Lighting Up Missing Links by Generative AI: A Case of Retinal Detachment

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Abstract

This paper proposes a generative-AI-assisted framework for utilizing 1st-person patient narratives to improve medical understanding and decision-making, particularly in the pre-diagnostic or subclinical stages. Contemporary medicine often relies on symptom confirmation, leading to delayed intervention and a heavy cognitive burden on physicians when patients present with fragmented or contradictory accounts. Using the author's personal experience with acute retinal detachment, this study illustrates how rare, fleeting visual phenomena, such as the preoperative perception of multicolored elliptical particles and postoperative transformation into geometric and network-like patterns, are typically dismissed or lost despite their potential informational value. This paper argues that such narratives, when structured and interpreted through generative AI, can be mapped onto disease progression scenarios and linked with medical knowledge, enabling "structural explanations" rather than passive watchful waiting. This approach, termed N1-Diagnoser, connects 1st-person volatile narratives with large-scale data, literature, and temporal relationships to highlight and clarify hidden events behind the missing links in understanding. These benefits include earlier patient reassurance, improved self-observation, reduced physician workload, and enhanced lifestyle guidance. More broadly, this study frames generative AI as a tool for lighting up missing links to enable novel human-centered decision-making via knowledge creation.

Introduction: Research Motivation

Current medical practice often proceeds on a "breakdown point basis," where diagnosis and treatment occur only after symptoms are confirmed. As a result, many cases involve "wait-and-see" at the very moment when treatment should be initiated. For example, in Spontaneous Primary Insulin-Dependent Diabetes Mellitus (SPIDDM) within type 1 diabetes, the onset is gradual, often leading to the misdiagnosis of type 2 diabetes and subsequent incorrect treatment. However, determining what constitutes a symptom and what is not inherently challenging makes confident diagnosis difficult. One contributing factor is that while they are well versed in physicians' prevention methods for diseases within their specialty, they often have limited personal experience with the condition itself. In recent years, data and AI utilization have been introduced across various fields to improve work quality and efficiency. However, even when using generative AI enhanced with medical databases to diagnose patients based on their statements as prompts (questions), misunderstandings still occur between the AI and patient. This poses a risk to patients and stress to physicians.

Particularly in the pre-diagnosis (subclinical) stage, symptoms are often fragmented, and patient statements may contradict each other. The labor involved in listening to patients who speak continuously is not straightforward for physicians. However, if detailed insights can be gathered from the patients themselves based on this information, it can be structurally visualized by annotating the simultaneous occurrence and sequence of various elements from a medical perspective and generating verbalized advice. The collection of fragmented information can be explained by positioning it within the structural processes of disease onset and progression. This enables a "structural explanation" that focuses on critical aspects within that structure, shifting from "wait-and-see" to "active observation" active observation' aimed at filling gaps within the overall structure. This approach reduces the physician workload while accelerating the necessary decision-making.

Generative AI has been used in various medical settings, among which the following example demonstrates the potential to satisfy the above expectations. As discussed later, Generative AIs have been tested in areas such as self-training of doctors in healthcare (Kaneda 2024) and answering questions about MRI images (Lee and Lee 2024). While they sometimes demonstrate capabilities comparable to doctors in specialized dialogues, it has been consistently shown that no matter how advanced the technology becomes, a human physician with empathy remains the essential support. The literature also suggests that when exploring solutions to issues, ChatGPT might not be able to cover detailed contexts, including life- or country-specific situations (Kaneda 2023). Thus, my laboratory has recently aimed to develop a method to position the personal experience of a patient within one's internal chronological scenario or the causality of events influenced by external situations that are hardly verbalized. This is a requirement of physicians, but also of a patient who seeks an explanation of the current status, even if a witnessed event is not in the chronological scenario.

By adding pieces of expert knowledge, we aimed to connect the fragments in a patient's 1st-person comments into an explanatory causal structure. By developing and applying this to diagnosis and treatment, we aimed to enable patients to gain reassurance and seek medical care earlier. Based on the resulting mental preparation and self-observation habits of patients, physicians can provide high-quality care encompassing lifestyle guidance, while alleviating their workload.

The following is based on the author's own experience of retinal detachment, where a large hole suddenly appears in the retina at the top of the eyeball. at least six hours before surgery, numerous oval-shaped particles were observed in red, blue, green, and yellow, moving in the dark. Immediately after surgery, these particles transformed into shapes such as triangles, squares, and rods, whereas the white background behind them deformed into a network-like structure. However, the attending ophthalmology professor, who heard this account, stated that it was not a cause for concern, as mentioned in a later section. He had no notes at hand because he had to focus solely on inspection tasks. Such experiences, even when preserved, exist only as retrospective interviews or memoirs; however, they are rare among patients and lack reproducibility.

Thus, I propose using 1st-person narratives—statements of experiences that patients themselves often forget—as prompts and data fed into generative AI with a request to reflect knowledge, that is, explanatory models obtained from relevant literature and data. This approach reduces physician workload while enabling focused "active observation" and "structural explanation," thereby streamlining the necessary decision-making processes for both physicians and patients. By linking these 1st-person narratives to vast datasets and specialized knowledge to generate explanations, patients gain early reassurance or treatment, along with mental preparation and self-observation before symptom onset. Physicians can gain the ability to provide lifestyle guidance and stress management for both parties.

Another effect of this approach is filling internal gaps in the knowledge (not *between* but) *of* both physicians and patients during this process. This realizes their creativity to enable previously unattainable decision-making and knowledge generation by *lighting up* the missing links, including unnoticed events behind the words of a patient. by utilizing the generative AI's inference function to structure pieces of knowledge.

A Case of Retinal Detachment

An Acute Retinal Tear in the Right Eye

The author experienced retinal detachment in November 2025. On November 29th, Saturday, a peculiar dark shadow appeared in the lower field of vision of the right eye. In fact, I saw such dark shadows the previous week. They would appear and disappear, and since I had floaters for decades due to my nearsightedness, allowing me to see blood vessels inside the eyeball, I had lightly thought, 'I see various things!' However, the new shadow at this time is different. It resembled a crouching bear at the bottom of my vision, complete with a fur. When I was indoors, it was opaque and black, which blocked the outside light. When I went outside, the area swayed like a small bag filled with polluted water. It seemed transparent, yet I could not see the scenery beyond it, an inexplicable obstacle in my vision. I thought it would probably disappear soon... However, that day, even after swimming in the pool and meeting people, the shadow did not vanish. By nightfall, the black bear had grown large and occupied almost the entire right-eye view.

I visited an eye clinic on Monday, where for years, I had planned to see a doctor if I had any concerns. The ophthalmologist's diagnosis was swift and clear, with a large retinal tear, indicating severe retinal detachment. Because the tear was near the top of the retina of the right eye, the progression might be rapid. This explanation made perfect sense, as I had indeed been terrified by how quickly it occurred. Therefore, surgery is an urgent requirement. I was transferred to a university hospital, where I was told, "Surgery tomorrow."

The Colored Ellipses in the Blind Right View and the Patient's Inference

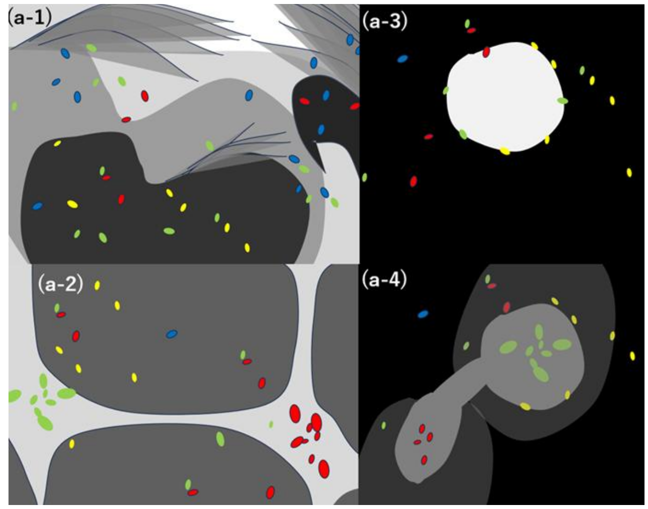
That night, with my blind right eye, I saw numerous small, colored elliptical specks (red, green, blue, and yellow) appearing like black bears, as shown in Figure 1(a). One can say that these colorful, small ellipses are twinkling-like constellations. The black area from the bottom to the center completely blocked the light. Even the slightly lighter black area surrounding the black area reveals nothing behind. The ellipses are particularly numerous in the black and dark areas, each moving along its major axis. The blue ellipses moved quickly within the black areas; therefore, they were difficult to observe.

I fell asleep once, and upon waking, the lighter-colored part in Figure 1 (a-1) appeared; upon closer inspection, it cracked, as in (a-2). Within the black area outside the black bear, there were holes, as in (a-3), with colored ellipses gathering around them. From somewhere throughout this entire space, five to ten small ellipses of the same color (e.g., only green ones in a certain crack of the view) appeared in a group, as in (a-3) and (a-4). These spots emerged everywhere, grew larger, and moved along their major axes.

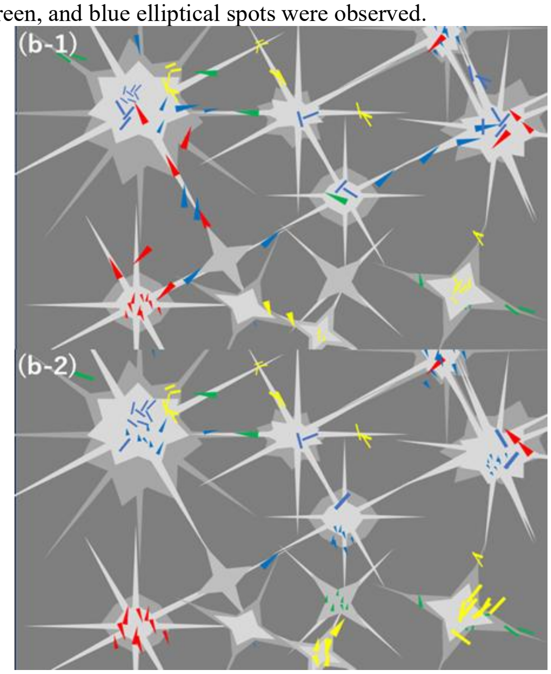
I hereby hypothesize that these spots might correspond to "cone cells" in the retina that connect to nerves. Cone cells are responsible for color perception in the retina and are easy to find on Wikipedia and other online encyclopedias. As my retina was severed from the inside wall of the eyeball, they might have perceived the color independently of the external scene and sent the raw signals to the brain. The L cones respond to red, M cones respond to green, and S cones respond to blue. I previously learned that the L and M cones evolved from the same cone type, and that the wavelength corresponding to yellow may be close to both. Although I assumed that, therefore, a yellow ellipse might be something sent by L or M cones, to my eyes, yellow appeared to be a distinctly different color from red or green (this may imply a new discovery of the fourth cone cell, but this is not the point of this paper). If this conjecture is correct, in healthy vision, stimulation from red in the external scene should cause the corresponding L cones in that location to fire, forming a cluster with cones of the same color. Subsequently, via the neural network, they might trigger other L-cones. Because my right eye was not healthy, I inferred that I saw only cone activity unrelated to the external scene.

In Figure 1, I find sketches made using PowerPoint with my left eye of the scenery I saw with my right eye. After viewing these figures, I painted myself and the colored ellipses seen by my right eye suddenly increased. However, because I saw PowerPoint with my left eye, it was difficult to explain it as an afterimage. This suggests that, regardless of which eye perceives color, humans may possess a function that activates the corresponding color cones in both eyes.

After the surgery, as shown in Figure 1 (b), the colored spots changed from ellipses to triangles, rectangles, or rods. The color-spot movement appeared slower than before surgery, as each spot moved while being bound to its assigned position. A more significant change was the disappearance of the pitch-black, bear-like area. The new white background resembles a scale-free network (although the raw pictures painted in the bed are shown here, a few large nodes in the network are linked to many smaller nodes). The mended connection between the retina and nerves may have been activated to enable the neural network to perceive the shapes.



(a)Before surgery for retinal detachment, rice-grain red, yellow, green, and blue elliptical spots were observed.



(b) After surgery, they became triangular or rod-shaped and the background became net-like (the spots moved from the upper to the lower). This implies that the postoperative course progressed well because the signals received by the retina were connected to the processing in V1-V4.

Figure 1: View from the right eye (a) During retinal detachment onset (b) After retinal detachment surgery

Consulting Human Experts and a Gen-AI

The above was based solely on the scenery I observed, filled with guesses and baseless hypotheses — irresponsible rambling, and not academic writing or expertise. When I mentioned this to an ophthalmology professor in the post-surgery round, he commented:

"*It's one of the things patients see after surgery; nothing to worry about specifically (as a symptom). I don't think you're actually seeing cells like cones or rods.* "

I, the author, express gratitude for the doctor's consideration of the patients' concerns. However, when I asked ChatGPT5, "Are there reports of seeing color spots like red, blue, green, and yellow due to retinal detachment?" it answered

"*Seeing a number of primary-colored spots like red, blue, green, or yellow is not commonly reported as a typical* *symptom of retinal detachment. However, similar states have been reported as 'other intraocular phenomena'.*"

The explanation of this "similar states" continued in detail, citing a few references (see Appendix A for this content). Even after digging deeper into follow-up questions on my personal concern, no answer matched the scenery I witnessed, implying that I was discovering something.

However, when I extended my time to input my detailed experience into ChatGPT5, I asked for explanations and evidence, including papers and data published by experts, corresponding to each unknown event in the given answer.

- The colored ellipses represent the areas in the receptive field (lateral geniculate nucleus: LGN) in the retina.
- After treatment, the LGN is connected to the mechanism in which the shape is captured in the V1 area of the optic nerve, and the structure is captured in V2 to V4, potentially enabling the recognition of the shape and structure.

However, no published papers or articles about this specific experience, having these events in sequence, were found.

1st-Person Narrative (N1) Diagnoser

Implication of the Case of Right-Eye View

The above clustering of colored ellipses is a novel and precious image visible only during the few days of this disease, when the inside wall of the eyeball and retina separate. This story can be viewed as an example of how despair can inspire ideas by viewing it as an opportunity to see something rarely encountered in life. However, if the network structure of spreading colored fires can be learned, it leads to the development of new AI systems: a system that infers partial color information and predicts the next appearance of moving objects at the terminal level, or even a system in which the network is split into a sensor (retina) side and a learning (brain/nerve) side, with the latter handling knowledge-based color diffusion. These ideas, despite the patient's difficult situation, serves as an example of how experiences seemingly unrelated to diagnosis or treatment can trigger breakthrough ideas. A point here is that the 1st-person narrative, which is an individual's personal statement about one's own perception or experience, can be reusable, if externalized, for scientific discoveries and decision making.

The Outline and Current State of N1-Diagnoser

The above example can be positioned as a case in which an explanation of state transitions is provided based on a patient's 1st-person narrative evidence corresponding to experiences that cannot be interpreted solely through knowledge learned from papers, medical records, or textbooks. Despite the potentially insufficient confidence, the explanation offers material for the patient's reassurance and cautionary points. This mechanism has not yet been artificially tooled; it is merely an example of generative AI. The patient gained reassurance after knowing that the post-surgery pigment receptor field (LGN) suggested restoration of its connection to higher-level processing areas V1 to V4.

Furthermore, if the literature (papers and specialized works) and data (medical records, test results, etc.) are linked to these explanations, physicians could also streamline the process of providing responsible explanations. To understand this, we compare Figures 2 and 3. In Figure 2, the upper-to-lower rectangles show the sheer flow of events, divided into conditions before and after the operation, which lead to the appearance of elliptical and shaped (triangles, bars, etc.) colored spots, respectively. On the other hand, Figure 3 shows a flowchart obtained by the framework we call the 1st-person Narrative Diagnoser (N1-Diagnoser), systematizing this retinal detachment case using a Gen AI.

Here, the role of N1-Diagnoser is to connect fragments of the 1st-person narrative with relevant parts of the vast data and knowledge to generate explanations to obtain the "scenario tree" in Figure 3. The scientific knowledge applied here is provided by experts or pre-trained from massive datasets on daily life activities, including diaries, SNS posts, conversations in hospitals, and scientific studies. The process tested so far has been executed simply by using a gen-AI with the prompt including 1st-person narratives and requesting for explanatory information of unknown events which appeared in the communication so far with the gen-AI (e.g., "In V1, shapes like triangles and rods are recognized, right?," "provide references regarding the perception of primary colors before and after retinal detachment treatment," etc.). The scenario tree in Figure 3 was obtained using ChatGPT5 for prompts stating (1) through (4) below:

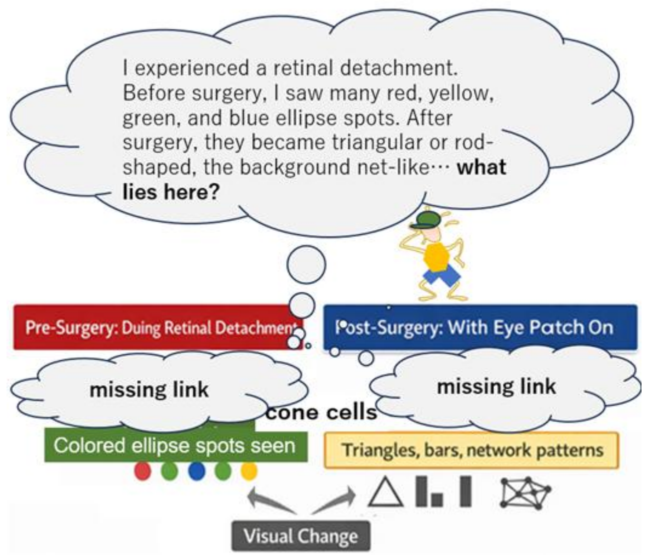


Figure 2: 1st-person narrative before and after surgery: clouds depict missing links

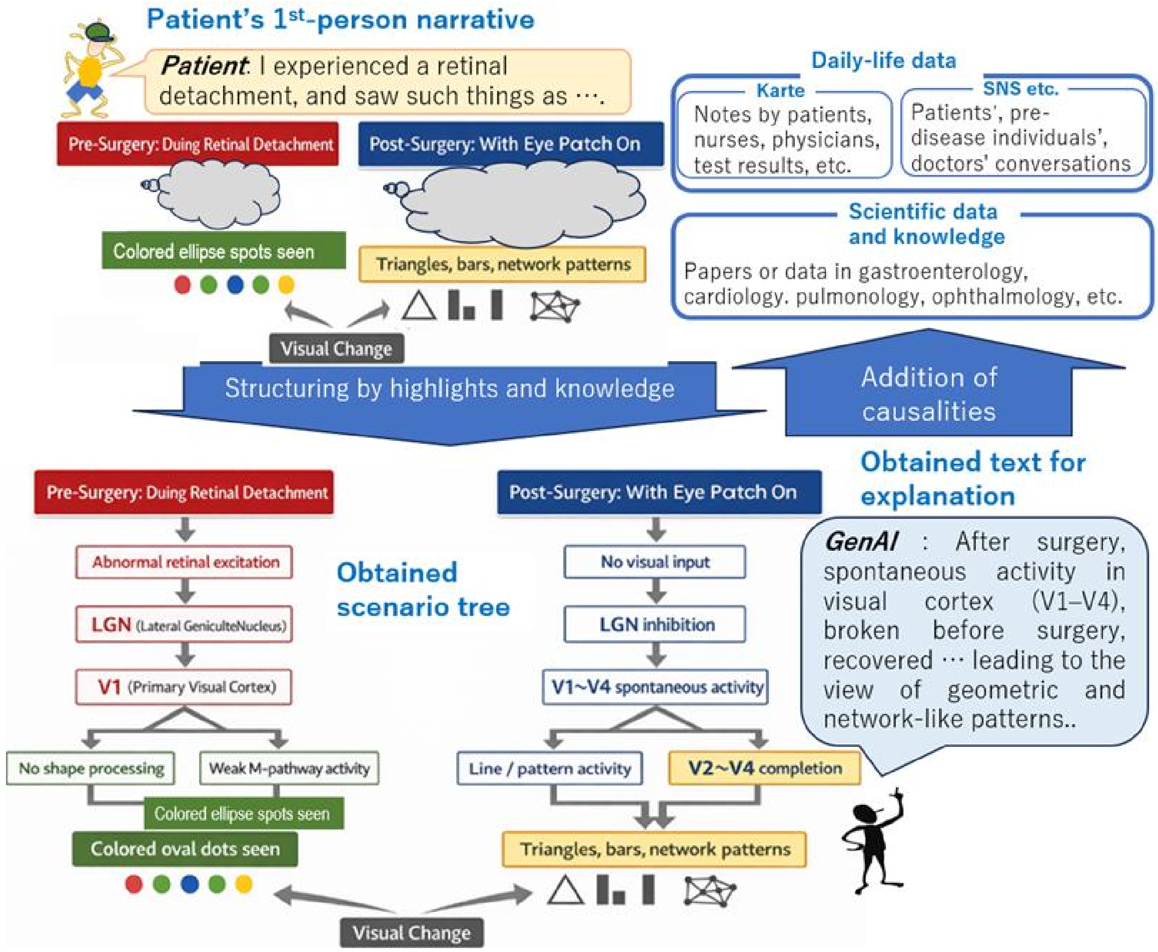


Figure 3: Patient knowledge structure before and after surgery, via the process calling for scientific data with ChatGPT-5: The scenario tree involves LGN, V1, V2-4 etc. for explain the appearance of colored spots.

(1) The witnessed spots and background image
(2) Request to ask about the causality behind the spots
(3) requests for evidence (reference articles); and
(4) Request to visualize the scenario tree.

This process is now further systematized, introducing an automated human interface for communication and databases on real-life activities and scientific studies. This should enable patients to gain early reassurance and treatment, along with mental preparation and self-observation, even before symptom onset. Physicians should be able to provide lifestyle guidance, and stress management for both parties is anticipated. Another effect of this approach is that it compensates for the gaps in the knowledge held by both physicians and patients during this process.

Furthermore, from a technical data analysis perspective, even if individual events within a 1st-person narrative have a small degree of association with disease onset and progression, adding simultaneity or sequence significantly increases the probability of disease diagnosis. That is, the combination of multiple factors increases the posterior probability, which is a basic consensus supported by Bayesian theory. The AI technology developed by the author for chance discovery and change explanation enables capturing and explaining even low-frequency yet essential changes (Ohsawa 2018, Nishikawa et al 2022, Liu et al 2025). In addition, table data and text containing a time axis can be integrated into a graph-type structure (Figure 2 and the large middle section of Figure 3), visualizing an explainable model in which each patient's state is assigned to individual nodes, allowing their positioning and risk assessment.

Discussions Toward the Future Work

While it is common knowledge that generative AI underwent rapid evolution shortly after this paper's publication (technically, e.g., the T5 model (Rafel 2020), its fundamental principle remains unchanged: deriving answers for users based on learning from past data reflecting the expert knowledge and data provided. The framework presented in this paper introduces only two novel elements: the use of 1st-person narrative as new information and the conferring of meaning to this fragmentary information by combining it with expert knowledge and data. However, the simplicity of this novelty allows our proposal to seamlessly inherit all previous research findings on the use of Gen AI as well as all underlying theoretical and technical research.

Kaneda et al. (2023, 2024) demonstrated that generative AI and chatbots utilizing large language models (LLMs) cannot sufficiently meet healthcare support needs on their own. Human involvement was required in Kaneda et al. to provide information about the situation of individuals, including patients. Chain of thoughts by answering step-by-step (Kojima et al 2023) can be regarded as a procedure to externalize hidden causality if applied to diagnosis, which works in improving the answer quality if the situation is hidden, as well as the situational descriptions in the prompt (Sun et al 2024). A point of N1-diagnoser is the following order of prompts:

(1) The patient provides comments on *what*" i.e., the witnessed events, and "*when/where*" i.e., the situation to the extent of details as possible,
(2) The request asking "*why*?" that is, the causality behind the colored spots,
(3) Requests to show evidence ("*who wrote it*?"), and
(4) Request to visualize the scenario tree.

Differently ordered prompts would be meaningless, for example, asking (2) before (1) makes no sense to the AI agent, (3) before (2) makes the AI agent ask "*evidence for what?*" and (4) before (3) apparently makes the tree poor. Thus, the ordered prompt is not as important a point here as just starting from (1) and aiming at the structure in (4).

Here, we should clarify that a traditional AI researcher tends to misunderstand the most important opportunity provided by N1-diagnozer for the patient. Many events are witnessed by the patient, most of which may be irrelevant to the progress of or recovery from a disease, and an interesting research topic for the AI domain may be to select, that is, pay *attention* to noteworthy events for diagnosis. However, it is an important principle that ATTENTION is NOT ALL that a patient, who worries about everything he/she witnesses, needs. The role of Generative AI here is to fill in the links within the aimed structure, missed owing to events that may be rare, correspond to points of minor shifts from/to known situations, or even be irrelevant to such causality. Such an event may not be expressed explicitly or may be expressed using the vague words of both patients and doctors because of their lack of common awareness or knowledge. However, patients often worry about such events, which can lead to mental instability. Thus, a difference of this study from Gen-AI-based diagnosis is that it "lights" up the missing links of medical knowledge of both patients and physicians in order to provide an explanation even if the link does not mean relevance to any disease – mental stability is essential for mental and physical health.

The opportunity due to this role of the N1-Diagnoser is not just to diagnose in the sense of classifying the symptoms into categories corresponding to known diseases. That is, a more essential opportunity is to aid the user in explaining the possible reasons for the encountered situation, including superficially inconsistent observations, which is an essential requirement if the situation cannot be clearly identified as a specific disease. So far, Gen-AI applications for medicine and healthcare are expanding, and the opportunities provided range across medical imaging, patient engagement, and diagnostic or predictive analysis, which, all in all, reduce healthcare costs. The analysis of unstructured data such as clinical notes and patient narratives is expected to provide a better understanding of patient conditions, reduce medical errors, and enhance treatment outcomes (Baig et al 2024). However, as pointed out in the introduction, medical practice often proceeds on a "breakdown point basis," where diagnosis and treatment occur only after symptoms are confirmed. Therefore, methods for explaining events with unclear symptoms are not within the central scope. Here is a new opportunity obtained by introducing the N1-Diagnoser to medical domains.

To the best of our knowledge, and according to a previous survey, the number of studies on GenAI applications for healthcare has been outstanding in the domain of mental health since 2023 (Wang et al 2025, McBain et al 2025, etc), and will be lessons for other healthcare domains. Here, diagnosis and assessment primarily used GenAI models to detect depression and suicidality through text data, and therapeutic applications investigated GenAI-based chatbots and adaptive systems for emotional and behavioral support, reporting promising outcomes but revealing limited real-world deployment and safety assurance. Clinician support studies have explored the role of GenAI in clinical decision making, documentation and summarization, therapy support, training and simulation, and psychoeducation.

For example, Li et al. (2024) presented a method for zero-shot explainable mental health analysis, where the input data are the mental scales completed by patients, and 1st-person narratives cannot be included. In Englhardt et al. (2024), the authors began to develop methods to use LLMs to output binary classifications for conditions such as depression. Instead, they found that the greatest potential value of LLM is not in diagnostic classification but rather in the analysis of diverse self-tracking data to generate natural language summaries that synthesize multiple data streams and identify potential concerns. The attempt of our laboratory may be positioned as a supporting method to add new data to the data sequence to the approach of Englhardt et al However, we do not synthesize multiple datastreams if there is any contradiction between them, but show them as multiple distinct scenarios to occur in distinct conditions, on the principle that additional data can be a solution for contradiction and have them as co-existing evidence (Shimomukai et al 2025).

Conclusion: Let's Utilize 1st-Person Narratives

Previous studies and developments have realized techniques to use vast amounts of multimodal data that are incorporated as evidence in generative AI to enhance the response performance. N1-Diagnoser, a framework for explanatory diagnosis based on knowledge related to incorporated 1st-person narratives including the predisease stage, can be applied for analytical decision support. It comprehensively utilizes elements drawn from 1st-person narratives, connects them to make insights emerge.

Generally speaking, experiences that remain unpublished as reproducible data or papers and are often unrecorded vanish from memory in an instant. Thus, we inevitably categorize them as "just one of the many things one begins to see." However, experiences seemingly irrelevant to diagnosis or treatment can spark breakthrough ideas, potentially advancing medicine or technologies in other fields. I propose creating a trend to develop and use methods to routinely record fleeting experiences and vanished memories in the realm of human-centered science, as recently developed for Long Covid (Greenhalgh 2024, Rushforth 2023).

words by the patient or missed in established scientific knowledge. This is beneficial because some patients' fragmented statements may correspond to events or situations overlaid on the disease onset and progression scenarios learned from vast amounts of data. When patients or predisease individuals describe their experiences as prompts that include terms not covered in the physician's existing knowledge, or when the missing links make the 1st person narrative unexplainable, the generative AI agent can support the physician in providing responsible advice and the patient in understanding the situation by providing an explainable scenario tree. Thus, in realizing practical creativity—specifically novel decision-making and knowledge creation—the meaning of "lighting up" lies in highlighting the missing links and showing events behind the hidden connection.

The reproducibility of the two senses is intentionally excluded from the scope of this study. First sense is that 1st person narrative itself cannot be reviewed by others, so the trustworthiness of the data may not be evaluated from a traditional scientific scope. In this regard, we essentially need a social consensus about *the objective science about subjective facts*. The second is quite out of scope since this paper shows a single case study as the title declares. Application of the proposed framework for other patients, including different diseases and situations for quantitative performance, is our current experimental challenge.

A: Scientific Evidence Considered Relevant to This Case (a Simple Survey)

Regarding preoperative findings, Brown 2015 ("*Photopsias: A Key to Diagnosis*") systematically investigated photopsia in 169 patients with vitreoretinal disease. Morrow 2019 describes photopsia using terms like "flash-like," "bar-like," "spot-like," and "colored spots," which is quite close to clinical perception. Ng et al, 2023 is a review which summarizes the presentation (location and characteristics) of photopsia typical of retinal tears and retinal detachment for general clinicians. Reading these together, "*elliptical primary color particles are naturally positioned as a variation of photopsia/phosphene associated with retinal detachment,*" as pointed out by to ChatGPT5, and *shapes (zig-zag / bar / spot, etc.), colors (white / yellow / other), and locations (temporal / central, etc.) can be organized*. This helps place primary-colored particles into medical categories.

Findings also indicate that, when visual input decreases, the brain spontaneously generates patterns or scenes (Pang 2016), providing a theoretical background for the situation of "spontaneous activity in the visual cortex in darkness."

Regarding closed-eye hallucinations after surgery with an eye patch, the Healthline explanation confirms that geometric patterns commonly occur, connecting to the concept of gradual CEV (closed-eye visualizations). Nan 2013 reports transient Charles Bonnet syndrome (CBS) appearing after eye surgery, where the sequence of abrupt visual input change, followed by visual cortex hypersensitization, followed by visual hallucinations, matches the "immediately post-surgery" situation in this paper. Özcan 2016 reports a case of an elderly woman who saw visual images resembling "burning candles" after cataract surgery. While interpreted as an example of CBS, it serves as a reference for phenomena possible after retinal detachment surgery, in the sense that "changes in visual input acted as a catalyst for image generation in the cortex." Tang 2006 previously described a case of CBS occurring during the visual recovery phase after central retinal artery occlusion, which also resembles the recovery process from retinal detachment.

Regarding the boundary between retinal-origin and cortical-origin phenomena, comparing Sevšek 2022with reviews on CBS/visual release facilitates literature-level clarification of the distinction between "points/ellipses completed at the retinal level" and "lines/grids/etc. structured at the cortical level." Sevšek combined entoptic phenomena (floaters, blue field, etc.) with photopsia/phosphene, noting patients often describe moving spots/dots, lines, clouds, spiders, etc. The Cleveland Clinic explains phosphenes as colored lights seen with eyes closed, under mechanical stimulation of the retina or spontaneous activity in the visual cortex.

Despite the vast literature, no category precisely matches a patient's experience.

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