Game Theory Decision Model for Differential Diagnosis of Epilepsy Symptomatic Patients

Rasvini Rajendran[1*], Zaitul Marlizawati Zainuddin[2*]

[1]Department of Mathematical Sciences, Faculty of Science, University Technology Malaysia, 81310 Johor Bahru, Johor, Malaysia

[2]UTM Centre for Industrial and Applied Mathematics (UTM-CIAM), University technology Malaysia, 81310 Johor Bahru, Johor, Malaysia

[*]Corresponding author

DOI: https://doi.org/10.51584/IJRIAS.2025.10030018

Received: 25 February 2025; Accepted: 28 February 2025; Published: 31 March 2025

ABSTRACT

Epilepsy misdiagnosis is a prevalent issue with significant clinical, psychological, and economic consequences. Existing diagnostic approaches, such as electroencephalography and neuroimaging, provide valuable insights into neurological activity and structural abnormalities. However, these methods have limitations in distinguishing epilepsy from psychogenic nonepileptic seizures and other conditions with similar presentations, often leading to diagnostic uncertainty or misclassification. This study introduces a novel game-theoretic framework to enhance diagnostic accuracy by modeling the physician-patient interaction as a sequential decision-making process. The model considers the strategic choices of physicians and patients, incorporating psychological factors to refine differential diagnosis. A hybrid payoff assignment method, integrating binary and multi-criteria utility approaches, ensures a realistic representation of medical decision-making. Equilibrium analysis, conducted across four psychological distress categories, identifies optimal diagnostic strategies based on patient adherence and physician recommendations. The results illustrate that while distress levels influence treatment direction where low and moderate distress favor continued neurological care and high distress suggests psychiatric referral, this decision-making process is not straightforward. The game-theoretic model formalizes the strategic interaction between physicians and patients, incorporating the probabilities of diagnostic accuracy, treatment adherence, and long-term patient outcomes into the decision framework. The payoff formulation accounts for both medical and psychological factors, ensuring that referrals are not solely based on distress levels but on an optimized diagnostic pathway that balances competing risks and benefits. This structured approach helps mitigate misdiagnosis and inappropriate treatment allocation, which simple distress scoring alone cannot achieve. These findings underscore the importance of integrating psychological assessments into diagnostic protocols to reduce misdiagnosis. The proposed framework provides a structured decision-support tool that improves diagnostic precision, optimizes resource allocation, and enhances patient outcomes. Future research should explore empirical validation, machine learning integration, and cross-cultural applicability to further refine this approach.

Keywords: differential diagnosis; game theory; epilepsy; DASS; triage.

INTRODUCTION

Medical misdiagnosis is a critical global health issue, with diagnostic errors contributing to up to 10% of patient deaths and 6–17% of adverse hospital events worldwide [1]. Epilepsy misdiagnosis, estimated at 20–30% globally, arises from symptom overlap with conditions like psychogenic nonepileptic seizures, migraines, and syncope [2]. Overreliance on incomplete patient histories, misinterpretation of EEG results, and diagnostic uncertainty among non-specialists exacerbate the problem. Patients wrongly diagnosed with epilepsy face unnecessary treatments and social stigma, while those with undiagnosed epilepsy risk severe neurological outcomes [3]. Limited access to advanced diagnostic tools, especially in resource-constrained settings, further complicates accurate diagnosis [4]. A structured decision-making framework is essential to improve diagnostic precision and mitigate these challenges.

Current diagnostic approaches rely primarily on clinical history, EEG findings, and neuroimaging to confirm epilepsy [5]. While these methods have significantly improved epilepsy management, they are not infallible. EEGs, for example, can yield false positives due to normal variants mistaken for epileptic activity, while false negatives occur when seizure activity is not captured during the recording session [6]. Imaging techniques such as MRI and CT scans help identify structural abnormalities but cannot always distinguish between epileptic and non-epileptic seizure disorders [7]. Furthermore, physician judgment remains a major factor in diagnosis, yet studies show that general practitioners and non-specialist neurologists frequently misdiagnose epilepsy, emphasizing the need for objective decision-support tools [8]. Despite these limitations, no standardized, evidence-based triage system currently exists to systematically guide differential diagnosis for epilepsy and its mimics.

Existing research on epilepsy misdiagnosis has primarily focused on improving EEG interpretation, identifying diagnostic pitfalls, and advocating for increased specialist involvement [9]. However, there is a notable gap in systematic decision-making frameworks that incorporate patient history, behavioral patterns, and probabilistic reasoning to enhance diagnostic accuracy. Moreover, while artificial intelligence (AI) and machine learning models have been explored for epilepsy classification, their applicability in real-world clinical settings remains limited due to data availability and validation challenges [10]. To date, no studies have proposed a game-theoretic approach to model the strategic interactions between physicians and patients during the diagnostic process, which could provide a structured, decision-theoretic basis for improving differential diagnosis.

This study introduces a novel game-theoretic model for improving epilepsy diagnosis by integrating patient history and clinical decision-making strategies. By modeling the diagnostic process as a strategic interaction between healthcare providers and patients, this framework aims to reduce diagnostic uncertainty and enhance the accuracy of distinguishing epilepsy from its mimics. The proposed model applies game theory principles to evaluate optimal diagnostic strategies based on available patient information, reducing reliance on subjective clinical judgment alone. This research contributes to the literature by introducing a structured mathematical framework for improving differential diagnosis in epilepsy. Furthermore, the findings have potential clinical applications in improving triage protocols, reducing healthcare costs associated with misdiagnosis, and ultimately improving patient outcomes.

The following sections discuss the limitations of current diagnostic approaches and highlight the need for a structured decision-making framework. Next, the proposed game-theoretic model is introduced, along with its payoff formulation. This is followed by an analysis of the results and their implications for differential diagnosis. Finally, the article concludes with key findings, limitations, and future research directions.

METHODOLOGY

Game-Theoretic Framework

Game theory provides a mathematical framework for analyzing strategic interactions where the outcomes depend on the choices of multiple decision-makers. In the context of medical decision-making, physicians and patients engage in a sequential process were diagnostic recommendations and patient adherence influence health outcomes. The differential diagnosis of epilepsy and its mimics presents a complex decision problem, requiring an approach that accounts for both rational decision-making and uncertainty. This study models the diagnostic process as a two-player sequential game, where a physician must decide between continuing neurological care or referring the patient for psychiatric evaluation. The patient, in turn, chooses to either adhere to or disregard the recommendation. This model captures the probabilistic nature of medical diagnosis, incorporating utility functions to quantify the expected benefits and costs associated with different decision paths.

Players and Strategies

In this game-theoretic framework, the two primary players are the physician and the patient. The physician's

Role is to recommend one of two possible diagnostic pathways: (i) continuing Neurological Care (N), where the patient remains under neurological observation, or (ii) making a Psychiatric Referral (Y) for further evaluation. The patient, upon receiving the physician's recommendation, can either Adhere (F) by following the doctor's advice or Disregard (O) by seeking alternative care or self-managing symptoms. These choices reflect real-world scenarios where patients may hesitate to accept a psychiatric diagnosis or may doubt the necessity of additional testing.

Utility Functions

Utility functions are used to quantify the players' incentives in the decision-making process. The doctor's utility function, U_D , incorporates factors such as diagnostic accuracy (A), resource allocation (R), and quality of care (Q). Each of these factors is assigned binary values (0 or 1) to reflect key decision outcomes. Specifically, A =1 if the diagnosis is correct and 0 otherwise, R =1 if the necessary resources are allocated and 0 if they are not, and Q =1 if the quality of care meets the required standard and 0 otherwise. This binary representation simplifies the utility model while capturing essential decision-making elements.

On the other hand, the patient's utility function, U_P, considers five key factor namely health outcomes (H), financial costs (C), perceived quality of care (Q), psychological stress (S), and health-seeking behavior (B). Similar to the doctor's utility function, each factor is assigned a binary value to reflect distinct outcomes.

Specifically, H=1 for a positive health outcome and 0 otherwise, C=1 if incurred costs are high and *0* if low, Q=1 if the quality of care meets the required standard and 0 otherwise, S=1 if psychological distress is present and 0 otherwise as well as B=1 for proactive behavior and 0 for non-compliance. These functions ensure that both physician and patient decisions are influenced by trade-offs between diagnostic certainty, economic constraints, and psychological factors.

Hybrid Approach for Payoff Assignment in Medical Decision-Making

A hybrid method combining binary payoff and multi-criteria utility was chosen for assigning payoffs in this study. The binary approach simplifies decision-making by categorizing outcomes into two states (e.g., correct vs. incorrect diagnosis), while the multi-criteria utility method captures the complexity of medical decisions, considering factors like diagnostic accuracy, patient well-being, and resource constraints. This hybrid approach ensures a balanced representation of the diagnostic process, making the game-theoretic model both computationally feasible and realistic in reflecting real-world decision-making.

Assumptions

To simplify the model, several assumptions are made. First, physicians are assumed to act rationally, seeking to maximize diagnostic accuracy while minimizing costs. Second, patient responses are based on perceived risk and trust in the physician rather than perfect knowledge of their condition. Third, diagnostic decisions are sequential, meaning the physician acts first, followed by the patient's response. Lastly, resource constraints exist, particularly in public healthcare settings, limiting access to advanced diagnostic tools. These assumptions help create a structured framework that aligns with real-world medical decision-making processes.

MODEL FORMULATION

Game Tree Representation

The decision-making process is represented as a sequential extensive-form game using a game tree as shown in Fig.1. Each decision node corresponds to a point at which either the physician or the patient selects an action. The terminal nodes of the game tree capture different clinical outcomes, such as accurate diagnosis, misdiagnosis, or the need for further evaluation. The structure of the tree reflects how different combinations of physician recommendations and patient choices lead to distinct outcomes, thereby illustrating the impact of strategic decision-making on diagnostic accuracy.

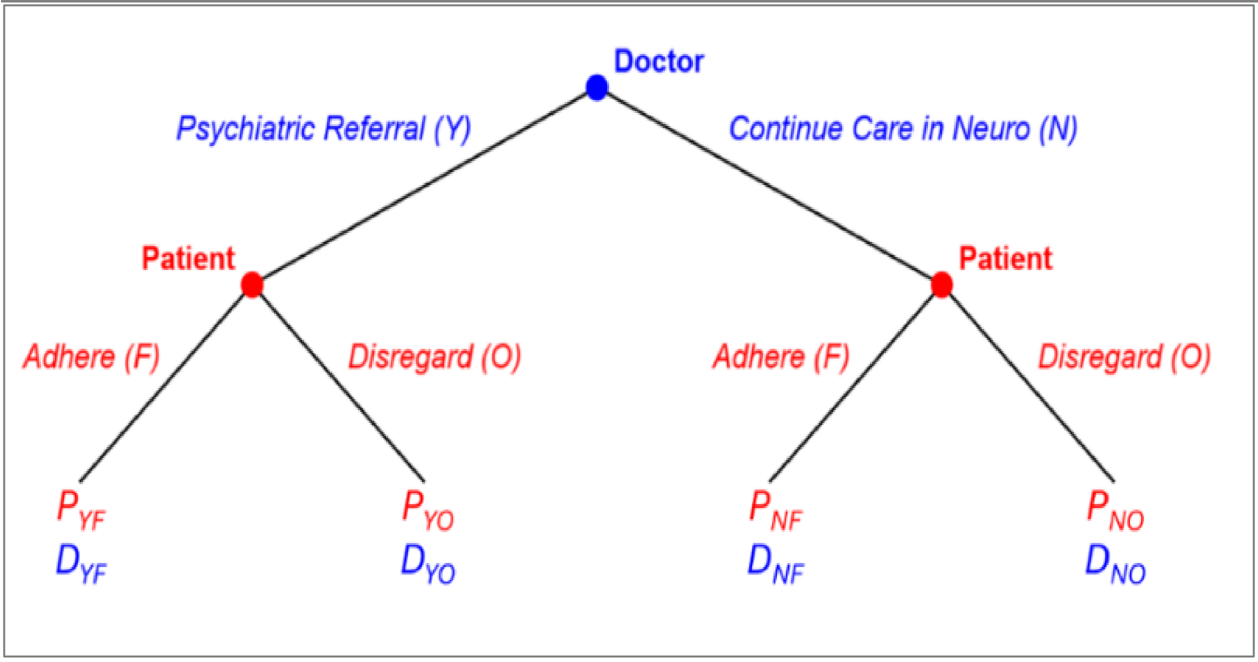

Fig. 1 Game Tree

Payoffs

Based on the formulated game tree, the corresponding game matrix systematically represents the strategic interactions between the doctor and the patient. The payoffs, denoted as D_{ij} for the doctor and P_{ij} for the patient, capture the utility derived from specific decision combinations, where i represents the doctor's chosen action and j represents the patient's response.

The doctor's payoff, $\boldsymbol{D_{ij}}$, is thus given by:

$$\boldsymbol{D_{ij} = w_A A + w_R R + w_Q Q}$$

where $\boldsymbol{w_A}$, $\boldsymbol{w_R}$ and $\boldsymbol{w_Q}$ are weighting coefficients representing the relative importance of each component in the doctor's decision-making. Whereas the patient's payoff, $\boldsymbol{P_{ij}}$, is given by:

$$\boldsymbol{P_{ij} = w_H H - w_C C + w_Q Q - w_S S + w_B B}$$

where $\boldsymbol{w_H}$,$\boldsymbol{w_C}$,$\boldsymbol{w_Q}$,$\boldsymbol{w_S}$ and $\boldsymbol{w_B}$ are weighting coefficients representing the relative importance of each factor to the patient.

Table 1 presents the strategic interactions between the doctor and the patient, outlining their available choices and corresponding payoffs. As mentioned previously, the doctor has two possible strategies: recommending psychiatric referral (Y) or continuing care in neurology (N). Similarly, the patient can either adhere to the doctor's recommendation (F) or disregard it (O). Each row in the table represents a specific decision combination, where the payoffs are denoted as D_{ij} for the doctor and P_{ij} for the patient.

Table 1: Strategy Combinations and Corresponding Payoffs

Payoff of Doctor	Payoff of Patient	Description
D_{YF}	P_{YF}	Doctor recommends psychiatric referral and patient adheres to the recommendation
D_{NF}	P_{NF}	Doctor recommends continued care in neurology and patient adheres to the recommendation

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue III March 2025

D_{YO}	P_{YO}	Doctor recommends psychiatric referral and patient disregards the recommendation
D_{NO}	P_{NO}	Doctor recommends continued care in neurology and patient disregards the recommendation

Table 2 presents the payoff matrix, illustrating the players' strategies and corresponding payoffs. Each cell contains a pair of values, representing the doctor's and patient's utilities. This structured representation facilitates the analysis of decision-making dynamics, with payoffs formulated as utility functions that account for factors influencing diagnostic accuracy and patient outcomes.

Table 2: Payoff Matrix of All Available Strategies

		Patient	
		Adhere (F)	Disregard (O)
Doctor	Psychiatric Referral (Y)	D_{YF}, P_{YF}	D_{YO}, P_{YO}
	Continue Care in Neurology (N)	D_{NF}, P_{NF}	D_{NO}, P_{NO}

Incorporating Psychological Assessment: DASS-21

The Depression, Anxiety, and Stress Scale (DASS) is a psychometric tool used to assess emotional distress, available in three versions: DASS-42, DASS-21, and DASS-10, each balancing comprehensiveness and efficiency. The DASS-42 provides a detailed evaluation but is less practical in time-sensitive clinical settings. The DASS-10 offers a rapid assessment but may lack sensitivity to nuanced psychological symptoms. The DASS-21 strikes an optimal balance, utilizing a 4-point Likert scale (0–3) to classify depression, anxiety, and stress into severity categories—normal, mild, moderate, severe, and extremely severe [11]. Research supports its reliability and efficiency in clinical and research contexts [12,13].

This study adopts DASS-21 to effectively quantify psychological distress while maintaining diagnostic feasibility. Emotional distress influences symptom perception and reporting, with some patients experiencing situational distress and others minimizing psychological symptoms due to stigma. Integrating DASS scores into diagnostic models provides a broader perspective on patient health, aiding in distinguishing between psychological and physiological symptom origins, a critical step for accurate diagnosis and treatment planning.

To systematically analyze the interplay between psychological distress and diagnostic outcomes, this study consolidates patient profiles into four broad categories: Low Distress, Balanced Moderate Distress, Depression-Dominant, and Anxiety and Stress-Dominant. These categories serve as a structured approach to triaging patients based on their DASS profiles, enabling targeted diagnostic strategies that align with clinical complexity and resource prioritization. By distinguishing cases based on the dominance or distribution of distress components, this framework enhances diagnostic accuracy and contributes to the broader goal of reducing misdiagnosis through a game-theoretic diagnostic model [11,14,15]. This categorization also optimizes resource allocation by prioritizing high-risk cases while ensuring that lower-risk patients receive appropriate but efficient care. By aligning psychological distress levels with diagnostic priority, clinicians can streamline decision-making, integrating psychological insights into medical evaluations for improved accuracy and efficacy.

DASS scores will be incorporated into a game-theoretic framework to model decision-making by patients and clinicians. The severity categories will inform payoff assignments in the diagnostic game tree, reflecting the impact of psychological distress on clinical outcomes. These payoffs will contribute to calculating Nash equilibria, identifying optimal diagnostic strategies under varying psychological conditions. A detailed analysis of the combined payoff matrix for all four categories will be conducted in the subsequent section on equilibrium analysis, providing a robust structure for systematically addressing the complex interdependencies between mental health, patient behavior, and diagnostic accuracy.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue III March 2025

RESULTS AND DISCUSSION

Payoff Matrix

The payoff values for both the doctor and the patient are derived from the formulated utility functions, which include weighting coefficients representing the relative importance of each component. In this analysis, all components are assumed to be of equal importance and are thus assigned a value of 1 for simplicity. However, future models or analyses should consider scenarios where components have unequal importance. For instance, if a decision-maker prioritizes the patient's quality of care over other factors, the corresponding weighting coefficient (w_Q) could be assigned a higher value than the others.

While individual utility components are assigned binary values, the total payoff is derived as a weighted sum of these components. Thus, the overall payoff is not necessarily binary but rather reflects an aggregate score. A detailed analysis of the combined payoff matrix for the four aforementioned categories will be presented in the subsequent sections.

Low Distress Category: This category includes cases with minimal psychological distress across depression, anxiety, and stress, reducing the risk of misreporting or psychological influences mimicking seizure-like behaviors. Literature supports that low distress has little impact on diagnostic accuracy, making these cases more straightforward to manage [16]. As such, the doctor's payoff is as outlined below:

- **Correct Diagnosis, Patient Complies (D_{NF}):**

This represents the optimal outcome for the doctor, with accurate diagnosis (A=1), appropriate resource allocation (R=1), and high-quality care (Q=1) contributing to a maximum payoff of 3.

- **Correct Diagnosis, Patient Does Not Comply (D_{NO}):**

Although diagnostic accuracy and resource allocation remain appropriate (A=1, R=1), the patient's non-compliance diminishes the quality of care (Q=0), reducing the payoff to 2.

- **Incorrect Diagnosis, Patient Complies (D_{YF}):**

A misdiagnosis (A=0) results in poor resource allocation (R=0) and suboptimal care (Q=0), leading to a payoff of 0.

- **Incorrect Diagnosis, Patient Does Not Comply (D_{YO}):**

This scenario combines diagnostic inaccuracy (A=0), poor resource use (R=0), and inadequate care (Q=0), representing the least favorable outcome with a payoff of 0.

Based on the earlier formulated utility functions, the payoffs for doctors within the Low Distress Category are detailed in Table 3 below.

Table 3: Component-wise Binary Utilities for Doctor in Low Distress Category

Strategy	D_{YF}	D_{NF}	D_{YO}	D_{NO}
Diagnostic Accuracy, A	0	1	0	1
Resource Allocation, R	0	1	0	1
Quality of Care, Q	0	1	0	0
Total Payoff	**0**	**3**	**0**	**2**

Similarly, the patient's payoff can be defined as follows:

- **Correct Diagnosis, Patient Complies (P_{NF}):**

  This is the optimal outcome for the patient. The correct diagnosis ensures a positive health outcome (H=1) with low costs (C=0), good quality of care (Q=1), low psychological distress (S=0), and proactive health-seeking behavior (B=1) contributing to a maximum payoff of 3.

- **Correct Diagnosis, Patient Does Not Comply (P_{NO}):**

  Despite a correct diagnosis, non-compliance (B=0) results in no health improvement (H=0) and poor quality of care (Q=0). Low psychological distress (S=0) and cost savings (C=0) do not offset the negative health outcome leading to an overall payoff of 0.

Incorrect Diagnosis, Patient Complies (P_{YF}):

Compliance with an incorrect diagnosis leads to a poor health outcome (H=0) and high costs (C=1). Quality of care is poor (Q=0), psychological distress is elevated (S=1), and proactive behavior (B=1) does not improve the situation, giving an unfavorable outcome with a payoff of -1.

Incorrect Diagnosis, Patient Does Not Comply (P_{YO}):

Here, the health outcome remains negative (H=0), but costs are low (C=0) due to non-compliance (B=0). Poor quality of care (Q=0) and elevated psychological distress (S=1) lead to a negative payoff, representing another unfavorable outcome with a payoff of -1.

Likewise, the payoffs for patients within the Low Distress Category are detailed in Table 4 below.

Table 4: Component-wise Binary Utilities for Patient in Low Distress Category

Strategy	**P_{YF}**	**P_{NF}**	**P_{YO}**	**P_{NO}**
Health Outcome, H	0	1	0	0
Cost, C	1	0	0	0
Quality of Care, Q	0	1	0	0
Psychological Factor, S	1	0	1	0
Health Seeking Behavior, B	1	1	0	0
Total Payoff	**-1**	**3**	**-1**	**0**

The corresponding binary payoffs for doctors and patients are integrated into the payoff matrix presented in Table 5.

Table 5: Combined Payoff Matrix in Low Distress Category

		Patient	
		Adhere (F)	Disregard (O)
Doctor	Psychiatric Referral (Y)	(0, -1)	(0, -1)
	Continued Care in Neurology (N)	(3, 3)	(2, 0)

The payoff matrices for the remaining three categories are derived using the same approach.

Balanced Moderate Distress Category: This category includes cases where moderate levels of depression, anxiety, and stress are evenly distributed. These cases present intermediate complexity, as psychological distress may subtly influence symptom reporting and diagnostic accuracy without reaching extreme levels.

Research suggests that moderate distress can affect cognitive and emotional processing, leading to slight variations in clinical presentation [14]. This category serves as a transitional reference between low and high-distress cases, aiding in the development of nuanced diagnostic frameworks. The corresponding binary payoffs for doctors and patients are integrated into the payoff matrix in Table 6.

Table 6: Combined Payoff Matrix in Balanced Moderate Distress Category

		Patient	
		Adhere (*F*)	Disregard (*O*)
Doctor	Psychiatric Referral (*Y*)	(0, -1)	(1, -1)
	Continued Care in Neurology (*N*)	(3, 3)	(2, 0)

Depression-Dominant Category: This category is characterized by high levels of depression with low-to-moderate anxiety and stress, significantly impacting patient communication and symptom reporting. Severe depression can impair cognitive and emotional engagement, leading to underreporting or inconsistent symptoms, which complicate diagnosis. Research highlights that depressive symptoms are often underreported due to stigma, denial, or lack of awareness, increasing the risk of misdiagnosis [15]. This necessitates careful assessment and integration of mental health evaluations to differentiate neurological conditions from psychological influences.

This category underscores the critical role of compliance and diagnostic accuracy, as misdiagnosis or non-compliance can lead to severe psychological and clinical consequences. The corresponding binary payoffs for doctors and patients are integrated into the payoff matrix in Table 7.

Table 7: Combined Payoff Matrix in Depression Dominant Category

		Patient	
		Adhere (*F*)	Disregard (*O*)
Doctor	Psychiatric Referral (*Y*)	(3,3)	(1, -1)
	Continued Care in Neurology (*N*)	(0,-1)	(1,-1)

Anxiety and Stress-Dominant Category*:* This category is defined by high levels of anxiety and stress, with lower levels of depression. This category is clinically significant due to the physiological and psychological manifestations, such as hyperventilation and tachycardia, that can mimic seizure activity or worsen pre-existing conditions, complicating diagnosis and treatment. Patients often present stress-induced conditions like PNES, which overlap symptomatically with epilepsy, requiring interdisciplinary care to differentiate between neurological and psychological conditions [16].

This category emphasizes the importance of integrating stress and anxiety assessments into diagnostic models to avoid misdiagnosis and enhance treatment outcomes. The corresponding binary payoffs for doctors and patients are integrated into the payoff matrix in Table 8.

Table 8: Combined Payoff Matrix in Anxiety and Stress – Dominant Category

		Patient	
		Adhere (*F*)	Disregard (*O*)
Doctor	Psychiatric Referral (*Y*)	(3,3)	(1, -1)
	Continued Care in Neurology (*N*)	(0,-1)	(1,-1)

Backward Induction & Equilibrium Analysis

Backward induction is a key solution technique in game theory, particularly for sequential decision-making processes where players act in a structured order. It involves solving the game by analyzing the final outcomes first and then working backward to determine the optimal strategies at earlier decision points [17]. This method ensures that each decision point reflects the rational expectations of future actions, leading to a subgame perfect Nash equilibrium (SPNE), a refinement of Nash equilibrium that ensures optimal decision-making at every stage of the interaction [18].

In the context of diagnostic decision-making, backward induction is used to evaluate the strategic interactions between the doctor and the patient. The doctor's strategy involves choosing between recommending a psychiatric referral or continuing care in neurology, while the patient must decide whether to adhere to the recommendation or disregard it. Since the patient's decision follows the doctor's recommendation, backward induction allows us to first assess the payoffs associated with the patient's choices and then determine the doctor's optimal recommendation based on the anticipated patient response.

By applying backward induction to this decision-making process, the optimal strategy for both the doctor and the patient can be systematically identified. This ensures that the equilibrium outcome reflects rational decision-making at each stage, leading to improved diagnostic accuracy, better resource allocation, and enhanced patient trust in the medical system [19].

Equilibrium Analysis

The decision-making process in medical diagnostics can be modeled as a two-player extensive-form game between a doctor and a patient, where the doctor moves first by either recommending a psychiatric referral or neurological care. Following the doctor's recommendation, the patient responds by either adhering to the prescribed course of action or disregarding it. The strategy sets are defined as

$$\boldsymbol{S_D \in \{Y, N\}}$$

for the doctor's strategy and

$$\boldsymbol{S_P (S_D) \in \{F, O\}}$$

for the patient's strategy.

To determine the SPNE using backward induction for the low distress category, the patient's best response is first analyzed. If the doctor chooses ***Y***, the patient is indifferent between ***F*** and ***O***, as both payoffs are equal. However, if the doctor chooses ***N***, the patient prefers ***F*** over ***O*** (since 3 > 0). Next, the doctor's best response is examined. If the doctor selects ***Y***, their payoffs are equal, and they gain nothing. However, if the doctor chooses ***N***, they prefer ***F*** (with a payoff of 3) over ***O*** (payoff of 2). Thus, the doctor's best response is to choose ***N***, and the patient's best response to ***N*** is ***F***.

The resulting equilibrium strategy profile is **(*N, F*)**, which is the SPNE. This outcome was validated using Game Theory Explorer v2.3.0, confirming the strategy profile **(*N, F*)** as the SPNE, as shown in Fig. 2.

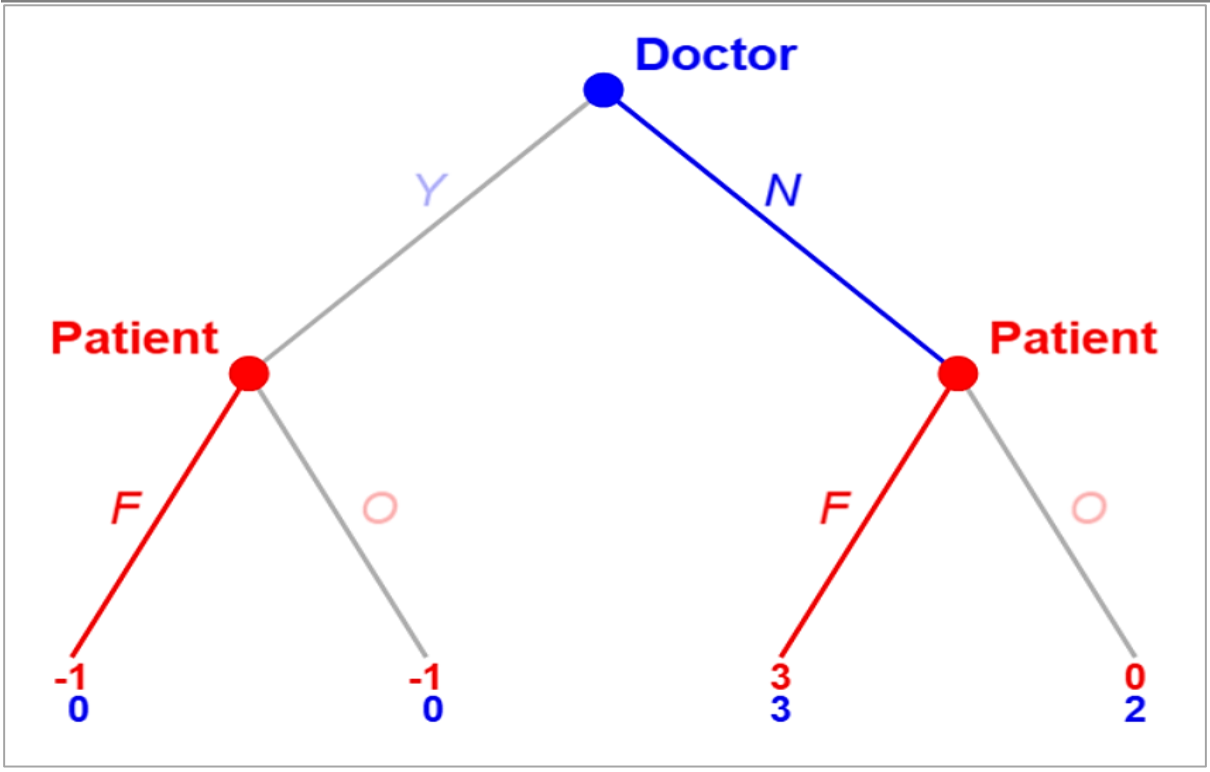

Fig. 2 SPNE of Low Distress Category

Similarly, the best responses for both the patient and the doctor are determined for the balanced moderate distress category. The resulting equilibrium strategy profile remains ***(N,F)***, establishing it as the SPNE for this category as well. This outcome is clearly illustrated in Fig. 3.

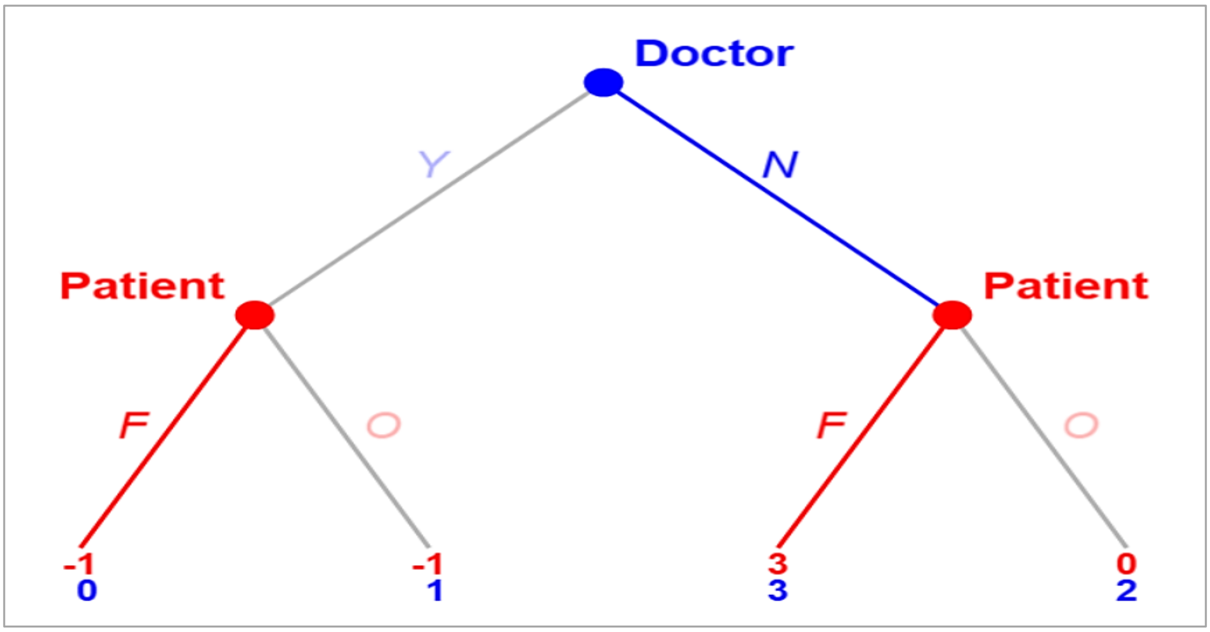

Fig.3 SPNE of Balanced Moderate Distress Category

In both the depression-dominant and anxiety and stress-dominant categories, the analysis of payoff matrices revealed similar structures, leading to the same SPNE. In both categories, the equilibrium strategy profile is ***(Y, F)***, where the doctor recommends a psychiatric referral and the patient adheres to the treatment. This consistent outcome across different psychological distress conditions highlights the robustness of the equilibrium. As illustrated in Fig. 4, the strategic interactions between the doctor and patient remain unchanged despite variations in distress types, indicating that the referral-adherence strategy is the optimal decision pathway under the given payoff conditions.

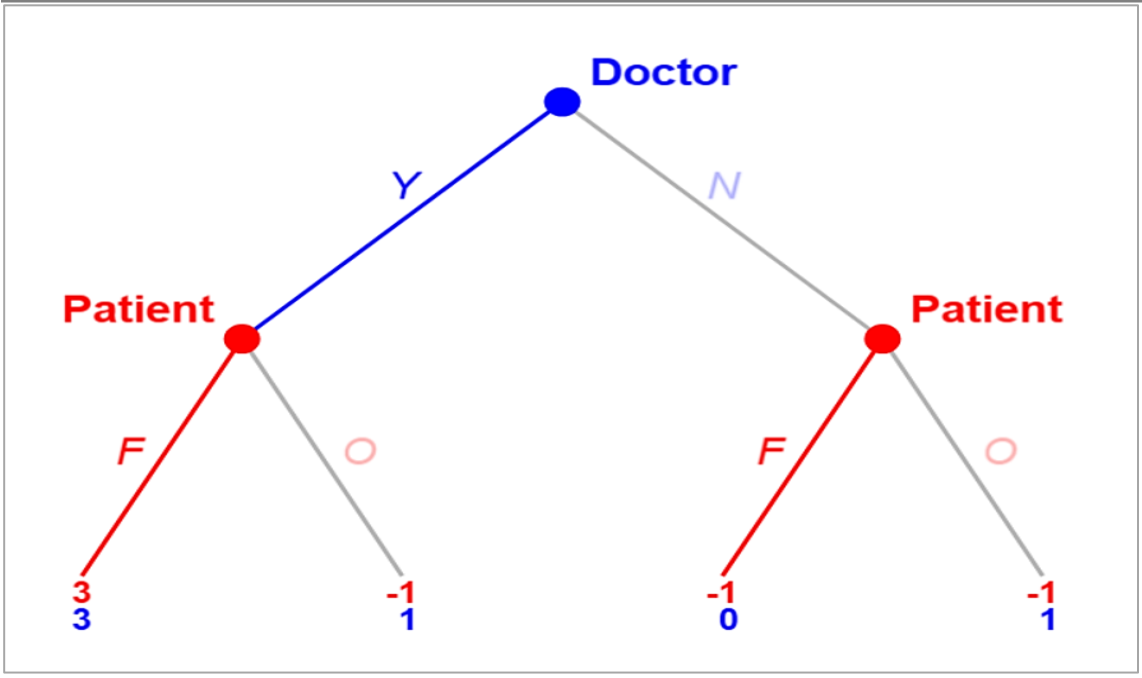

Fig. 4 SPNE of Depression-Dominant & Anxiety and Stress-Dominant Category

The equilibrium analysis across four psychological distress categories, low distress, balanced moderate distress, depression-dominant as well as anxiety and stress-dominant, reveals distinct decision patterns. In the low and balanced moderate distress categories, the equilibrium strategy is **(*N*,*F*)**, where the doctor prefers continued neurological care, and the patient adheres to the treatment. In contrast, in the depression-dominant and anxiety and stress-dominant categories, the equilibrium is **(*Y*,*F*)**, with the doctor recommending a psychiatric referral, and the patient follows the recommendation. These findings underscore the influence of psychological distress on medical decision-making, with more pronounced distress leading to psychiatric referral. The consistency of patient adherence highlights the importance of treatment engagement, providing a framework for optimizing differential diagnosis and intervention strategies in healthcare.

Clinical Implications

The findings of this study have several clinical implications. First, the model enhances diagnostic accuracy by systematically analyzing decision paths, reducing misdiagnosis rates. Second, it allows for better resource allocation by prioritizing cost-effective diagnostic strategies. Finally, by incorporating patient behavior into the model, it promotes patient-centered care, improving adherence and overall treatment outcomes. Implementing this framework in clinical practice could significantly enhance epilepsy diagnostics, leading to better patient management and healthcare efficiency.

CONCLUSION

Summary of Findings

This study developed a game-theoretic framework to improve the differential diagnosis of epilepsy and non-epileptic seizure conditions. By modeling the diagnostic process as a sequential game between physicians and patients, the research introduced a structured decision-making approach that accounts for both strategic interactions and psychological influences. The equilibrium analysis revealed that physician recommendations and patient adherence are highly influenced by psychological distress levels, with different equilibria emerging based on the severity of anxiety and depression. The results underscore the importance of integrating psychological assessments into diagnostic protocols to minimize misdiagnosis and optimize treatment pathways.

Moreover, the study highlighted key limitations in existing diagnostic approaches, such as over-reliance on EEG results and physician intuition, which contribute to high misdiagnosis rates. The proposed model provides an alternative by formalizing decision-making through utility functions that incorporate diagnostic accuracy, patient adherence, and resource allocation. By structuring the diagnostic process as a strategic game, this research offers a new perspective on improving epilepsy diagnosis and mitigating the consequences of misdiagnosis.

Limitations and Potential Improvements

Despite its contributions, this study has several limitations. First, the model simplifies physician-patient decision-making into binary choices, which may not fully capture the complexity of real-world diagnostic processes. In reality, physicians may consider multiple diagnostic and treatment options beyond the two presented in this model, and patients may exhibit partial adherence rather than making absolute choices. Future refinements could introduce more nuanced decision pathways to better reflect clinical complexity.

Another limitation lies in the assumption of rational behavior by both physicians and patients. While game theory assumes players act strategically to maximize their utility, real-world medical decisions are often influenced by cognitive biases, limited information, and external constraints such as healthcare policies or socioeconomic factors. Incorporating stochastic elements, such as Bayesian updating, could enhance the model's ability to adapt to evolving patient conditions and diagnostic uncertainty.

Additionally, the study focuses exclusively on young and middle-aged adults, omitting pediatric and elderly populations where epilepsy presents unique diagnostic challenges. Future research should extend the framework to account for age-related diagnostic variations and explore its applicability in diverse demographic settings. Furthermore, while the model assumes physician recommendations are based solely on medical criteria, in practice, external pressures – such as resource limitations and institutional guidelines – may also shape decision-making. Expanding the model to incorporate these factors would enhance its real-world applicability.

Future Research Directions

Building on the findings of this study, several avenues for future research can be explored. First, empirical validation of the game-theoretic model through clinical trials and retrospective patient data analysis would be essential for assessing its real-world accuracy and effectiveness. Comparing model predictions with actual patient outcomes would provide insights into its predictive power and areas for refinement.

Second, integrating machine learning techniques with the game-theoretic framework could enhance its diagnostic precision. AI models trained on large-scale clinical datasets could refine the estimated payoffs and transition probabilities in the decision tree, allowing for more adaptive and personalized diagnostic strategies. Such hybrid approaches would bridge the gap between theoretical modeling and data-driven decision support systems.

Additionally, future research could explore cross-cultural and socioeconomic factors influencing diagnostic behaviors. The model currently assumes a uniform decision-making process, but patient adherence and health-seeking behaviors vary across different cultural and economic backgrounds. Studying these variations would help tailor the framework to diverse healthcare settings, improving its applicability in both high- and low-resource environments.

Finally, expanding the model to include multidisciplinary decision-making could provide a more holistic perspective on epilepsy diagnosis. Collaboration between neurologists, psychiatrists, and general practitioners could introduce additional strategic layers, enriching the diagnostic process. Future studies could examine how interdisciplinary cooperation impacts diagnostic accuracy and patient outcomes.

In conclusion, this research presents a novel application of game theory in medical diagnostics, offering a structured approach to reducing epilepsy misdiagnosis. While limitations exist, the study lays the groundwork for future advancements in decision-support models, with the potential to transform clinical practice and enhance patient care.

ACKNOWLEDGMENTS

The authors would like to thank the Malaysian Ministry of Higher Education for their financial funding through

Fundamental Research Grant Scheme (FRGS) vote number R.J130000.7854.5F138. This support is gratefully acknowledged.

REFERENCES

1. Singh, H., Schiff, G. D., Graber, M. L., Onakpoya, I., & Thompson, M. J. (2017). The global burden of diagnostic errors in primary care. BMJ quality & safety, 26(6), 484–494.
2. Benbadis, S. R. (2009). The differential diagnosis of epilepsy: A critical review. Epilepsy & Behavior, 15(1), 15-21.
3. Asadi-Pooya, A. A., & Sperling, M. R. (2015). Epidemiology of psychogenic nonepileptic seizures. Epilepsy & behavior: E&B, 46, 60–65.
4. World Health Organization. (2019). Epilepsy: A public health imperative. World Health Organization.
5. Fisher, R. S., Cross, J. H., French, J. A., Higurashi, N., Hirsch, E., Jansen, F. E., & Zuberi, S. M. (2017). Operational classification of seizure types by the International League Against Epilepsy. Epilepsia, 58(4), 522–530.
6. Benbadis, S. R. (2007). The EEG in the diagnosis of epilepsy: What is its role? Current Neurology and Neuroscience Reports, 7(4), 305–310.
7. Scheffer, I. E., Berkovic, S., Capovilla, G., Connolly, M. B., French, J., Guilhoto, L., & Zuberi, S. M. (2017). ILAE classification of the epilepsies: Position paper of the ILAE Commission for Classification and Terminology. Epilepsia, 58(4), 512–521.
8. Devinsky, O., Gazzola, D., & LaFrance, W. C. (2016). Differentiating between nonepileptic and epileptic seizures. Nature Reviews Neurology, 12(4), 210–223.
9. Xu, Y., Nguyen, D., Mohamed, A., Carcel, C., Li, Q., Kutlubaev, M. A., Anderson, C. S., & Hackett, M. L. (2016). Frequency of false positive diagnosis of epilepsy: A systematic review of observational studies. Seizure, 38, 64–75.
10. Narayan, P., Sharma, K., & Lee, S. H. (2021). AI-assisted diagnosis in epilepsy care: A systematic review of recent advancements. Journal of Neurology and Artificial Intelligence, 4(1), 45–60.
11. Lovibond, P. F., & Lovibond, S. H. (1995). Manual for the Depression Anxiety Stress Scales (2nd ed.). Sydney: Psychology Foundation.
12. Henry, J. D., & Crawford, J. R. (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. British Journal of Clinical Psychology, 44(2), 227-239.
13. Bottesi, G., Ruggiero, G. M., & Fava, G. A. (2015). A psychometric evaluation of the Depression Anxiety Stress Scales (DASS-21) in a large sample of Italian adolescents. Journal of Psychopathology, 21(1), 66-73.
14. Schmitz, N., Mühlan, H., & Schäfer, S. (2021). The relationship between depression and anxiety with quality of life in patients with chronic diseases. Journal of Clinical Psychology, 77(7), 1511-1523.
15. Brown, T. A., Chorpita, B. F., & Barlow, D. H. (2018). Psychometric properties of the Revised Anxiety and Depression Scale (DASS-21). Journal of Anxiety Disorders, 58, 65-73.
16. Cuthbert, B. N. (2020). The RDoC framework: A new method to classify mental disorders. Psychological Science Agenda, 33(4), 45-56.
17. Osborne, M. J., & Rubinstein, A. (1994). A course in game theory. MIT Press.
18. Fudenberg, D., & Tirole, J. (1991). Game theory. MIT Press.
19. Gibbons, R. (1992). Game theory for applied economists. Princeton University Press.