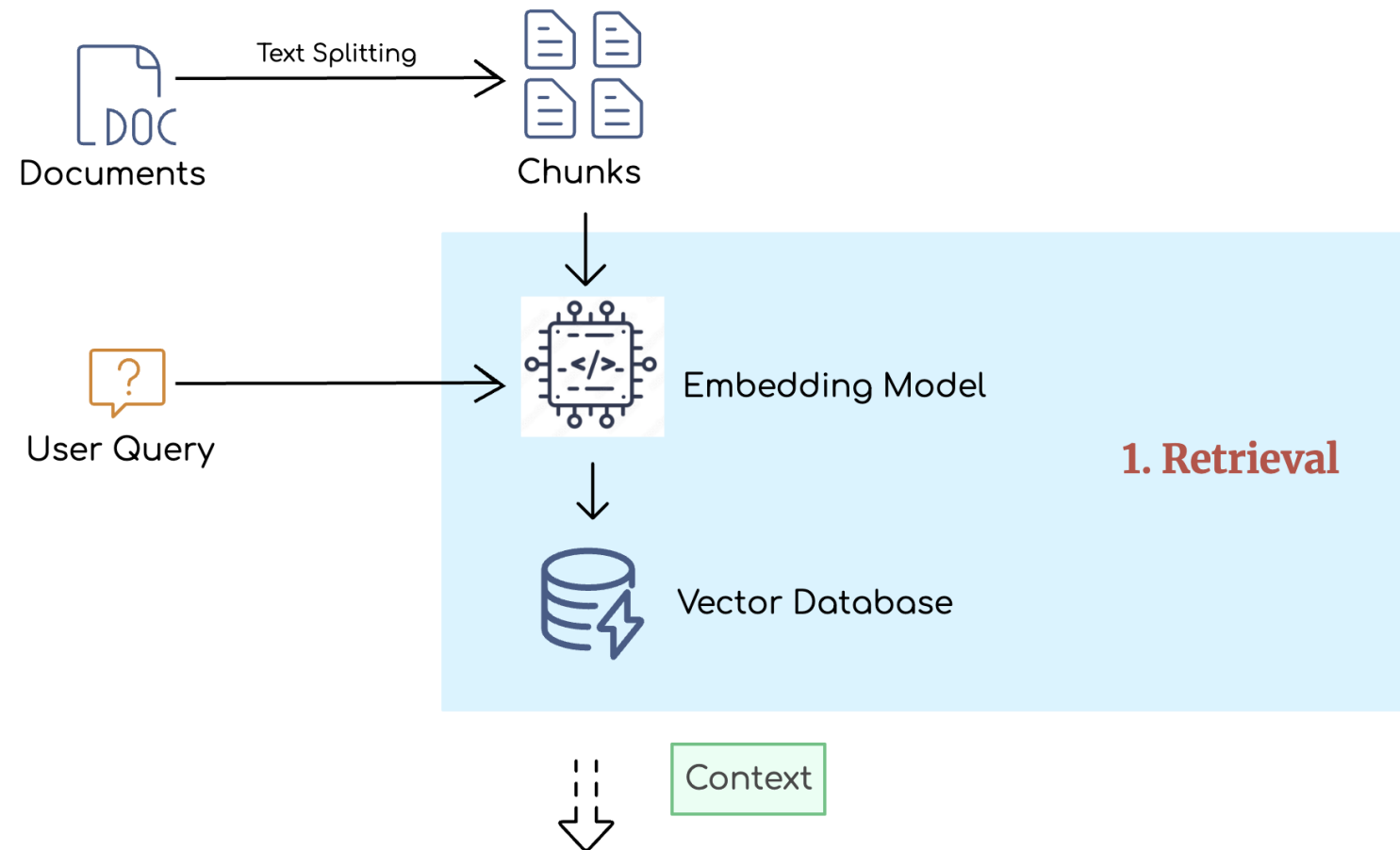
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## Data Ingestion



# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

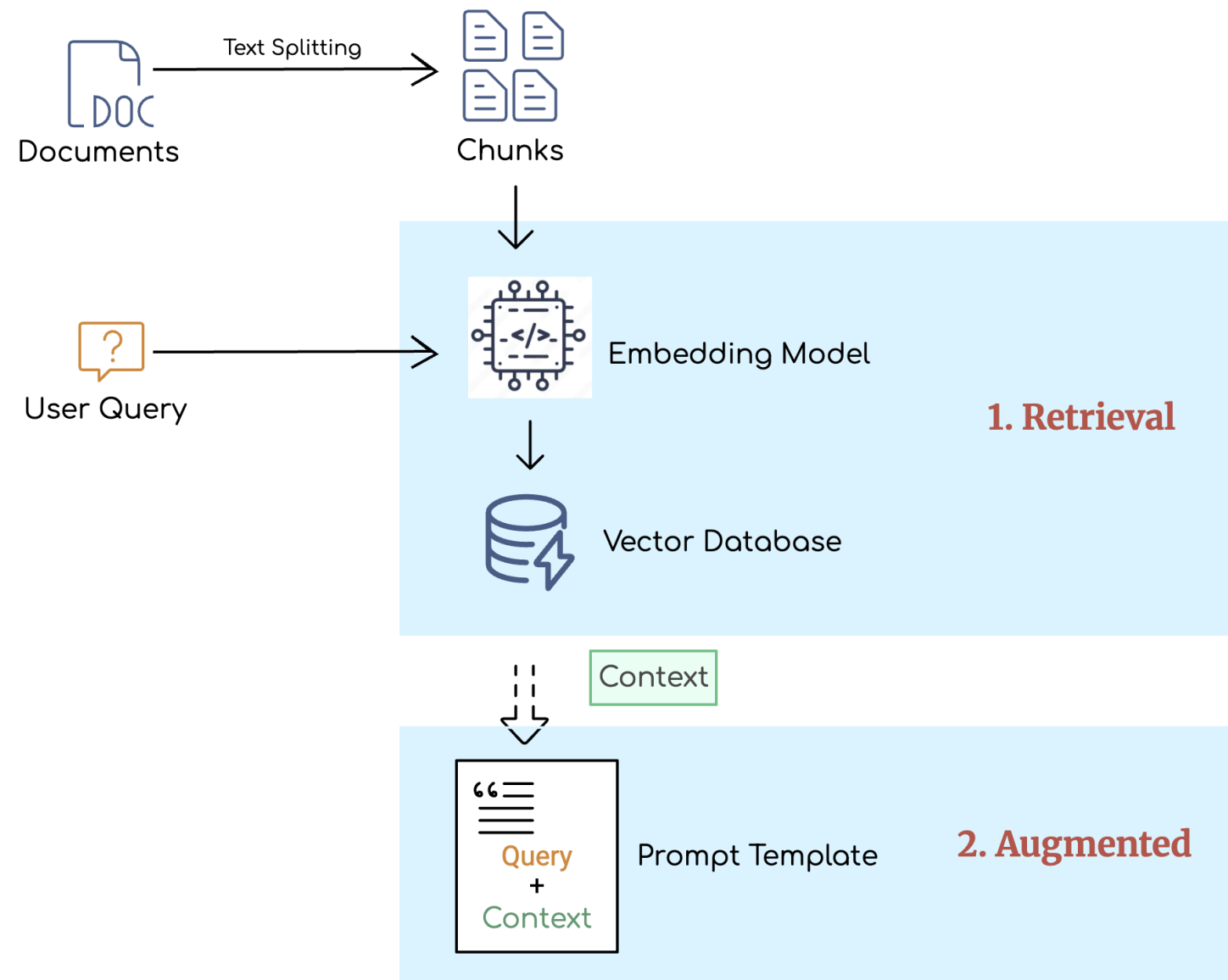
## Data Ingestion





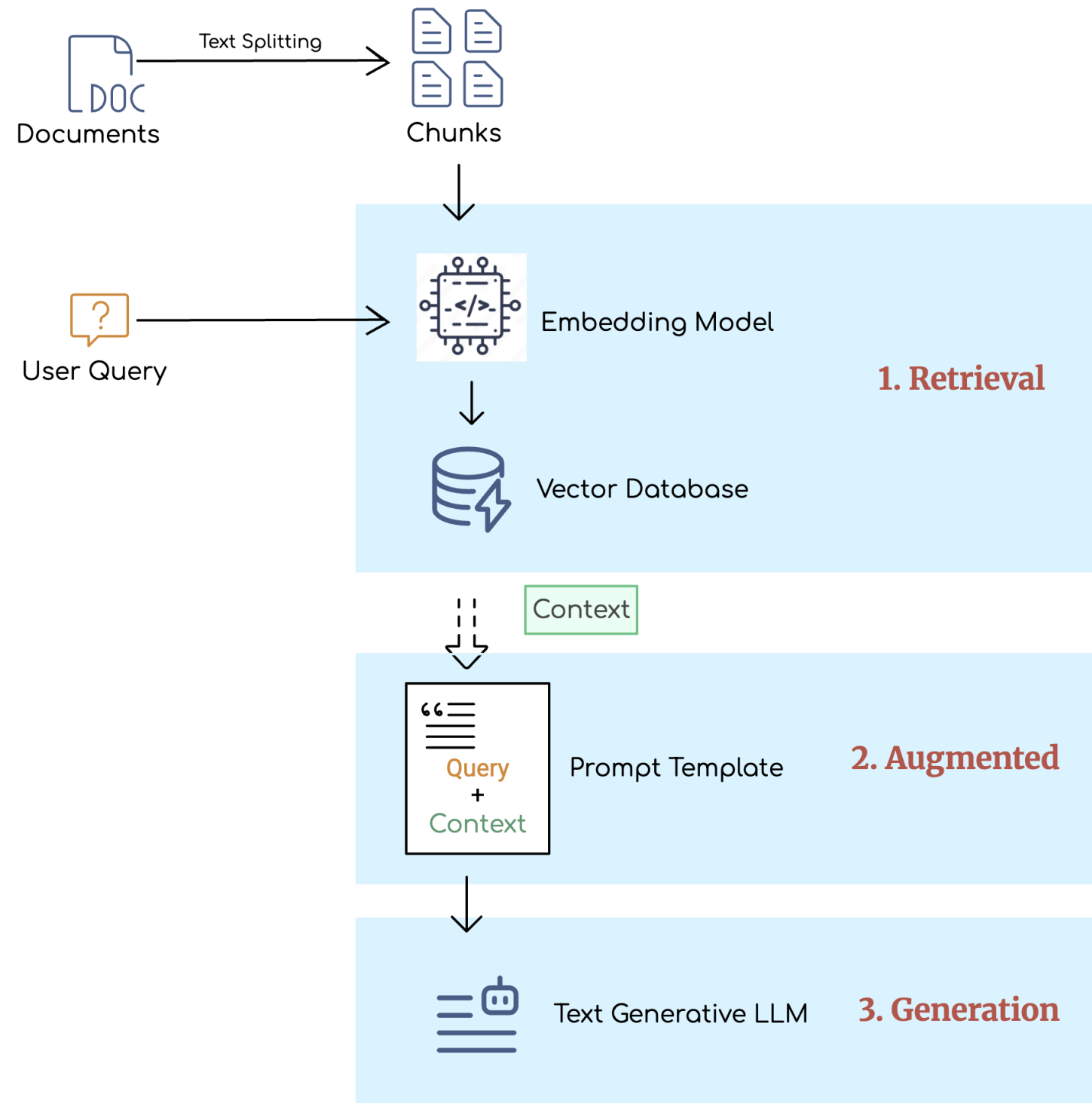
# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

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# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

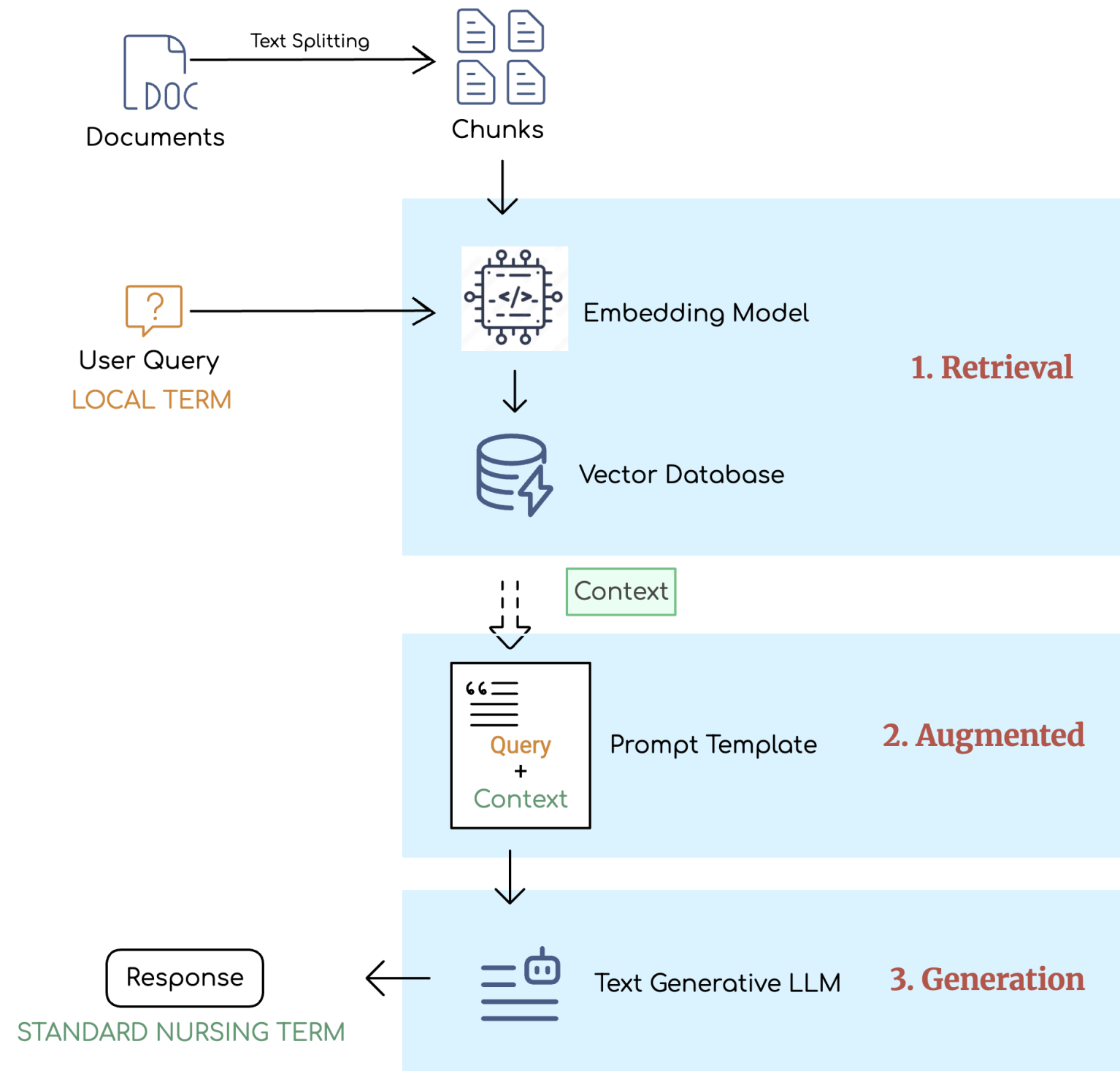
## Data Ingestion





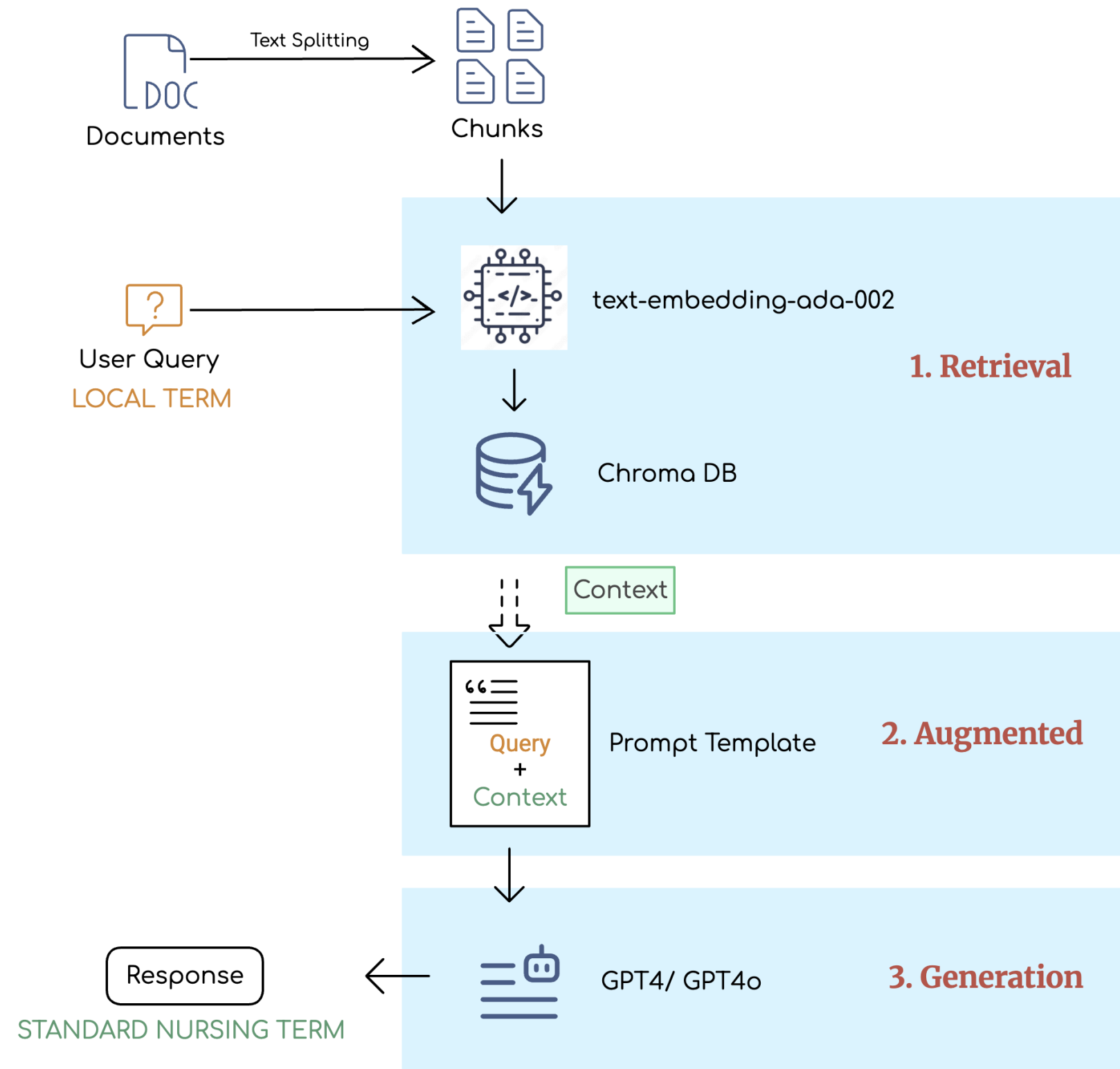
# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

## Data Ingestion



# Our current approach: Implementing a retrieval augmented generation (RAG) pipeline

## Data Ingestion



## Features of RAG Pipeline

- Avails access to precise domain-specific answers from LLMs
- Scales to handle diverse clinical queries with reliability
- Supports embedding of structured datasets (CSV, TXT, DOCX, etc.)
- Leverages LLM intelligence grounded with Deep knowledge of Nursing Terminologies.
- Infuses Prompts with real-time knowledge
- **Improves accuracy and reduces hallucinations**





**How can we incorporate LLMs into nursing practice?**

HANDSFreeNurse

Moxie






handsfreenurse@gmail.com  
gkeen@ufl.edu





# Introducing the “Siri” for nurses

Moxie

-  Bypasses outdated technology
-  Voice-to-text 2-way EHR documentation
-  Artificial intelligence enabled
-  Vendor agnostic
-  Anytime, anywhere, HANDS FREE



# HOW Moxie Works

Moxie

Listening for commands...

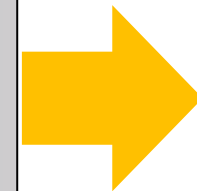
Hey Moxie, Patient X is a 65 yo African American male who has been experiencing excruciating pain in his lower back over the past few hours. His urine is slightly pink. He has a history of diabetes type 2 and kidney stones. He is 5 feet 10 in and weighs 170lbs. He takes Metformin 500mg 2x a day. His current BP is 160/90, P is 92, R is 22,T is 98.4 and pulse ox is 95. Please suggest a care plan with no more than 2 problems for Patient X.

Care Plan

**1NANDA:** Acute Pain  
**2NOC:** Pain Level  
Current Rating 3  
Expected Rating 5  
**3NIC:** Medication Administration  
**4NIC:** Pain Monitoring  
**5NOC:** Vital Signs  
Current Rating 5  
Expected Rating 5  
**6NIC:** Vital Sign Monitoring

**7NANDA:** Risk for Infection  
**8NOC:** Risk Control Infectious Process  
Current Rating 3  
Expected Rating 5  
**9NIC:** Teaching: Disease Process  
**10NIC:** Surveillance

Scratch Pad



Moxie

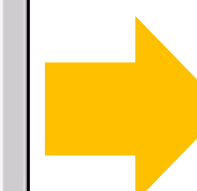
Listening for commands...

Hey Moxie, change Current Rating 5NOC to 4, delete 7NANDA, and save care plan

Care Plan

**1NANDA:** Acute Pain  
**2NOC:** Pain Level  
Current Rating 3  
Expected Rating 5  
**3NIC:** Medication Administration  
**4NIC:** Pain Monitoring  
**5NOC:** Vital Signs  
Current Rating 4  
Expected Rating 5  
**6NIC:** Vital Sign Monitoring

Scratch Pad



Moxie

Listening for commands...

Hey Moxie, get Patient X's latest vital signs and medication list

Date/Time	5.8.25 / 1630	
Vital Signs		Medication List
BP	160/90	Tramadol 75mg/PRN q3h - 1600
P	92	Metformin 500 mg 2x/d - 0800
R	22	
T	98.4	
SPO2	95	

Scratch Pad





# Created by nurses for nurses



Gail Keenan, PhD, RN  
Founder and CEO



Ashfaq Khokhar, PhD  
CTO



Tamara Macieira, PhD, RN  
Nursing & IT Manager



Karen Priola, MS-CIS  
Operations Manager



Shakira Henderson, PhD, RN, DNP  
Board Chair



Nico Torteli, ME  
CRO



# 1. CREATE SPACE



## 2. IDENTIFY CHAMPIONS

# 3. IDENTIFY INCENTIVES



# 4. THINK BIG



**AI CAN TRANSFORM HEALTHCARE,  
YOU HOLD THE KEY!**

# Thank You

**YOU should lead the change to enable an AI-driven future for nursing excellence**

