Outcome First or Overview First? Optimizing Patient-Oriented Framework for Evidence-Based Healthcare Treatment Selections with XAI Tools

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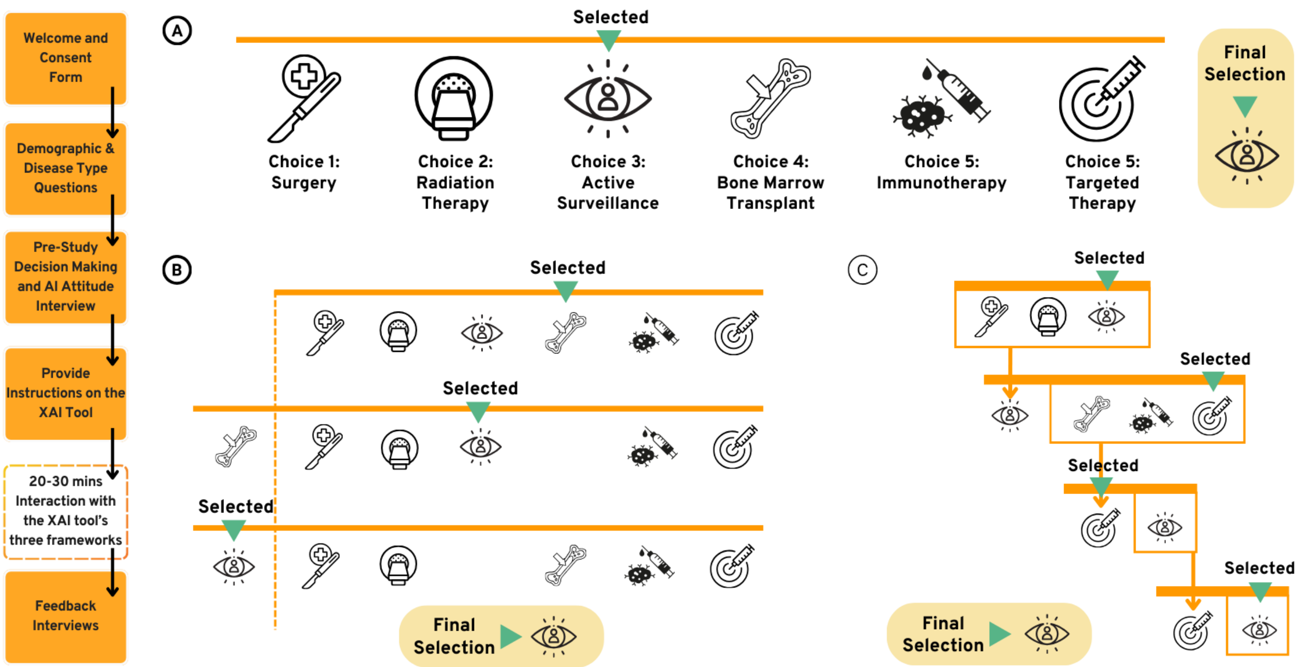

Figure 1: Three representations of healthcare treatment option selections with a final healthcare treatment selection on active surveillance. (A) is an Overview-Oriented Framework in comparing the treatment options; (B) is an Outcome-Oriented Framework; and (C) showcases the Group-Oriented Framework, a sub-framework derived from the Outcome-Oriented Framework.

ABSTRACT

Amid the Covid-19 challenges, limited access to clinicians highlighted a growing need for personalized care. However, personalized care can be difficult for patients with limited medical knowledge to understand their care management options to make an optimal decision that meets their needs and circumstances. This paper introduces two broadly applicable Explainable Artificial Intelligence (XAI) approaches — namely, the outcome-first framework and its group variant —specifically designed to alleviate the decision-making burden in treatment plan selection. Diverging from traditional overview-centered frameworks, both outcome-first and group-first frameworks introduce an innovative approach by providing patients lacking AI or clinical backgrounds with a transparent decision-making structure. These frameworks were evaluated through efficiency testing and a pilot study involving ten clinicians and patients. The findings reveal that the outcome-first framework can significantly reduce the number of comparisons. This reduction streamlines the decision-making process and proves advantageous for patients, enabling them to select the optimal option that aligns with their criteria.

CSCW Companion '24, November 9–13, 2024, San Jose, Costa Rica.

ACM ISBN 979-8-4007-1114-5/24/11.
https://doi.org/10.1145/XXXXXX.XXXXXX

CCS CONCEPTS

• **Human-centered computing** → *Visualization systems and tools*; • **Applied computing** → **Health informatics**; • **Computing methodologies** → **Artificial intelligence**;

KEYWORDS

Outcome-first framework, Overview-first framework, Group-first framework, XAI, patient-centered decision making.

ACM Reference Format:

Yuexing Hao. 2024. Outcome First or Overview First? Optimizing Patient-Oriented Framework for Evidence-Based Healthcare Treatment Selections with XAI Tools. In *Companion of the 2024 Computer-Supported Cooperative Work and Social Computing (CSCW Companion '24), November 9–13, 2024, San Jose, Costa Rica.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/XXXXXX.XXXXXX

1 BACKGROUND AND RELATED WORKS

Making an optimal decision for health care management is hard. When confronted with multiple options, choosing the best option requires assessing the validity of each option, comparing the options against each other, and considering the potential tradeoffs within the options. During the Covid-19 pandemic, decision-making for healthcare management became even more challenging as many patients had limited access to their physicians. During this unprecedented time of uncertainty, patients turn to maintaining the same quality care management at home, under physicians' suggestions. These patients self-monitor their daily health conditions, treatment progress, and future treatment options, etc. However, without support, it can be difficult for these patients to make sense of their treatment options and make a decision that best meets their needs and conditions.

Care management and health information visualization have been important research topics for the digital health community. In 2018, 1.55 million patients were taken care of through patient-centered care management services in the United States. The demands for patient-centered care in the US are still increasing: the ratio between physicians/medical professionals and patients increases from 1:4 in 2018 to 1:9 in 2030 [2]. The doubled number of patients may cause more misunderstandings and fewer connections with patients' illness for their family members or guardians [15]. We could see a huge potential market that acquires more patient-centered care. To determine a specific care management plan, the clinician and patient jointly discuss each option and work together to reach a mutual decision about the preferred option. This shared decision-making process has become an increasingly accepted ideal for medical practice [7, 8]. To help non-expert audiences explore options freely, some scholars are also working on interactive interfaces or approaches that improve comprehension in the clinical field [5, 6, 9].

2 PROBLEM AND MOTIVATION

Discussions around care management systems have highlighted challenges in the traditional clinician-centric decision-making approach. Care management selection involves various aspects like choosing treatment options, medications, and screening tests, as displayed in Figure 1. Recognizing the complexity of evaluating a physician's service delivery, it's acknowledged that no single assessment method can cover all the necessary data [11]. In traditional medical frameworks, XAI tool usually follows an "overview first, zoom and filter, then details-on-demand" approach [3, 11, 12]. The healthcare treatment selections first start with existing treatments and delve into specific patient details. However, there's a growing conversation challenging this conventional overview-first approach (Figure 1, part A), with some researchers proposing an innovative reversal of the process (Figure 1, parts B and C) [10, 16].

This paper addresses the research question: **how can Outcome-First framework enhance evidence-based healthcare treatment selections through the design of XAI tools?** It presents an XAI approach and proposes an outcome-first framework for decision-making in healthcare. After evaluating patients' state of illness, the outcome-first framework provides treatment selections from all experts or physicians and displays the visualization of each care management plan. The design of the Outcome-First XAI tool follows the evidence-based practice (EBP) guidelines with three aims: to *replicate* the EBP of others, to *use* evidence summaries for EBP, and to *do* the more time-intensive five steps of EBP (including ask a question, access the information, appraise the articles found, apply the information, and audit) [13, 14]. It shows a great example of how science and technology reconnect different groups of stakeholders and benefit the patients who need more help during the pandemic time.

We evaluate and demonstrate the effectiveness of our proposed patient-oriented framework in two ways: 1) the theoretical complexity of the tasks when using the framework to make health-related decisions (Figure 2); 2) a pilot study of the frameworks' assessments based on patients' and clinicians' feedback.

3 FRAMEWORKS

3.1 Overview-First Framework

The Overview-First technique, while offering a comprehensive view of all models, poses challenges during optimized model selections (Figure 2: Left). Users may experience time inefficiencies when dealing with a large number of comparison models, leading to a lengthy process of reviewing and comparing each model. The *many-to-many* nature of comparisons results in exponential increases in comparison time. Additionally, the technique, starting from the models' end, may overlook crucial outcomes and user-centric factors such as standards, criteria, preferences, or needs. In response, we advocate for a reversal of the information-seeking mantra, beginning with outcomes and concluding with overviews.

3.2 Outcome-First Framework

The Outcome-First technique adopts a user-centric approach, initiating the selection process from the users' perspective (Figure 2: Middle). It provides default options based on preferences and historical data, enabling users to compare the selected plan with other options. This technique leverages data from users' previous choices, displaying options through interactive visualizations. Users can visually compare model differences, transforming the comparison process from many-to-many to one-to-many. The temporary selected model is compared with others until finding the optimized choice, streamlining the selection process.

The Outcome-First technique recommends models by calculating accuracy, error rate, and F1-score for each model option. It identifies the optimal option based on these factors, presenting differences between models in a user-friendly and comparable manner. This

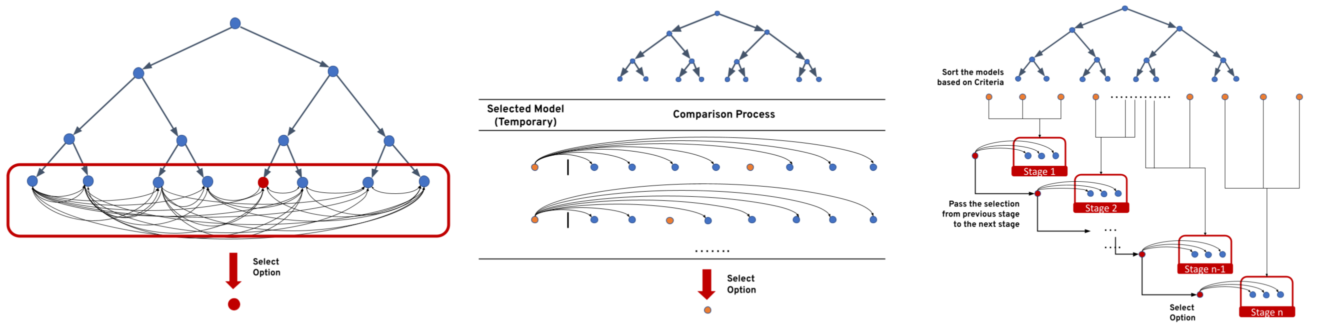

Figure 2: Visualizations of the three explainable Machine Learning (ML)-based frameworks. Left: Overview-first framework. Middle: Outcome-first framework. Right: Group-first framework.

approach facilitates users' decision-making processes by enhancing comprehension.

3.2.1 Group-First Framework. While the Outcome-First technique reduces selection time and enhances comprehension, the Group-First technique offers an alternative for users to make selections in smaller, user-defined groups.

The Group-First technique divides models into stages based on user-set criteria, allowing multiple pair-wise comparisons within each stage (Figure 2: Right). Users can make informed decisions, leveraging Outcome-First framework with group-wise comparisons. Users can choose among options in their selected stage, optimizing runtime. Progressing or retreating between stages allows for comparisons to validate decisions. The option to submit the selected model in stages promotes early informed decisions. Users can return to the first stage, preserving the user-centric technique for further comparisons.

The first stage features models highly matched with users' criteria. Users can set criteria, rate models, and see them categorized into stages, facilitating efficient decision-making. For instance, after setting up criteria A, models are displayed in different stages based on matchability, empowering users with a clear and user-friendly decision-making process.

4 METHODS

The three frameworks were integrated into the user interfaces of the same XAI tool designed for patient care management selection. To assess their efficiencies and effects, we conducted experiments using a hypothetical clinical case of a prostate cancer patient, as illustrated in Figure 1. The case involved six healthcare treatment selections for prostate cancer patients: surgery, radiation therapy, active surveillance, bone marrow transplant, immunotherapy, and targeted therapy. The sequence of treatment options adhered to the recommendations of clinicians.

In the Overview-First framework, all treatment options were compared and evaluated comprehensively. For the Outcome-First framework, participants were prompted to select their preferred treatment option based on specific outcomes of interest, which was then compared with other treatment alternatives. Through iterative cycles, participants refined their preferences, ultimately reaching an optimized option. The Group-First framework organized treatment options into groups, categorized as "local" and "systematic" treatments, based on specific criteria [1]. Participants were then tasked with selecting the optimal option from each group. Following several stages of this grouping process, participants could choose the optimized treatment option from the selected group. These frameworks were tested and evaluated using the patient care management selection XAI tool, employing the hypothetical prostate cancer patient case as a standardized evaluation scenario. The goal was to understand how each framework impacted decision-making efficiency and effectiveness.

Overview-First technique is currently the most used technique in model selection. The overview starts with the available treatment options and ends with the details of users. It simply displays all possible model options and users have the possibility to go over each model option carefully. As Figure 2 shows, each end-model compares with other end-models until the optimized model. After comparing through all the models, users find the most optimized model and finalize it.

The procedures for the pilot study received approval from the university's Institutional Review Board (IRB) before the commencement of any research activities. Following IRB approval, a targeted recruitment strategy was implemented to engage potential participants, comprising cancer patients/survivors with a history of cancer or other chronic illnesses, as well as clinicians involved in cancer-related care or experienced in treating cancer patients. Invitations to participate in the study were circulated through email lists and the university's social media platforms, including local senior centers, cancer care centers, senior housing groups, and the medical school. To express gratitude for their time, each participant was offered a $10 gift card.

The XAI visualization tool was crafted to enhance the consideration of treatment options and their effective presentation to patients. The prototype integrates multiple existing treatment options using the Wizard of Oz (WoZ) method, exclusively for quality control in treatment option presentations for cancer patients. This approach aids in refining the prototype design and optimizing information presentation to users.

I conducted the study with a total of 10 participants: 3 clinicians (Mean Years of Practice: 17.7 years) and 7 patients (3 women, 4 men, mean age 58.1). The patient The demographic data from the 10 participants are displayed in Table 1 and 2.

Participant interviews were structured into three key sections: recent treatment decision-making experiences, XAI tool prototype usability testing, and suggestions for future XAI tool enhancements. Initial discussions covered participants' general perspectives on current healthcare treatment decision-making without exposing them to the XAI tool. Then, the XAI visualization prototype was introduced for feedback. Beyond evaluating the system's interface and usability, participants were prompted to share their insights on the potential of XAI in reducing medical errors and improving healthcare outcomes.

5 RESULTS

5.1 Framework Evaluation

The overview-first framework exhibits a time complexity $O(n^2)$ across all conditions, involving comparisons among all models. While comprehensive, this approach's time complexity becomes burdensome, particularly when dealing with a large number of models and multiple influencing factors, potentially resulting in significant time wastage during comparisons.

Compared to the overview-first approach, the outcome-first has much lower time complexity in the best condition. The Outcome-First technique, involving one-to-many comparisons, achieves a time complexity of O(n) in the best scenario. The worst-case time complexity is $O(n^2)$, which iterates through each treatment option and makes comparisons. The average condition is $O(k * n)$, with k representing the frequency of users selecting models from comparisons.

The group-first Framework also presents reduced time complexity in various conditions. Users can select matching models within each group, sorted by specific criteria. In the best condition, the time complexity is O(k), given one-to-multiple comparisons in each stage. The worst case scenario is $O(k^2)$ if users traverse all stages or move back and forth between them. The average condition maintains O(k), as users typically select optimized models in the initial stages.

We consider the "model selection" problem as a "multiple comparison" challenge in which a user needs to perform $O(n^2)$ comparisons when given n models. The goal of the visualization designs can then be posed as a design challenge to reduce the complexity. In the case of the outcome-first technique, the visualization design is aimed to reduce the amortized complexity to O(n) with an upper bound of $O(n^2)$. In the case of the group-first technique, the design aims to minimize complexity to $O(k^2)$, where k is less than n. The comparisons of the three frameworks are displayed in Table 3.

5.2 Pilot Study Evaluation

To evaluate the XAI tool user experience, we conducted a pilot interview study with cancer-related clinicians and patients with cancer and non-cancer chronological illness. Since chronological illness and cancer are both a long-term illness, clinicians incorporate patients' preferences and opinions in their treatment decision-making process. Patients also sometimes need to adjust to other care management options if necessary. Here, we consider each care management option as a model and set our users as patients.

During the study, the participants experienced the selection of their care management plans under overview-first, outcome-first, and group-first XAI tool interfaces. The workflows of all three XAI tool pipelines are presented in Figure 1. In illness progress, physicians usually suggest multiple options for the patients about their next step in care management plans. After comparing factors such as costs, time, and survival rates, patients can decide jointly with physicians which care management plan they would like to proceed with. The outcome-first XAI tool benefits patients without clinical background and visually measures different aspects of a care management plan.

6 out of 10 participants agreed that "*the old overview-first technique has lots of problems*" and 9 out of 10 participants agreed "*outcome-first XAI tool reduces a significant amount of time*". 5 out of 10 participants agreed that "*the visualizations in XAI tool improve understandings to each care management plan*", and 8 out of 10 expressed willingness to "*recommend this XAI tool to their friends.*" The results of the pilot study evaluation is presented in Figure 3.

The cancer patient participant P4 expressed specific concerns on the current overview-first framework: "*It's super scary to face all the treatment options at once without any explanations. Since I don't have much background in the cancer field, I'd rather start with a specific treatment option and take it step by step, comparing them one by one.*" This emphasizes the need for the XAI tool to enhance confidence and efficiency. Adopting an outcome-first approach that aligns with patients' preferences can empower them to better understand treatment options and streamline the decision-making process.

Furthermore, cancer clinician C1 highlighted the importance of "*providing iterations and stages of the treatment options*" to involve patients without clinical backgrounds in the patient-centered decision-making process. This approach was seen as beneficial in enhancing patient engagement and comprehension.

6 DISCUSSION

The feedback from the pilot study interviews highlighted a shared understanding among clinicians and patients about the effectiveness of the XAI approach in simplifying treatment decision-making. Both groups recognized the challenges posed by the perceived "black boxes" in the decision-making process and AI algorithms, especially for non-expert users [4]. The introduction of the outcome-first XAI tool was seen as beneficial, improving clinician-patient communication and decision outcomes. A key advantage of this XAI approach was its ability to enhance communication by providing clear information about medical treatments through visual aids like graphs and illustrations.

It should be noted that the sample size in this study is quite small. Additional research needs to be conducted to confirm the findings with a more diverse participant sample. Furthermore, the findings in these interviews involved creative speculation about potential technological benefits, rather than an evaluation of a specific, actually existing platform. Additional robust user-testing will be needed to evaluate the usefulness of a completed product design in clinical decision-making processes. The next stage in this project will be to engage a larger and more diverse sample of chronic disease patients and clinicians to expand our findings

Patient Participant ID	Age	Gender	Education Level
P1	82	F	High School
P2	46	M	M.S.
P3	33	F	M.S.
P4	59	F	B.S.
P5	51	M	M.S.
P6	73	M	Ph.D.
P7	63	M	High School

Table 1: Study 1 patient participant profiles, including age, gender, education level, race/ethnicity group, and cancer type.

Clinician Participant ID	Clinical Domain	Experience
C1	Cancer	33 yrs
C2	Breast Cancer	15 yrs
C3	Cancer	5 yrs

Table 2: Study 2 clinician participant profiles, including practice domain, years of clinical experience, and self-report SDM rate in the current practice.

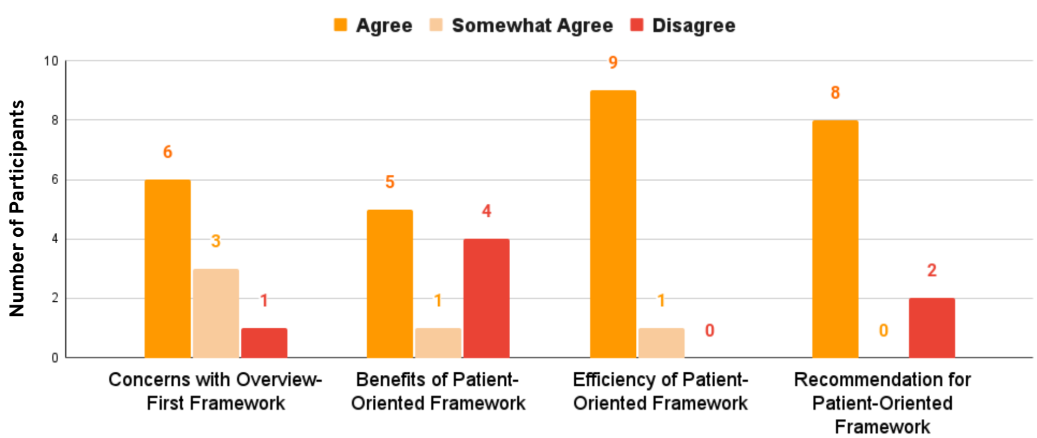

Figure 3: Barplot result of the POF XAI tool's participant feedback

Framework	Time Complexity (Best)	Time Complexity (Worst)	Time Complexity (Average)
Overview-First Framework	$O(n^2)$	$O(n^2)$	$O(n^2)$
Outcome-First Framework	O(k)	$O(n^2)$	O(n)
Group-First Framework	O(k)	$O(n^2)$	O(k*n)

Table 3: Time Complexity Comparisons for All Three Frameworks. k is a constant number where k < n.

about the optimal roles of technology in XAI tool. We then plan to develop a XAI platform to assist in clinical decision-making process, and conduct usability testing.

7 LIMITATIONS

There are several limitations when using the outcome-first XAI tool: First of all, the default plan selection will affect the plan selections. The default plan may cause some bias or errors since it may be recommended by AI [17]. Patients may always weigh the default plan higher than other care management plans. Sometimes, patients who lack clinical knowledge may still choose the default model in the final selection. Although outcome-first and group-first techniques are faster and easier to reach the optimized model option, it is still possible that some of the potential optimized models are missing. Especially in the group-first framework, based on users' criteria, users may only choose from the first or second stage and submit their results without exploring all the options in other stages.

Secondly, patients may have limited background knowledge or understanding of their diseases and care management plans. In this scenario, it is hard for patients to set up criteria for their targeted care management plans. The patient-oriented problem will happen when patients have some basic idea about the selection criteria.

Thirdly, the liability and privacy of patient-centric decision-making are also important. Patients may opt for the least recommended care management plan, potentially resulting in serious harm. Transparent display of side/adverse effects, ethical considerations, and other concerns during selections is crucial. Notably, the outcome-first focuses on adults (18-55 years old), warranting additional considerations for other age groups, such as children or aging individuals who may have more sensitive health conditions. This paper only focuses on cancer and chronic diseases and still needs to validate and evaluate the frameworks for other types of care management illnesses.

8 FUTURE WORK

Drawing from our study, there are two major obstacles that such a patient-oriented XAI platform will need to overcome:

- **Tailoring to Individual Patient Needs**: Most diseases often exhibit variability in stages and characteristics. Our XAI tool for healthcare treatment plan selection acknowledges this variability, providing nuanced information pages tailored to individual patients. This ensures that the tool effectively addresses the unique situations of each patient, taking into account the interconnected nature of their diseases and other aspects of their life, facilitating POF-guided treatment decisions.
- **Addressing Resource Constraints in Clinical Care**: Developing the healthcare XAI tool acknowledges the resource limitations patients face in providing in-depth discussions about treatment options. The healthcare system's constraints often impede effective patient-oriented decision-making processes. Our XAI tool serves as an enhancement, recognizing that it may be unrealistic to expect clinicians to dedicate extensive time to a patient-centered decision-making process. It aims to alleviate communication burdens during decision-making without replacing the vital clinician-patient relationships, thus aligning with the patient-oriented framework for healthcare decision-making.

9 CONCLUSION

This paper proposed two reversed directions of the traditional overview-first frameworks for the healthcare decision-making system. Each of the three XAI frameworks serves distinct functions in selecting treatment management plans. Specifically, the outcome-first framework proves advantageous for individuals with limited clinical knowledge. The outcome-first XAI tool prompts patients to actively *re-think* and *re-evaluate* their care management plans. Also, the group-first framework streamlines comparisons through smaller group pair-wise assessments. Both the time complexity analysis and pilot study results affirm the effectiveness of these frameworks in meeting patient needs. In addition, the contribution of these XAI tools extends to potentially mitigating selection bias by developing more refined criteria aligned with individualized patient needs and preferences. In summary, with the two patient-oriented frameworks, these approaches ensure a more personalized and patient-centric clinical decision-making process.

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