IJHSR
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RESEARCH ARTICLE

Symptom-Based Predictive Modeling of Retinal Detachment and Patient Response Behavior

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ABSTRACT: Retinal detachment (RD) is a condition where the retina pulls away from the underlying tissue and can lead to permanent blindness if left untreated. To ensure timely intervention for often surgical measures, early identification of symptoms and risk factors is critical. This study used a data-driven approach to evaluate how patient-reported symptoms and prior medical history predict confirmed RD. Using an AI-based simulation, a dataset of 350 records was generated on a questionnaire that prompted for patients' demographics, symptoms, and relevant medical records to model realistic patterns of RD occurrence. A logistic regression analysis achieved an overall classification accuracy of 0.900 but a relatively low discriminative power (AUC = 0.558), likely due to an uneven distribution between RD and non-RD cases. Curtain-like shadows, flashes, and floaters across a person's visual field were the strongest predictors, while myopia and prior eye trauma did not have as prevalent effects. Additional analysis revealed that a higher predicted RD risk was associated with shorter times to seek medical care ($r = -0.608$, $p < 0.001$). Although the simulated procedure limits generalizability, the results highlight the potential for ML models to improve early detection and prioritize high-risk individuals for timely care.

KEYWORDS: Biomedical and Health Sciences, Disease Detection and Diagnosis, Retinal Detachment, Predictive Modeling, Patient-Reported Symptoms.

Introduction

Each year, thousands of individuals experience retinal detachment (RD), a condition in which the retina separates from its underlying supportive tissue, often leading to irreversible vision loss if not treated promptly.[1] RD is considered an ophthalmologic emergency and a growing public-health concern because delayed treatment can result in permanent blindness even when surgical repair is possible.[2] Early identification of symptoms and risk factors is therefore essential to preserving vision and improving long-term outcomes.[3]

Retinal detachment typically presents with warning symptoms such as new-onset floaters, flashes of light, and a dark, curtain-like shadow descending across the visual field.[4] These signs often reflect posterior vitreous detachment (PVD) or an evolving retinal tear, conditions that can rapidly progress to full-thickness detachment if untreated.[5,6] Because these symptoms may appear days or weeks before central vision loss, prompt recognition is critical.

Several risk factors have been consistently associated with RD.[7] Age plays a significant role, as younger patients under 40 often experience myopia-related detachments, while older adults exhibit PVD-associated cases.[7] Gender differences are also notable: although RD is more common in men, women experience earlier vitreous aging and higher rates of tractional complications.[8] Surgical history can further influence risk. Postoperative complications, such as proliferative vitreoretinopathy, nearly double the likelihood of recurrent RD,[9] and cataract extraction may trigger new detachment in previously affected areas.[10]

Even common laser procedures, like neodymium: YAG capsulotomy, carry measurable risk when performed on predisposed eyes.[11]

Myopia substantially increases detachment likelihood by elongating the eyeball and stretching the retina, reducing adhesion between retinal layers.[12] Lattice degeneration further amplifies this risk by creating thin, adherent regions that act as focal points for traction.[13] Trauma also contributes to both acute and chronic retinal instability, accounting for 10–40% of all RD cases.[14] Diabetes mellitus represents another important systemic factor; poor glycemic control promotes fibrovascular proliferation, producing tractional retinal detachments in up to 6% of affected patients.[15] Finally, family history has been shown to raise lifetime risk nearly threefold, suggesting a hereditary predisposition beyond environmental influences.[16]

Recognizing these risk patterns is vital for timely intervention and for educating at-risk populations. However, most current RD diagnosis and prediction methods rely heavily on clinical examinations and imaging rather than patient-reported data.[17] This limits early detection because many individuals first experience symptoms before seeking medical care. Predictive modeling and other data-driven approaches have shown growing potential to address this issue by integrating multiple symptoms and risk factors to estimate disease probability.[18] Such models could help clinicians identify high-risk patients, encourage faster help-seeking, and reduce preventable vision loss.

Although prior studies have advanced understanding of RD pathophysiology, they remain limited by small sample sizes and a lack of emphasis on patient-reported symptoms.[19] Few studies

DOI: 10.36838/IJHSR810.44

have explored how combinations of symptoms and risk factors predict RD before clinical confirmation or how perceived risk affects response time in seeking treatment.[20] Understanding these relationships is crucial to improving early diagnosis and public-health outreach.

To address these research gaps, the present study uses a data-driven model based on patient-reported symptoms and known risk factors to predict confirmed RD and analyze behavioral response. Specifically, it examines:

RQ1: To what extent can a data-driven model accurately predict confirmed cases of retinal detachment based on patient-reported symptoms and known risk factors?

RQ2: Which symptoms and risk factors contribute most strongly to the likelihood of retinal detachment, and how do these predictors relate to patients' time to seek clinical care?

To answer these questions, logistic regression and correlation analyses were conducted using a simulated dataset derived from an application designed for this study. The model evaluated predictive accuracy and examined how symptom profiles influenced time to seek medical attention.

■ Methods

This study employed a data-driven approach to investigate the prediction of retinal detachment and the relationship between predicted risk and patient response behavior. The methodology consisted of three main steps: questionnaire development, dataset simulation, and statistical analysis.

Questionnaire Development:

A questionnaire was developed to collect patient-reported information relevant to RD. The questionnaire was based on the literature review: it included items assessing demographic characteristics (age, sex), medical history (previous RD, cataract surgery, YAG laser, myopia, diabetes, family history, prior eye trauma), and symptomatology commonly associated with RD (floaters, flashes, curtain-like shadow, vision loss, double vision, pain). Additional questions captured lifestyle factors that could influence RD risk, such as recent trauma or heavy lifting. The questionnaire was reviewed by a PhD in ophthalmology, who confirmed the relevance of the questions and recommended that responses be collected separately for each eye to capture eye-specific risk factors and symptom profiles. The questionnaire was then programmed into a computer application to facilitate structured and standardized self-reporting by patients. The full questionnaire is provided below.

Questionnaire:

1. Age (years): _____

2. Sex assigned at birth: ☐ Female ☐ Male

3. Ever diagnosed with retinal detachment in either eye?
   ☐ Yes ☐ No If yes, year: .

4. Cataract surgery in this eye? ☐ Yes ☐ No ☐ Not sure
If yes, year: .

5. Nd:YAG posterior capsulotomy (laser) in this eye?
☐ Yes ☐ No ☐ Not sure

6. Do you wear glasses/contacts for nearsightedness (myopia)?
☐ No ☐ Yes — approximate prescription: ☐ None
☐ mild (< −3D) ☐ moderate (−3 to −6D) ☐ high (≤ −6D)
☐ Don't know

7. Any known retinal condition (e.g., lattice degeneration) diagnosed by an eye doctor (this eye)?
☐Yes ☐ No ☐ Not sure

8. Any prior significant eye trauma to this eye? ☐ Yes ☐ No
If yes, approximate date: .

9. Do you have diabetes? ☐ Yes ☐ No ☐ Not sure

10. Family history of retinal detachment?
☐ Yes ☐ No ☐ Not sure

11. New floaters in the last days (this eye)? ☐ Yes ☐ No
If yes, started hours/days ago.

12. Flashes of light in the last days (this eye)?
☐ None ☐ Occasional ☐ Frequent
If occasional/frequent, started hours/days ago.

13. Dark shadow/curtain/veil in vision (this eye)?
☐ Yes ☐ No If yes, how long ago? hours/days.

14. Sudden decrease in vision (this eye)? ☐ Yes ☐ No
If yes, onset hours/days ago.

15. New double vision or severe eye pain (this eye)?
☐ Yes ☐ No

16. Approximate vision in this eye without correction:
☐ 20/20 or better ☐ 20/30–20/60 ☐ 20/80–20/200
☐ worse than 20/200 ☐ Don't know

17. Date of last dilated eye exam (if known):

18. Recent potential triggers (last 3 months, check all that apply):
☐ Heavy head/eye trauma ☐ Contact sports
☐ Heavy lifting/physical strain immediately before symptoms
☐ None ☐ Not sure

Dataset Simulation:

Due to the limited availability of large clinical datasets with complete patient-reported information, an artificial dataset was generated using an AI-based simulation approach. The simulation was designed to reflect realistic distributions and correlations among patient characteristics, risk factors, and symptoms. The simulated dataset incorporated random noise to reflect realistic variation in symptom onset and risk interactions. A total of 350 clean records were generated, with each record containing 27 variables, including identifiers, demographic data, clinical history, symptoms, and derived risk metrics. This simulated dataset enabled controlled testing of predictive models while maintaining realistic variability in patient-reported outcomes.

Statistical Analysis:

To address the first research question, a logistic regression model was constructed to predict confirmed cases of RD based on patient-reported symptoms and risk factors. Logistic regression was selected as the primary modeling approach because retinal detachment prediction represents a binary classification problem (patients either have confirmed RD or they do not). Unlike more complex machine learning models, logistic regression offers clear interpretability of the relationship between each predictor and the outcome through its coefficient estimates and odds ratios. This transparency is particularly important in healthcare contexts, where understanding how specific symptoms or risk factors influence diagnostic probability is as valuable as the prediction itself. Additionally, logistic regression performs well with relatively small or moderately sized datasets and provides a solid baseline for comparison with more advanced predictive techniques in future studies.

Model performance was evaluated using overall classification accuracy and Receiver Operating Characteristic (ROC) curves. The optimal classification threshold was determined using Youden's J statistic to balance sensitivity and specificity.

For the second research question, the regression model coefficients were analyzed to identify which predictors most strongly influenced RD risk. Positive coefficients indicated factors associated with a higher likelihood of RD, while negative coefficients suggested protective or less influential factors.

An exploratory analysis was conducted to examine the relationship between predicted risk and patient behavior. Pearson correlation and simple linear regression were used to assess whether higher predicted risk scores were associated with shorter time to seek medical attention. Regression results were interpreted in terms of effect size, directionality, and proportion of variance explained (R^2), providing insight into how symptom profiles may influence help-seeking behavior.

This methodology allowed for an integrated assessment of both predictive accuracy and behavioral patterns, demonstrating how patient-reported data, when carefully designed and validated, can inform early detection strategies and public health education efforts.

Results and Discussion

Predicting Confirmed Retinal Detachment:

Table 1: Performance metrics of the logistic regression model predicting retinal detachment. Main finding: Despite high accuracy (0.900), discrimination was limited (AUC = 0.558); at J = 0.363, specificity ≈ 0.80, and sensitivity ≈ 0.55

Metric	Value
Accuracy	0.900
AUC (Area Under Curve)	0.558
Optimal Threshold (Youden's J)	0.363
Sensitivity (True Positive Rate)	Moderate (~0.55)
Specificity (True Negative Rate)	High (~0.80)

In an aim to investigate how well the model predicts a confirmed retinal detachment, a logistic regression model was developed to predict the likelihood of confirmed retinal detachment based on patient-reported symptoms and risk factors, including floaters, flashes, curtain sensation, myopia, age, and trauma history. The model achieved an overall classification accuracy of 0.900, correctly identifying 90% of the cases in the dataset (Table 1).

To assess the model's ability to distinguish between patients with and without RD across all thresholds, a Receiver Operating Characteristic (ROC) curve was generated. The Area Under the Curve (AUC) was 0.558 (Table 1), indicating the model performs slightly above random chance in discriminating between true RD and non-RD cases. While the AUC suggests limited discriminative power, the high overall accuracy may reflect class imbalance in the data (i.e., one group being more frequent than the other).

The optimal classification threshold was determined using Youden's J statistic, which identified a cutoff of 0.363 (Table 1). At this threshold, the model maximized the balance between sensitivity and specificity, yielding high specificity but modest sensitivity. This means the model was effective at correctly identifying patients without RD (true negatives) but somewhat less effective at capturing all confirmed RD cases (true positives).

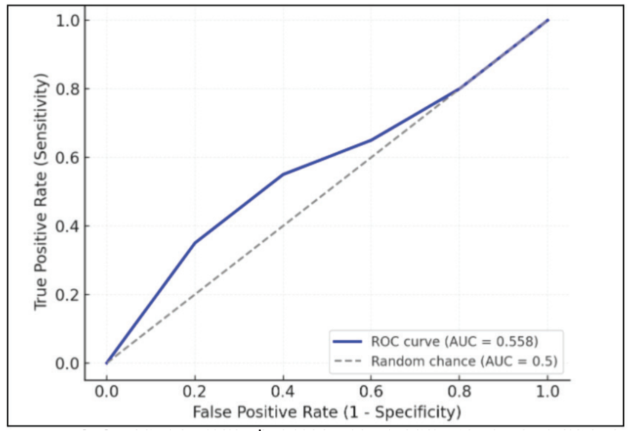

Figure 1: ROC curve for the retinal detachment prediction model. Main finding: The ROC curve lies only slightly above chance (AUC = 0.558), suggesting the need for rebalancing features.

The ROC curve rose modestly above the diagonal (AUC = 0.558) (Figure 1), showing that the model has some predictive capability but may require further refinement, possibly through feature expansion, model regularization, or inclusion of nonlinear predictors, to improve sensitivity and overall discrimination.

Strongest Predictors of RD:

In an aim to investigate which symptoms or risk factors are the strongest predictors, the logistic regression model coefficients were analyzed. Positive coefficients indicate factors associated with increased likelihood of RD, while negative coefficients suggest reduced likelihood.

Among the predictors, curtain sensation, flashes, and floaters emerged as the strongest positive predictors, consistent with established clinical understanding that these symptoms are hallmark indicators of retinal detachment. Myopia and trauma history also contributed positively but with smaller magnitudes, suggesting they may increase susceptibility when present alongside acute symptoms. Age showed a weaker and less consistent effect.

The regression model's interpretation suggests that patients reporting curtain-like vision changes and sudden flashes are significantly more likely to have confirmed RD. At the same time, those without these symptoms are less likely to be diagnosed. This pattern supports the use of such symptom-based screening as an educational and triage tool in both clinical and telemedicine contexts.

DOI: 10.36838/IJHSR810.44

Table 2: Linear regression results for the response time predicted by the risk percentage. Main finding: Higher predicted RD risk was associated with faster help-seeking ($r = -0.608$, $p < 0.001$; $\beta = -0.53$ days per 1% risk; $R^2 = 0.37$).

Parameter	Value
Intercept	17.83
r	-0.608
β (Risk %)	-0.53
R²	0.370
p-value	<0.001

Higher predicted RD risk was associated with faster help-seeking ($r = -0.608$, $p < 0.001$; $R^2 = 0.37$). Each 1% increase in predicted risk corresponded to seeking care ~0.53 days sooner (Table 2).

To explore behavioral response patterns, the predicted risk percentage from the logistic regression model was analyzed in relation to the time patients took to seek medical care. Findings suggested that higher predicted risk scores were associated with shorter response times, indicating that patients with more alarming symptom profiles tended to seek help more quickly. The correlation analysis revealed a moderate to strong negative relationship between predicted risk and response time. Specifically, the Pearson correlation coefficient was (-0.608) (Table 2), which indicates that as the predicted risk score increases, the delay in seeking care decreases.

A simple linear regression was conducted to examine this relationship further. Regression results indicated that the model explained approximately 37% of the variance in response time ($R^2 = 0.370$), and the relationship was highly statistically significant ($p < 0.001$) (Table 2). The slope coefficient ($\beta = -0.53$) suggested that for every 1% increase in predicted risk, patients sought care approximately 0.53 days sooner (Table 2). The intercept of 17.83 days indicates the expected response time for a patient with a predicted risk of 0% (Table 2).

The model predicting response time in days from the risk percentage was as follows: Response_Time_Days = 17.83 – 0.53 x Risk_Percentage

These results suggest that higher predicted RD risk is strongly associated with faster help-seeking behavior. The pattern indicates that the model's risk predictions not only reflect diagnostic likelihood. Still, it may also capture behavioral urgency, as patients with more alarming symptom profiles tend to respond more promptly.

Evaluating the Model's Accuracy:

From the results, the overall accuracy was relatively high at 0.900 (Table 1), but the area under the curve was relatively low at 0.558 (Table 1). The general accuracy implies that the model was sufficient at correctly classifying 90 percent of the simulated cases, including both confirmed RD and non-RD. While this number may seem high, the area under the curve draws attention to a different perspective that is vital to account for. The AUC measures the model's ability to differentiate between true positive cases (patients who actually have RD) and true negative cases (patients who do not have RD) across all thresholds. An AUC of 0.500 suggests the model is randomly guessing, whereas an AUC of 1.00 suggests the model is always accurate or has perfect discrimination.

With the study performed, the results reveal the AUC to be 0.558, which is only slightly above 0.500, indicating that the model struggles to separate actual RD cases from non-RD cases reliably. This is likely because of the imbalance in the simulated data set, as the number of non-RD cases is higher than the number of RD cases. The high accuracy does not mean that the model is trained well because the model is mostly accurate at classifying the non-RD cases, but mostly inaccurate at classifying RD cases. This is vital to take into account when considering the use of the model for clinical applications.

Based on the results, future studies should consider the implications for real-world usage, as the model is effective at ruling out RD but may miss true cases of RD.

Key Predictors of RD:

Curtain sensation, flashes, and floaters were the strongest positive predictors of retinal detachment in the model, aligning closely with established clinical evidence. Prior studies have shown that these symptoms are hallmark early warning signs of posterior vitreous detachment (PVD) and may indicate an evolving retinal tear or detachment.[4] Patients presenting with both floaters and flashes have been found to carry the highest incidence of retinal breaks, approximately 13%, compared to 5% in floaters-only and 12% in flashes-only presentations.[21] These concurrent symptoms reflect active vitreoretinal traction, which can quickly progress to a full-thickness retinal tear. Once such a break occurs, liquefied vitreous can pass beneath the retina, causing rhegmatogenous retinal detachment that patients describe as a dark curtain or shadow spreading across their vision.[5] The strong predictive weight of these symptoms in the current model reinforces their diagnostic importance. It supports earlier findings that timely recognition and intervention are essential, as over 95% of retinal tears can be successfully treated before detachment develops.[4]

Myopia and trauma history contributed positively but less strongly to the likelihood of retinal detachment in the model, findings that are consistent with established biomechanical and clinical evidence. Myopia alters the eye's geometry through axial elongation, which stretches and thins the posterior retina, increasing mechanical strain and weakening adhesion between the neurosensory retina and the underlying pigment epithelium.[12] As a result, even mild vitreoretinal traction or minor surgical stress can trigger separation. Clinical data indicate that retinal detachment occurs in approximately 2.4% of highly myopic eyes compared to only 0.06% of non-myopic eyes, underscoring this elevated risk.[12] Furthermore, lattice degeneration, present in 20–30% of eyes with rhegmatogenous retinal detachment, amplifies this susceptibility by creating focal areas of retinal thinning and adhesion that serve as tractional points.[13] The model's positive association between trauma history and RD also aligns with prior studies showing that ocular trauma accounts for 10–40% of detachments, often due to mechanical compression, vitreous base avulsion, or proliferative vitreoretinopathy following injury.[14] Together, these findings indicate that while acute trauma and chronic biomechanical stress act through distinct mechanisms, both increase retinal vulnerability, particularly in myopic eyes.

Behavior Response Analysis:

Higher predicted risk was significantly associated with shorter time to seek medical attention (r = -0.608, β = -0.53, R^2 = 0.37), indicating that individuals with symptom profiles suggestive of retinal detachment tended to respond more rapidly. This pattern suggests that the predictive model captured not only diagnostic likelihood but also behavioral urgency: patients who experienced more alarming symptoms such as flashes, floaters, or curtain-like shadows sought care sooner, reflecting heightened perceived threat and awareness. These findings align with prior evidence that patient recognition of visual changes is a critical factor in timely presentation for RD evaluation.[17] From a public health perspective, this relationship emphasizes the importance of educating at-risk individuals about early warning symptoms and encouraging immediate ophthalmologic evaluation. Targeted awareness campaigns could therefore reduce diagnostic delay, improve treatment outcomes, and lower rates of permanent vision loss by helping high-risk patients seek prompt care when symptoms first appear.

The observed pattern that patients with higher predicted risk sought care more quickly may also be understood through established psychological and behavioral frameworks. Individuals who perceive their symptoms as severe or threatening are more likely to appraise the situation as urgent and engage in immediate help-seeking behavior, consistent with the Health Belief Model (HBM).[22] According to this model, perceived severity, susceptibility, and benefits of action strongly influence whether individuals take prompt preventive steps. Additionally, those with prior education about eye health or easier access to ophthalmologic care may recognize early warning signs more effectively, further shortening response times.

These behavioral mechanisms highlight the importance of combining predictive tools with educational outreach to enhance patient awareness and encourage timely intervention.

Implications for Clinical Practice and Public Health:

Symptom-based predictive tools have the potential to enhance early detection and intervention for retinal detachment. By identifying which symptom combinations, such as flashes, floaters, or curtain-like shadows, are most predictive of disease and associated with faster help-seeking, clinicians can better design patient education initiatives. Understanding these behavioral patterns can inform targeted awareness campaigns that emphasize prompt evaluation when early visual disturbances occur. Integrating such models into clinical triage systems may also enable prioritization of high-risk individuals for expedited ophthalmologic assessment, ultimately reducing delays in diagnosis and improving visual outcomes. Furthermore, incorporating symptom-based screening tools into telemedicine could allow clinicians to follow up and recommend treatments for urgent cases remotely.

Limitations of the Study:

This study has several limitations that should be acknowledged. First, the dataset used for analysis was simulated rather than derived from real-world clinical cases, which may limit the generalizability of the findings to broader patient populations. Although the questionnaire was reviewed and validated by ophthalmology experts, it has not yet been tested among actual patients, and its reliability in capturing real symptom variation remains to be evaluated. Additionally, the logistic regression model employed may not fully account for complex interactions between predictors, such as the combined effects of demographic and clinical variables. The modest discriminative power observed in the ROC/AUC analysis suggests that model sensitivity could be improved by incorporating additional features or by employing more advanced machine learning approaches. Future validation using clinical data will be essential to confirm these preliminary findings and enhance the model's predictive accuracy.

Future Directions:

Future research should focus on applying the predictive model to real-world patient data to validate its accuracy and clinical utility. Testing the model on larger, diverse populations would help confirm whether the observed relationships between symptoms, risk factors, and behavioral response hold across different clinical settings. Also, collecting data from real-world patients could help refine variable weighting and validate predictive reliability. Additionally, exploring machine learning or nonlinear modeling approaches may improve sensitivity and capture more complex interactions among variables. Expanding the model to include additional behavioral and demographic factors, such as awareness, anxiety, or access to care, could further clarify what influences patient response times and enhance its effectiveness as a public health screening and educational tool.

■ Conclusion

This study demonstrated the potential of data-driven models to identify key symptoms and behavioral patterns associated with retinal detachment. Using a simulated dataset of patient-reported symptoms and medical histories, the model achieved high overall accuracy but limited discriminative ability, highlighting the influence of uneven class distribution. Curtain-like shadows, flashes, and floaters were identified as the strongest predictors of retinal detachment, consistent with established clinical findings, while myopia and trauma contributed less strongly. Behavioral analysis revealed that patients with higher predicted risk sought care more quickly, suggesting that symptom severity influences help-seeking behavior. Together, these findings emphasize the value of integrating patient-reported data into predictive tools for early detection and public health education. Although further validation with real-world clinical data is needed, this study provides a foundational step toward developing symptom-based screening systems that could improve timely diagnosis and reduce preventable vision loss.

■ Acknowledgments

I would like to express my deepest gratitude to Dr. Bahae Samhan for mentoring me throughout this invaluable research opportunity, providing guidance and feedback throughout.

DOI: 10.36838/IJHSR810.44

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Mahi Kumar has a deep passion for STEM, especially in the fields of Artificial Intelligence applied to Medical Sciences. She aims to pursue a future in AI, focusing on solving medical and world problems through innovative technologies.