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Authors

Andalib, Saman

Spina, Aidin

Halaseh, Faris F.

et al.

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An Organized Approach to Using Large Language Models for Medical Information

Saman Andalib, BS
Aidin Spina, BS
Faris F. Halaseh, BS
Anagha B. Thiagarajan, BS
Rishi Vermani, BS
Jason Liang, BS
Warren F. Wiechmann, MD

University of California, Irvine, School of Medicine, Irvine, California

Section Editor: Phillips Perera, MD, RDMS

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Introduction: ChatGPT and other large language models (LLM) have increased in popularity. Despite the rapid rise in the implementation of such technologies, frameworks for implementing appropriate prompting techniques in medical applications are limited. In this paper we establish the nomenclature of “variable” and “clause” in the prompting of a LLM, while providing example interviews that outline the utility of such an approach in medical applications.

Methods: In this study assessing the LLM ChatGPT-4, we define terms used in prompting procedures including “input prompt,” “variable,” “demographic variable and clause,” “independent variable and clause,” “dependent variable and clause,” “generative clause,” and “output.” This methodology was implemented with three sample patient cases from both a patient and physician perspective.

Results: As demonstrated in our three cases, precise combinations of variables and clauses that consider the patient’s age, gender, weight, height, and education level can yield unique outputs. The software can do so quickly and in a personalized, patient-specific manner. Our findings demonstrate that LLMs can be used to generate comprehensive sets of educational material to augment current limitations, with the potential of improving healthcare outcomes as the use of LLM is further explored.

Conclusion: The framework we describe represents a unique attempt to standardize a methodology for medical inputs into a large language model. Doing so expands the potential for outlining patient-specific information that can be implemented in a query by either a patient or a physician. Most notably, future projects should consider the specialty- and presentation-specific input changes that may yield the best outputs for the desired goals. [West J Emerg Med. 2026;27(1)194–204.]

INTRODUCTION

Technology has entered an era of rapid progress with the advent and implementation of artificial intelligence (AI). Large language models (LLM), such as ChatGPT (developed and released by OpenAI, available at chat.openai.com), are among the fastest growing internet applications since their release in late 2022.¹ Initial iterations of ChatGPT were bounded by 175 billion parameters, making them the most

comprehensive LLMs to date.²

The rapid rise in the use of LLMs like ChatGPT has recently entered the medical field, yet their reliability, safety, and clinical relevance remain underexplored.^{3–5} Existing studies have evaluated LLMs’ ability to answer medical knowledge questions, generate novel research ideas, and translate medical documentation. ChatGPT has demonstrated high accuracy on publicly available United States Medical

Licensing Examination Step 1 and Step 2-Clinical Knowledge questions and has been used in specialties such as plastic surgery to identify topics for exploration in systematic reviews.^{6,7} Additionally, ChatGPT showed high accuracy in generating responses to general medical questions.⁸ Furthermore, one study demonstrated that ChatGPT responses to patient questions have been rated highly for both quality and empathy.⁹

Despite the potential of LLMs to revolutionize the medical field, limitations exist in the current capabilities of such software. Most notably, conversational models like ChatGPT have depicted prevalent and pervasive “hallucinations” in their outputs.¹⁰⁻¹² These are generally known as fabricated LLM outputs and are often noted in medical applications as falsified references to medical literature that do not exist.¹³⁻¹⁶ Hallucinations in LLMs pose a significant challenge to the successful implementation of LLMs in medical settings, as variations in input structure and clarity significantly influence model outputs.¹⁷ Implementing a standardized prompting framework may mitigate hallucinations by ensuring consistent, well-structured inputs that guide LLMs toward more accurate and clinically relevant outputs.^{4,18,19} In this paper our goal was to present a unique iteration of standardizing medically relevant LLM search strategies by proposing a framework of “clauses” and “variables.” The framework introduced here has the potential to personalize the answers that LLMs provide to patients while ensuring a level of control over the entry methodology used to develop medical outputs from LLMs.

METHODS

Operational Definitions (Figure 1)

Variable

A variable limits the bounds of LLM processing. Variables specify the parameters that guide the model’s reasoning and are expressed within clauses. Three variable types are used in this framework:

- Demographic variable (DMV) defines patient background (eg, “52-year-old male, weight 221 lbs”).
- Independent variable (IV) represents the primary concern or condition (eg, “diagnosis of type 2 diabetes”).
- Dependent variable (DPV) reflects specialty-specific details or measurable outcomes (eg, “blood glucose level 152 mg/dL” or “recommended metformin regimen”).

Clause

A clause connects variables into meaningful sentences within the input prompt. Each clause narrows how the LLM processes information. Four clause types structure medically relevant prompts:

- Demographic clause (DMC) links demographic variables (eg, “I am a 52-year-old male patient living in Miami”).
- Independent clause (IC) introduces the main clinical concern (eg, “I was just diagnosed with type 2 diabetes”).

Population Health Research Capsule

What do we already know about this issue?
Patient education materials are not tailored to the patient’s background and are written at a reading level above the average patient’s comprehension.

What was the research question?
Can a large language model (LLM) generate personalized, patient-specific education materials using structured clinical prompts?

What was the major finding of the study?
Across three cases, structured prompts generated unique outputs tailored to patient demographics, demonstrating personalization.

How does this improve population health?
Structured LLM prompts generating personalized, accessible education may improve patient understanding, engagement, and adherence.

LEGEND	
Input Prompt:	Types:
Variable: A variable limits the bounds of LLM processing. A variable is written in terms of a clause that connects the variable to other segments of the input prompt into ChatGPT.	<u>Demographic Variable (DMV)</u> Independent Variable (IV) Dependent Variable (DPV)
Clause: A clause is a group of words (containing at least a subject and predicate) that conveys part of an idea. Clauses can be connected to one another to create further bounds upon the processing of the LLM in question.	Demographic Clauses (DMC) Independent Clauses (IC) Dependent Clauses (DPC) Generative Clause (GC)

Figure 1. Left column: term definitions; right column: color-highlighted phrases and abbreviations delineate text breakdown. LLM, large language model.

- Dependent clause (DPC) adds measurable or treatment-specific details (eg, “My blood glucose came back as 152 mg/dL, and my doctor recommended metformin”).
- Generative clause (GC) specifies the task for the model, integrating all prior clauses into a focused request (eg, “Please explain why this treatment was recommended, and provide a comprehensive overview tailored to my case”).

Annotated Input Prompt 1	
Hello, I am a 52-year-old male patient. I am 6'2" and weigh 221 lbs. I live at home in Miami with my daughter and I own my own small business. The highest level of education I have achieved is completing my associate's degree. A	Hello, I am a DMV patient. I am DMV and weigh DMV. I live at DMV and I DMV. The highest level of education I have achieved is completing my DMV B
I was just diagnosed with type 2 diabetes. C	I was just diagnosed with IV. D
My blood glucose just came back as 152mg/dL. My doctor recommended that I take metformin, alter my diet, and exercise daily. E	My DPV just came back as DPV. My doctor recommended DPV. F
What advice do you have for best managing my type 2 diabetes? Can you also explain to me why my doctor recommended this specific treatment regimen, given the information I have provided you about myself. Can you make this response extremely comprehensive to provide me with an in-depth understanding of what is going on. G	What advice do you have for best managing my IV? Can you also explain to me why my doctor recommended this specific treatment regimen, given the information I have provided you about myself? Can you make this response extremely comprehensive, to provide me with an in-depth understanding of what is going on? H

Figure 2. Example of ChatGPT annotated input prompt for a patient perspective regarding their diagnosis of Type II Diabetes (scenario 1).
A,B) Demographic clause with demographic variables.
C,D) Independent clause with independent variables.
E,F) Dependent clause with dependent variables.
G,H) Generative clause.
All variables within each clause have been codified as bolded letters. Color-highlighted phrases in left column delineate text breakdown by type of clause.
DMV, demographic variables; IV, independent variables; DPV, dependent variables.

The generative clause serves as the culmination of the system, effectively optimizing the abstraction of relevant information while reducing the likelihood of false or incomplete outputs.

Input Prompt Construction

An input prompt is the complete entry submitted to ChatGPT. Each prompt is built sequentially using the three variable categories (DMV, IV, DPV) embedded within the four clause types (DMC, IC, DPC, GC). This layered design standardizes inputs, ensuring clarity and reproducibility across queries. A fully annotated input prompt is shown in Figure 2.

Quantitative Analysis

We analyzed all prompts generated by the LLM for word count and readability via a Flesch-Kincaid Reading Ease (FKRE) score. The FKRE score is a readability formula evaluating how easy a text is to read based on average sentence length and average number of syllables per word. The FKRE scores range from 0- 100, with higher scores indicating easier reading levels. Full quantitative analysis of readability can be found in Table 1.

RESULTS

Annotated Input Prompts

We structured and annotated six different input prompts to provide broad examples of the outlined prompting structure (Figures 4A-B, S1A-D). Three of these prompts were written from the patient perspective (Figures 4A, S1A, C), and three from the physician perspective (Figures 4B, S1B, D) to further illustrate prompting utility. All annotated input prompts yielded an output, with scenario 1 included in the paper (5A, B), and two addition scenarios (2, 3) included as supplemental figures (S2A-S2D).

Quantitative Analysis

We calculated word count and readability via FKRE scores for each LLM output. The FKRE scores range from 0-100, with higher scores indicating easier reading levels (Table).

DISCUSSION

Overview

There is currently limited research exploring the standardization of input prompts for LLMs in the medical field. Prior studies have shown that unstructured input prompts to an LLM yield significant deficiencies in their generated output, pointing to a need to explore the quality of structured input prompts.²⁰ Our goal in this paper was to establish a reproducible and systematic approach to healthcare-related inputs to LLMs.

There are many benefits to developing and refining such a framework for input prompting techniques.¹⁹ Firstly, the outlined patient-specific information in medical queries can help tailor responses more effectively to individual patients. A comparison of Figure 3 and Figure 5A clearly depicts this difference in output. ChatGPT provided detailed information

Table. Word count and readability via FKRE scores for each LLM output.

	Word count	FKRE score
Unstructured input prompt	415	51.4
Patient perspective – diabetes	948	49.8
Physician perspective – diabetes	408	79.8
Patient perspective - outpatient TJA	760	39.7
Physician perspective - outpatient TJA	528	62.6
Patient perspective - adolescent STI education	524	52.6
Physician perspective - adolescent STI education	383	65.7

FKRE, Flesch-Kincaid Reading Ease score (0-100 scale, higher scores are easier to read); TJA, Total Joint Arthroplasty; STI, sexually transmitted infection.

Interview 1: Unstructured

Hello, I was just diagnosed with hyperglycemia and type 2 diabetes. What advice do you have for best managing my type 2 diabetes?

I'm really glad you reached out — getting a new diagnosis like type 2 diabetes can feel overwhelming, but with the right tools and support, it is absolutely manageable. Here's a clear and actionable guide to help you take control of your health:

1. Understand Your Diagnosis

Type 2 diabetes means your body is not using insulin effectively (insulin resistance), and over time, your pancreas may not make enough insulin. This causes high blood sugar (hyperglycemia), which, if left uncontrolled, can affect your heart, kidneys, eyes, nerves, and more.

2. Lifestyle Changes Are Your Foundation

These are often more powerful than medications early on:

A. Nutrition

- *Focus on whole, unprocessed foods: vegetables, lean proteins, whole grains, nuts, and healthy fats.*
- *Limit simple carbohydrates and sugar: avoid sugary drinks, white bread, desserts, and processed snacks.*
- *Control portion sizes: use the plate method—½ veggies, ¼ lean protein, ¼ complex carbs.*
- *Watch for hidden carbs in sauces, dressings, and drinks.*

B. Physical Activity

- *Aim for at least 150 minutes/week of moderate-intensity aerobic activity (eg, brisk walking, biking).*
- *Add resistance training 2–3 times/week (eg, weights, resistance bands) to improve insulin sensitivity.*
- *Start gradually and find something you enjoy to help make it a habit.*

C. Weight Management

If you're overweight, even a 5–10% weight loss can dramatically improve blood sugar control and reduce insulin resistance.

3. Monitor Your Blood Sugar

- *Your provider may recommend a glucometer to check your blood sugar levels at home.*
- *Ask what your target range should be (often 80–130 mg/dL fasting and <180 mg/dL after meals).*
- *Keep a log of your readings to see how food, activity, and medications affect your levels.*

4. Medications

- *If prescribed metformin or other medications, take them as directed.*
- *Never adjust doses on your own—always talk to your provider first.*
- *Ask about side effects and when you should contact your care team.*

5. Regular Medical Follow-Up

- *A1c blood test every 3–6 months (goal usually < 7%).*
- *Cholesterol, blood pressure, kidney function, and eye exams at least yearly.*
- *Foot exams at every visit—diabetes can cause nerve damage and poor healing.*

6. Build Your Support Team

- *Primary care physician or endocrinologist*
- *Registered dietitian (especially one certified in diabetes education)*
- *Pharmacist, diabetes educator, or counselor if needed*
- *Family and friends—include them so they can support your changes*

7. Stay Informed and Empowered

- *Consider a diabetes education program (ask your provider for referrals).*
- *Use trusted sources like:*
- *CDC Diabetes*
- *ADA (American Diabetes Association)*
- *MyPlate.gov*

Figure 3. Unstructured ChatGPT input prompt and generated output for a patient perspective regarding their diagnosis of diabetes (scenario 1).

Output generated by GPT-4 on July 22, 2025.

CDC, Centers for Disease Control and Prevention.

Annotated Input Prompt 1: Patient Perspective - Diabetes

"Hello, I am a 52-year-old male patient. I am 6'2" and weigh 221 lbs. I live at home in Miami with my daughter and I own my own small business. The highest level of education I have achieved is completing my associate's degree. I was just diagnosed with hyperglycemia and type 2 diabetes. In the emergency department, my blood glucose just came back as 152mg/dL and I had an HbA1c level of 6.8%. My doctor recommended that I take 500 mg metformin twice a day, alter my diet, and exercise daily. What advice do you have for best managing my hyperglycemia and type 2 diabetes? Can you also explain to me why my doctor recommended this specific treatment regimen, given the information I have provided you about myself. Can you make this response extremely comprehensive, in order to provide me with an in-depth understanding of what is going on."

Figure 4A. Chat GPT annotated input prompt for a patient perspective regarding their diagnosis of diabetes (scenario 1). Color-highlighted phrases delineate text breakdown by type of clause

Annotated Input Prompt 2: Physician Perspective - Diabetes

"Hello, I am a primary care specialist. I am treating a 52-year old, male patient. He is 6'2" and weighs 221 lbs. He lives at home in Miami with his daughter and owns his own small business. This patient's highest level of education is an associate's degree. I am currently managing this patient's hyperglycemia and type 2 diabetes. I recommend that he start treatment with 500 mg metformin twice a day, alter his diet and exercise daily to help him manage his condition. Can you help me develop a complimentary handout that I can give this patient to facilitate their treatment compliance? Can you personalize this handout to the patient, based on the information I have provided above?"

Figure 4B. Chat GPT annotated input prompt for a physician perspective regarding a care plan for their patient with a diagnosis of type 2 diabetes (scenario 2).

Color-highlighted phrases delineate text breakdown by type of clause.

about the medication prescribed (metformin), specific advice on dietary changes, and explicit guidelines for a recommended exercise regimen when properly prompted. On the other hand, the unstructured input prompt elicited a broader but shallower output from ChatGPT. This comparison underscores the capability of ChatGPT and other LLMs to change output information presentation in clinical vignettes when given additional patient-specific information in the initial input prompt.

Additionally, although LLMs like ChatGPT have unparalleled flexibility in their understanding of input prompts, this flexibility introduces variability, potential inaccuracies in the content, and bias in the output information provided. The structure outlined in this paper may provide a foundation for future research into the medical applications of LLMs by offering a systematic way to assess input prompts.

Input Prompt Structure

As shown in the three cases, combinations of specific variables and clauses can provide unique outputs that may significantly enhance patient education and serve as a supportive tool for physicians in patient care. Each input prompt starts with a set of demographic clauses, each

composed of demographic variables. We chose demographic variables that have been shown in the literature to have a substantial impact on patient care outcomes, while remaining concise.^{13,21} More research needs to be done to determine the optimal number and combination of demographic variables that can consistently produce the best outputs from LLMs. It is likely that the best combinations of demographic clauses and variables are contingent on the independent clause.

Following each set of demographic clauses is the independent clause, containing the independent variable. The independent clause is unique to each medical scenario and can be thought of as a sentence that represents the patient's chief concern. Most notably, chief concerns vary widely among different medical specialties.²² Thus, independent clause structuring could be crucial for optimizing the LLM's understanding of the independent variable. Dependent variables, housed within various dependent clauses, follow the independent clause. As shown in the example input prompts, the dependent clause structuring changed depending on the specific elements of the independent clause and variable. Subsequently, this input prompt element becomes the most challenging to further research and optimize for specialty-specific goals in LLM use. Finally, the last section of our

Interview 1: Patient perspective - diabetes

"Hello, I am a 52-year-old male patient. I am 6'2" and weigh 221 lbs. I live at home in Miami with my daughter and I own my own small business. The highest level of education I have achieved is completing my associate's degree. I was just diagnosed with hyperglycemia and type 2 diabetes. In the Emergency Department, my blood glucose just came back as 152mg/dL and I had an HbA1c level of 6.8%. My doctor recommended that I take 500 mg metformin twice a day, alter my diet, and exercise daily. What advice do you have for best managing my hyperglycemia and type 2 diabetes? Can you also explain to me why my doctor recommended this specific treatment regimen, given the information I have provided you about myself. Can you make this response extremely comprehensive, in order to provide me with an in-depth understanding of what is going on."

Absolutely — thank you for sharing your background. Based on the information you've provided, I'll explain your diagnosis, break down your treatment plan, and offer detailed, personalized guidance on how to manage your condition successfully. Let's start with the basics and move step by step into practical advice.

Understanding your diagnosis

1. What is Hyperglycemia?

Hyperglycemia means elevated blood glucose (sugar) levels. It usually reflects a problem with insulin, a hormone made by your pancreas that allows your cells to absorb glucose from your bloodstream. When insulin doesn't work well (called insulin resistance) or your body doesn't make enough of it, blood glucose builds up, causing hyperglycemia.

2. What is Type 2 Diabetes?

Type 2 diabetes is a chronic metabolic condition where:

- Your body becomes resistant to insulin, or
- Your pancreas doesn't produce enough insulin to keep blood glucose in a normal range.

Over time, high blood sugar can damage blood vessels and nerves, increasing the risk of:

- Heart attack, stroke
- Kidney disease
- Eye damage
- Nerve damage (especially in hands/feet)
- Poor wound healing

Interpreting your numbers

Test	Your result	What it means
Blood glucose	152 mg/dl	Elevated — normal fasting is <100 mg/dL
Hemoglobin A1c	6.8%	Diabetes — diagnosis made if ≥6.5%

Your HbA1c of 6.8% indicates your average blood sugar has been high (around 147 mg/dL) over the last 2-3 months.

This is early-stage type 2 diabetes — meaning you have a great chance to reverse the trend or maintain control with lifestyle changes and medication.

Why did your doctor choose this treatment?

1. Metformin (500 mg twice a day)

Metformin is the first-line medication for type 2 diabetes. Here's why:

- Reduces liver glucose production
- Improves insulin sensitivity (helps your body respond better to insulin)
- Does NOT cause low blood sugar (hypoglycemia) when used alone
- Weight neutral or modest weight loss (a bonus since weight plays a role in diabetes)
- Well tolerated and taken orally

Your dose (500 mg twice daily) is a conservative starting dose to minimize stomach side effects (like bloating or nausea). The dose may be adjusted over time.

Figure 5A. Chat GPT input prompt and generated output for a patient perspective regarding their diagnosis of type 2 diabetes (scenario 1). Output generated by GPT-4 on July 22, 2025, <https://openai.com>.

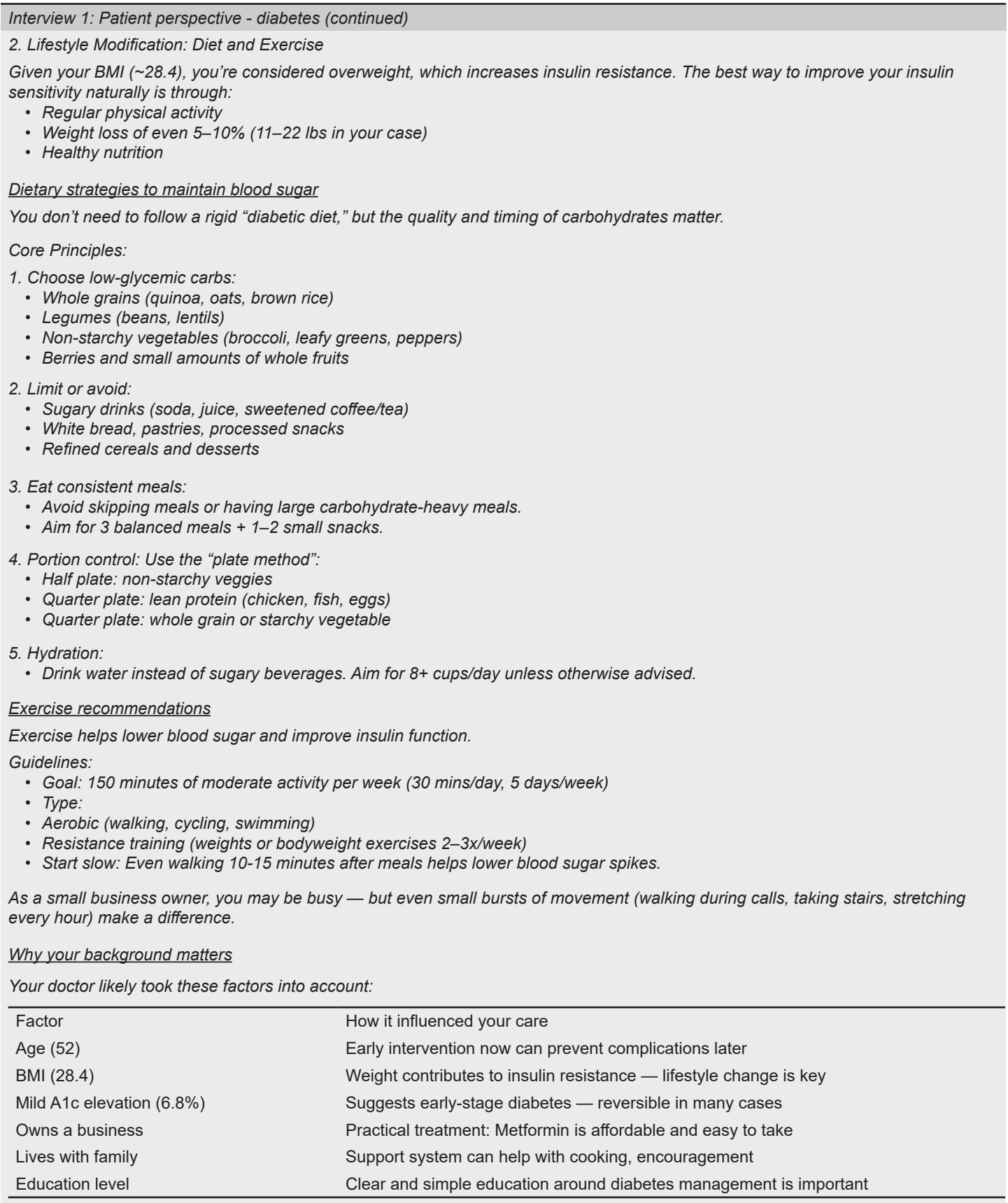


Figure 5A. Continued.
BMI, body mass index.

<i>Interview 1: Patient perspective - diabetes (continued)</i> <u>Putting it all together – your action plan</u> Medication • Take metformin 500 mg twice a day (usually with breakfast and dinner) • If stomach upset occurs, take it with food and speak to your doctor about extended-release options Diet • Shift to whole, minimally processed foods • Reduce sugary drinks and refined carbs • Control portion sizes Exercise • Start with walking 15–30 minutes/day • Add strength training if possible Tracking • Monitor blood sugar if advised (some doctors recommend home glucose testing early on) • Track weight, energy, food choices in a journal or app • Follow up with your doctor in 3 months — they'll recheck your A1c <u>When to seek help</u> Call your doctor if you experience: • Very high blood sugar consistently (>250-300 mg/dL) • Very low blood sugar symptoms (shaking, sweating, confusion — though unlikely with metformin alone) • Stomach issues that don't go away • Fatigue, blurry vision, or frequent urination that worsens <u>Key takeaways for you</u> • You've caught this early — a 6.8% A1c is manageable and often reversible. • Metformin is safe, affordable, and highly effective for newly diagnosed patients. • Diet and exercise changes are the foundation of diabetes management — they'll help more than any medication alone. • You don't need perfection — just small, consistent improvements. If you'd like, I can also help you: • Create a 7-day meal plan • Set up a simple exercise calendar • Draft questions for your next doctor visit You're not alone in this — you've already taken the most important step by seeking to understand your diagnosis. Let me know how else I can support you.
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Figure 5A. Continued.

methodology for structuring medically related LLM input prompts is the generative clause. As goals for LLM use can range widely, future research is recommended for optimization of this prompting component.

Quantitatively, the outputs were assessed for their FKRE level. Outputs intended for patient consumption interestingly scored lower on the FKRE scoring system than physician-intended outputs, showing a limitation of the models in attempting to tailor the information to the intended audience. Although other work has shown LLMs to be capable and proficient at tailoring their information to intended populations, this paper shows data contrary to these findings, suggesting another area for continued research and optimization.

Clinical Significance - Scenario 1: Type 2 Diabetic

Type 2 diabetes is prevalent, affecting over 30 million residents of the US in 2022.²³ Management of diabetes is complex and often requires various interventions, including pharmaceuticals, dietary changes, and exercise.^{18,24,25} This

multivariable approach to diabetes requires significant lifestyle changes, which can be challenging for patients to sustain over long periods.

One of the most popular approaches to combat limitations in diabetes management has been the use of programs focused on diabetes self-management education (DSME), which have been proven to help lower A1C levels.²⁶ The DSME can be personalized and often comes in many forms, depending on many factors.²⁷ The output generated in both the patient and physician diabetes scenarios (Figure 5A, 5B) shows the potential benefit of using an LLM as a part of DSME. Each response is tailored specifically to the individual based on the details provided within the demographic, independent, and dependent clauses (Figure 5A,B). Thus, the outputs demonstrated in this paper show the potential of GPT-4 in providing pertinent information tailored to the example patient scenario. These LLMs can potentially break down one of the most significant hindrances in type 2 diabetes management, socioeconomic status, by providing access to a digital form of DSME.²⁸

"Hello, I am a primary care specialist. I am treating a 52-year-old, male patient. He is 6'2" and weighs 221 lbs. He lives at home in Miami with his daughter and owns his own small business. This patient's highest level of education is an associate's degree. I am currently managing this patient's hyperglycemia and type 2 diabetes. I recommend that he start treatment with 500 mg metformin twice a day, alter his diet and exercise daily to help him manage his condition. Can you help me develop a complimentary handout that I can give this patient to facilitate their treatment compliance? Can you personalize this handout to the patient, based on the information I have provided above?"

Title: Your Personalized Type 2 Diabetes Management Plan

Dear [Patient's Name],

You have been diagnosed with type 2 diabetes, a condition where your body has trouble using sugar (glucose) the right way. This can lead to high blood sugar, which can harm your heart, kidneys, eyes, and nerves over time.

Your Medication: Metformin 500 mg (Twice Daily)

You will start taking metformin, a medication that helps lower your blood sugar by:

- Reducing sugar made by your liver
- Helping your body use insulin better

Take it with food to help avoid stomach upset. If you miss a dose, take it as soon as you remember — unless it's close to your next dose. Do not double up.

Healthy Eating Tips (No Need to Be Perfect!)

Because you're a busy small business owner, here are simple tips that fit your lifestyle:

Instead of this...:	Try this instead...:
Sugary drinks (soda, juice);	Water, unsweetened tea, or sparkling water
White bread or rice;	Whole-grain bread or brown rice
Large portions;	Use a smaller plate and stop when you're 80% full
Skipping meals;	Eat 3 balanced meals per day to keep blood sugar steady

Try the "Plate Method":

- ½ plate = non-starchy vegetables (broccoli, spinach, peppers)
- ¼ plate = lean protein (chicken, turkey, beans)
- ¼ plate = whole grains or starchy foods (brown rice, sweet potatoes)

Exercise That Works for Your Life

Even just 30 minutes a day of activity helps control blood sugar. You don't have to go to the gym! Ideas for You:

- Walk around the block or nearby park before/after work
- Do stretches or light movement while watching TV with your daughter
- Park farther away at stores to get in extra steps

Start small and build up — every bit counts.

Your Goals

Goal	Target
Weight	~200-210 lbs (talk to your doctor for a specific goal)
HbA1c	Below 7.0%
Blood sugar (fasting)	80-130 mg/dL

Your Next Steps

1. Start metformin 500 mg twice daily with meals.
2. Track your meals and activity in a small notebook or app.
3. Follow up with your doctor in 3 months to check progress.
4. Get lab tests as needed (blood sugar, HbA1c, cholesterol, kidney tests).

You've Got This

Managing diabetes doesn't mean being perfect. It means doing your best every day — and getting support when you need it. As a dad, business owner, and provider, taking care of your health means you're taking care of your family, too.

Sincerely,
[Your Name]
Primary Care Specialist

Figure 5B. Chat GPT input prompt and generated output for a physician perspective regarding a care plan for their patient with a diagnosis of type 2 diabetes (scenario 2). Output generated by GPT-4 on 7/22/25, <https://openai.com>.

LIMITATIONS

This study has several limitations. We did not assess inter-rater reliability across independent users applying this framework, nor did we systematically test how altering single variables might change the generative clause output. Future work should incorporate reproducibility testing with agreement metrics (eg, the Cohen kappa) and sensitivity analyses of variable perturbations to strengthen the robustness of this framework. Second, the conceptualized framework was tested on only three scenarios, restricting generalizability across medical specialties or to more complex medical scenarios. Third, the methodology of this study remains conceptual and without formal validation, as it serves primarily as a foundation for future empirical work. Future studies are required to enhance the generalizability and reproducibility of this foundational work. Lastly, further work needs to be conducted to assess the feasibility of implementing such infrastructures, to mitigate concerns regarding patient privacy and compliance with laws mandating protection of sensitive health information as they relate to new technologies in clinical workflows.

CONCLUSION

Establishing more standardized prompting methodologies is crucial for maximizing the utility of large language models. This paper introduces a prompting methodology to improve the accuracy and relevance of medical outputs for both patients and clinicians. We applied this methodology to three patient case examples, demonstrating its potential in clinical contexts. Future research should explore specialty- and presentation-specific prompting strategies to further enhance model performance.

Address for Correspondence: Saman Andalib, BS, University of California, Irvine School of Medicine, Department of Orthopaedic Surgery, 101 The City Drive South, Orange, CA 92668; Email: sandalib@hs.uci.edu.

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