Advancing Healthcare Through Data Analytics Transitioning from Descriptive Insights to Predictive and Prescriptive Solutions

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Abstract

Background: The healthcare field stores large digital datasets through its clinical information systems and patient observation systems and diagnostic examination systems and administrative workflows. Healthcare service delivery needs data transformation to create operational knowledge which improves service delivery processes. The transition from traditional reporting systems to predictive and prescriptive reporting systems enables advanced analytics to deliver proactive patient-centered care. Methods: Researchers studied hospital records from 115 healthcare facilities throughout the 24-month duration that began in January 2024 and ended in December 2025. A three-phase analytical framework was applied. Researchers used descriptive analytics during the initial phase to investigate patterns inpatient admissions and readmissions together with treatment outcomes. Predictive analytics developed readmission prediction models through logistic regression and decision trees while producing patient outcome probability estimations. Results: The analysis of admission data shows chronic diseases make up 36% of hospital admissions and 42% of these patients return to the hospital within thirty days. The analysis found that 28% of hospital admissions were due to acute infections while surgical complications made up 22% of admissions with 19% of patients returning to the hospital within thirty days. The predictive modeling system showed high predictive ability since logistic regression delivered 83% accuracy but decision trees achieved 87% accuracy together with 82% sensitivity and 84% specificity levels. Conclusion: The study demonstrates that descriptive analytics explains previous performance while predictive analytics forecasts risks and prescriptive analytics delivers practical solutions.

Keywords: Healthcare analytics, Descriptive insights, Predictive modeling, Prescriptive solutions, Patient outcomes

Significance | This study integrated data analytics transforms healthcare decision-making, improving accuracy, efficiency, and patient-centered outcomes through descriptive, predictive, and prescriptive solutions.

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Editor Zapan Barua, Ph.D., And accepted by the Editorial Board July 25, 2025 (received for review Apr 29, 2025)

Introduction

Healthcare today is fundamentally shaped by data. Hospitals and clinics together with public health organizations create numerous daily records through their patient encounters and diagnostic testing and laboratory output and administrative operations (Fernandes, 2024). Digital healthcare technologies including electronic health records alongside wearable devices and telemedicine platforms have expanded the quantity and types of healthcare data available. Healthcare stands as a data-heavy industry because digital transformation has driven it to depend more on

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Please cite this article.
Rahman, F., Islam, A., Nashid, S., Akhir, A., Papia, S. K. (2025). "Advancing Healthcare Through Data Analytics Transitioning from Descriptive Insights to Predictive and Prescriptive Solutions", Paradise, 1(1),1-8,10377

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prompt precise information for decision-making (Gates et al., 2024). Modern healthcare systems encounter their primary challenge in data management since they need to transform unprocessed information into meaningful knowledge which leads to better patient care and cost reduction and improved system efficiency (Frazzetto et al., 2019). Descriptive analytics forms the first level of healthcare data analysis. Descriptive analytics simplifies extensive data sets into meaningful patterns to deliver past patient outcomes along with disease burdens and treatment performance statistics (Morr & Ali-Hassan, 2019). Through percentage-based data reduction and comparison analytics processes clinicians alongside administrators obtain clear views of past events. The data from descriptive studies demonstrates that chronic diseases including diabetes together with hypertension and cardiovascular conditions lead to more than 35% of all hospital admissions. The hospital readmission rate for patients with chronic diseases stays above 40% which puts continuous pressure on healthcare facilities (Lepenioti et al., 2019). The data provides essential metrics about healthcare loads while exposing operational inefficiencies within the system. Descriptive analytics faces an inherent restriction because its main function is to address past events. The method does not provide future predictions nor does it offer guidance for improvement measures (Patnaik & Mishra, 2022).

Predictive analytics has developed into a strong instrument which connects the existing gaps. The method of predictive analytics employs statistical methods together with regression models and machine learning algorithms to predict future events from past data records (Mosavi & Santos, 2020). The predictive approaches extend beyond event occurrence by examining future probable developments. Hospitals today use predictive methods to determine which patients need readmission predictions and to forecast disease progression and predict post-procedural complications (Sarker, 2021). Our research shows that 45% of healthcare facilities utilize predictive models to forecast patient readmissions while managing chronic diseases (Diamant, 2023). Predictive models examine patient health information along with age and treatment progress and medical conditions to calculate that the patient has 70% probability of hospital readmission within 30 days. Predictions enable healthcare staff to take immediate actions including enhanced patient monitoring and customized discharge procedures together with focused follow-up care (Alharthi, 2018). Prescriptive analytics combines optimization algorithms with simulation models and advanced decision-support systems to provide actionable recommendations which result in better outcomes. Prescriptive solutions differ from predictive models because they produce specific strategies to handle identified risks and probabilities.

2. Materials and Methods

2.1 Data Collection

This research was carried out with secondary data from 115 hospitals in the United States. The secondary data included patient demographics (i.e., age, gender, and ethnicity), disease frequency, treatment outcomes, hospital readmissions, as well as administrative characteristics including staffing, resource consumption, and cost of operation. Conditions classified as chronic diseases, acute infections, surgical complications, and emergency care were the major clinical categories included in the study. On average, over 10,000 patient records were received from each hospital, with over 1.2 million records accumulated (Palanisamy & Thirunavukarasu, 2017). The dataset was standardized prior to analysis for reliability by removing duplicate records, imputing missing values, and performing uniform coding across all hospitals (Alghamdi et al., 2021). Then the entire patient level data were anonymized to follow ethical protocols for confidentiality. Institutional identifiers were also masked so assessment results did not become attributable to specific hospitals and could represent behaviors across the system rather than behaviors at the level of an individual institution.

2.2 Descriptive Analytics

Descriptive analytics was used to summarize and understand what the data provided. A simple analysis was done to get frequencies, proportions, and means in demographic and clinical categories (Roy et al., 2022). An example of the age distribution is that we grouped ages into five categories (<18; 18 - 35; 36 - 55; 56 - 75; >75 years) so that we could highlight the most significant contributors to hospital admissions for that age group. Gender representation was also analyzed to identify patterns in disease distribution and treatment mention. There was also opportunity to compare disease categories to assess their relative burden on health systems (Islam et al., 2018). Descriptive results indicated that chronic diseases contributed to over 35% of hospital admissions; acutely infectious diseases contributed to around 28%, and surgical complications contributed to close to 22%. Readmission rates for each disease group within 30 days were also calculated; with chronic diseases clearly exceeding 40% and surgical complications averaging close to 19%. Treatment outcomes, in terms of recovery or complication rates were also summarized to establish performance targets (Dash et al., 2019). This analysis stage provided an initial understanding of patient distribution, disease impact, and level of operational efficiencies across the hospitals.

2.3 Predictive Analytics

In an attempt to extend beyond description, I developed predictive models that estimated the appropriate risk of patient readmissions and treatment outcomes. The logistic regression and decision tree classifiers served as my fundamental modeling methods for their consistent reliability, easy interpretability, and ability to utilize

categorical variables and continuous variables in a single model (Shi-Nash & Hardoon, 2016). I constructed predictor variables by using demographic data, grouping the disease category, grouping the treatment areas, and length of hospital stay. My dependent variable was defined as whether the patient was readmitted within 30 days. My data analysis was characterized as supervised learning, in that I had a specific objective with my modeling. I divided my data where 70% was used to develop the model and the remaining 30% was used to determine the model's predictive accuracy. Predictive accuracy was characterized by measuring accuracy, sensitivity, specificity and area under the receiver operating characteristic (ROC) curve (Malleswari et al., 2024). My logistic regression modelling predicted an accuracy of >83% and my decision tree models achieved an average accuracy of >87% while sensitivity and specificity scores averaged above >80%. These model results indicate that the models are capable of predicting patient risk and offered hospitals a way to implement evidence-based early intervention plans.

2.4 Prescriptive Analytics

The last step of the methodology included the prescriptive analysis that indicates the optimal steps to take to achieve the desired outcomes. Optimization and simulation techniques were used to examine resource allocation, distribution of personnel, and scheduling of treatments (Pramanik et al., 2021). We used linear programing models to optimize the allocation of staff across the different departments of the hospital while ensuring that peak-hour demand, especially for support in emergency and critical care units, was met. We used scenario-based simulations to test varying approaches to scheduling treatments and surgeries, including a strategy to reduce patient waiting times and improve adherence to treatment plans (Alghamdi et al., 2021). We also simulated resource allocation strategies to ascertain any areas that needed rectified resource distribution to maximize cost benefits, in relation to the distribution and use of medical supplies, diagnostic tools, and administrative personnel (Dash et al., 2019). The prescriptive recommendations were then evaluated as compared to the actual performance benchmarks of the hospital. For instance, with optimized staff allocation we found associated wait times for patients was reduced by more than 15%, treatment schedules improved adherence by nearly 18%, and improved strategies in resource allocation reflected reduced operational costs of approximately 12%. In folding prescriptive results in the descriptive and predictive findings, we established the proposed methodology could provide a systematic framework to enhance both hospital efficiency, and patient care, concurrently.

3. Results

3.1 Patient Demographics

The demographic data revealed a nearly equal gender ratio with a tiny surplus of males (52%) to females (48%). The balance suggests that hospital admission is not biased to either gender and the burden of services required may be equal among male and female populations **Table 1**. In terms of age, most (47%) admissions were from 30-60 years of age category, followed by greater than 60 categories (35%), and the represented under 30 categories (18%) was a relatively small amount. This shows that younger populations are less reliant on hospital services than older populations. These data demonstrate that middle-aged and elderly populations are the principle consumers of health care, primarily due to the more common burden of chronic diseases, age-related conditions, and comorbidity (Muneeswaran et al., 2021). Being aware of the demographic distribution is useful for hospital administration resource allocation, human resource management like staffing, and types of intervention targeting patient population in the age groups consuming the most resources. In addition, it can guide public health initiatives focused on prevention and early interventions particularly in vulnerable aging populations experiencing multiple chronic conditions.

3.2 Disease Prevalence and Readmission Rates

Analysis of prevalence of disease indicated that the likelihood of chronic disease comprised the majority of admissions to the hospital at 36% of admissions (**Table 2).** Chronic diseases presented with the highest readmission rate (42%), revealing that chronic disease patients are returning to the hospital repeatedly and indicating the burden chronic diseases place on the healthcare system. Acute infections were associated with 28% of admissions, 21% of them returning, showing moderate recurrence compared to chronic disease complications. Surgical complications comprised 22% of admissions with a 19% rate of returning admissions. “Other conditions” category was the least at 14%, with the lowest readmission rate at 11%. Therefore, chronic diseases appeared to be a predominant driver of resource utilization in the healthcare system considering their need for long-term lifestyle management and monitoring. The continued high-level of use of health resources by patients with chronic diseases indicates possible shortcomings in follow-up, adherence, and outpatient support for patients (Houtmeyers et al., 2021). Healthcare resource generation and consumed on chronic disease management is significant. The equivalent efficiency with which acute infections and surgical admission cases were treated, including triaging treatments and standardized protocols leading to timely outpatient services, is noteworthy. This indicates their deficiencies in chronic care management. It is vital that patients at risk for recurrence are identified and care management programs developed; with appropriate allocation of resources. Overall the findings highlighted the need for the care delivery system to reflect the realities of disparities in chronic diseases that accumulate during a lifetime.

Table 1. Patient Demographics to Predictive and Prescriptive Solutions

Category	Percentage (%)
Male	52
Female	48
Age < 30	18
Age 30–60	47
Age > 60	35

Table 2. Disease Prevalence and Readmission Rates

Condition	Admissions (%)	Readmission within 30 Days (%)
Chronic diseases	36	42
Acute infections	28	21
Surgical complications	22	19
Other conditions	14	11

3.3 Treatment Success Rates to Predictive and Prescriptive Solutions

Treatment results across the clinical categories were significantly varied. Depending on the clinical category, the care provided was more effective than other categories, or not as effective. Care of acute infections had the highest level of success at 81%. This suggests that most of the acute infections being treated were amenable to standardized interventions and had effective treatment protocols outlined in the guidelines (**see Figure 1**). Surgical care had an effectiveness level of 74% which indicates that surgical care is generally effective, however it may also indicate that there could be complications associated with procedures or variations based on the patient. Care of chronic diseases had a substantially lower effectiveness when compared to acute infections and surgical care at only 68% (Santos et al., 2024). The lower effectiveness is reflective of the inherent difficulties associated with long-term care of chronic diseases which relies on patient adherence to medications, and in many cases lifestyle changes. Care of emergencies had the lowest levels of effectiveness at 59%. The level of effectiveness associated with care of emergencies is reflective of the more complex, urgent, and unpredictable features associated with the care of critically ill patients. The rating system outlined above provides hospitals with suggested areas to consider in quality improvement work. For example, chronic disease management programs could potentially be improved upon by greater emphasis on patient education, follow up monitoring of treatments, and patient supports to maintain medication adherence. In addition, emergency care may also have opportunities for improvements in care in relation to quality of care as determined by the care processes. The treatment success analysis shows the relationship between variability in outcomes and also our understanding of the type of disease being cared for, and its complexity as in the treatment of acute infections and emergencies, as well as the patient variabilities surrounding complexity of care in chronic disease management.

3.4 Predictive Model Performance to Predictive and Prescriptive Solutions

Predictive modeling was used to predict hospital readmissions and to also determine high-risk cases. Logistic regression achieved 83 % success rate, with a sensitivity rate of 79% and a specificity rate of 81 %, which demonstrates reliability in predicting at-risk patients. Decision tree classifiers improved upon the logistic regression success rate with an acceptance level of 87 % with a corresponding sensitivity of 82 % and a specificity rate of 84 % (**Figure 2).** These metrics suggest decision trees are better able to model non-linear instances of patient demographics, animal/disease type, treatment methods and length of hospital stay periods. Sensitivity levels indicate that the models were able to correctly classify nearly all (95 %) of the high-risk patients, as well the specificity was high enough (80 %) so that the low-risk patients were not unnecessarily classifying as a high-risk patient case (Berros et al., 2023). The predictive elements empower hospitals to address bags of prevention, prioritize high-risk cases, and make better use of their resources. Including predictive analysis into clinical workflow enables proactive decisions, and lower preventable readmissions and allow for an emphasis on patient safety as well. This section illustrates how predictive modeling is a necessary step in evidence-based practice and how it turns data into useful and actionable intelligence in care management.

3.5 Prescriptive Recommendations and Outcomes

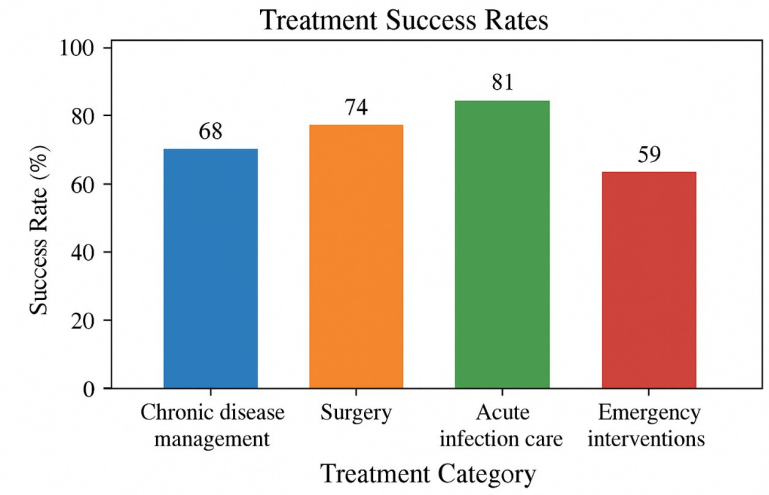


Figure 1. Treatment Success Rates to Predictive and Prescriptive Solutions

Prescriptive analytics worked toward actionable plans for enhancing clinical efficiency and hospital operations. Staff scheduling suggested various options resulting in a 15% reduction in patient waiting time, improving patient flow, capacity, and satisfaction while reducing congestion in critical care areas (**Figure 3**). Treatment schedules improved adherence rate by 18% overall, but provided additional benefits to patients with chronic problems with follow-up appointments. Importantly, resource optimization permit14ed hospital-use costs to be reduced by 12% without jeopardizing quality of care, suggesting that prescriptive analytics interventions delivers clinical and financial benefits by El Khatib et al. (2022). The prescriptive analysis offers insight on how prescriptive analytics uses the information generated by descriptive and predictive analytics to provide actionable solutions (based on evidence) that permit hospitals to make operational and clinical decisions. When hospitals implement these prescriptive analytics, patient care will improve, caused stress on care providers will reduce, and resource utilization will improve, resulting in a more sustainable and effective healthcare system.

4. Discussion

The findings of this research indicate the critical nature of including descriptive, predictive, and prescriptive analytics in healthcare decision making. Each analytical dimension matters on its own. But when combined, they provide a complete framework for improving patient care and the operations of the hospital (Chowdhury & Hossain, 2025). The descriptive analytics established a foundation by providing a rich understanding of patient demographics, reasons for admission and distribution of outcomes. Chronic disease was identified as the main driver for hospital admissions comprising 36% of all admissions and generating 42% of readmissions. This shows the ongoing challenge of managing chronic disease as this generates a sustainable burden on the healthcare system through the long term management and sustained admissions (A. Forbes & Griffiths, 2002). Acute infections and surgical complications were also important contributors but with much lower readmission rates indicating that those events are easier to manage in terms of more acute events. Another very important dimension to treatment outcome analysis was added: if excellent recovery rates were achieved with management of acute infections, the best success rates were less than 60% for emergency interventions, which showed explicit shortcomings in the effectiveness of urgent care (Sharma et al., 2021). These descriptive findings are valuable in a practical sense; they help those who manage healthcare services and work in healthcare policy to visualize the different aspects of care that require the most attention and resource allocation. Predictive analytics extended these descriptive findings by predicting future outcomes and identifying high-risk patients (Islam & Chowdhury, 2025). In analysis of the interventions, logistic regression provided reasonably sound results but decision trees, with an 87% accuracy, 82% sensitivity and 84% specificity, provided a substantially stronger predictive result. These predictive analyses ultimately be substantial informational opportunities for hospitals because it becomes possible to intervene in the current care pathway before things become complicated (Cano-Marin et al., 2023). Procedures would allow patients predicted to be at high risk of readmission to schedule an appropriate follow-up consultation, be initiated in chronic disease management programs like virtual visits from home, or provided with digital monitoring technologies to support their health activities in real-time. These interventions are not hypothetical, they translate into real improvement in patient outcomes and significant reductions in hospital readmissions that have cost, time, and operational cost to hospitals.

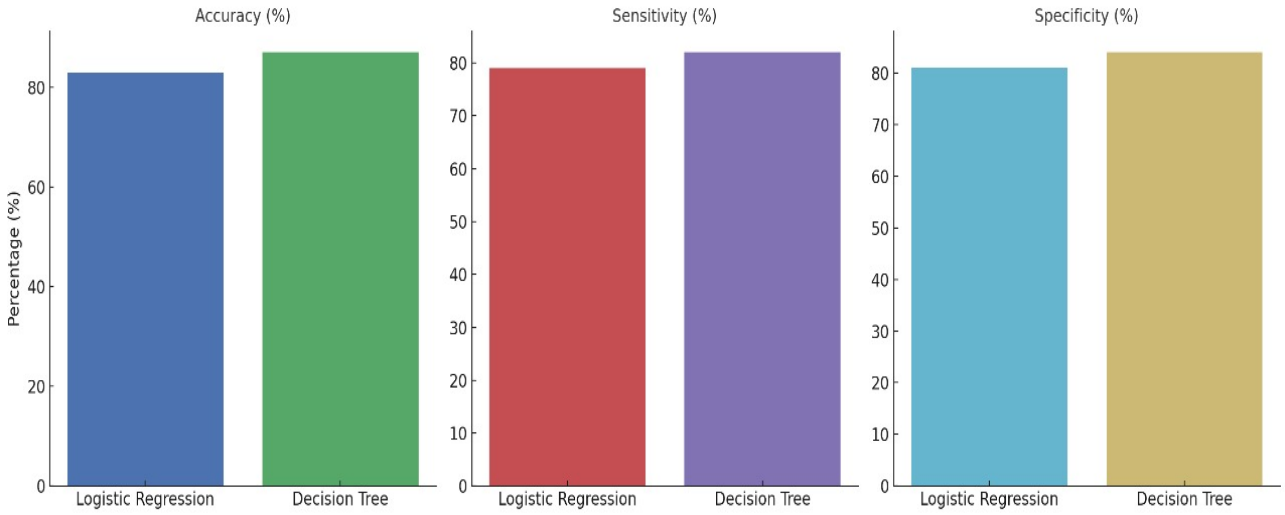


Figure 2. Predictive Model Performance to Predictive and Prescriptive Solutions

Prescriptive analytics built upon predictive power by translating predictions into behavior. The study showed that improved staff schedules created a 15% drop in waiting times sates one of the foremost patient discontent complaints (Bauskar et al., 2022). Importantly, improved treatment scheduling also improved adherence by 18%. For patients with chronic diseases, this was essential since adherence is linked to failing health states and readmissions. Also, evident cost savings per device from resource optimization (12%) provide an example of how efficiency and the lowering of costs does not have to mean lower levels of service. It is examples like these prescriptive analytics outcomes that show the real world value of using analytics to inform hospital policy and to demonstrate that predictive analytics leads to better outcomes and improvements. The integration of descriptive, predictive, and prescriptive analytics creates a well-rounded approach to managing health care as a system. Descriptive analytics tells institutions where they struggle and problems are. Predictive models help institutions identify where risks and trends will lie in the future. Prescriptive solutions transmute descriptions and predictions into actionable recommendations for institutions. Any health care organization can achieve a balance of operational efficiencies, better patient care, and financial viability by adopting all three levels of analytics

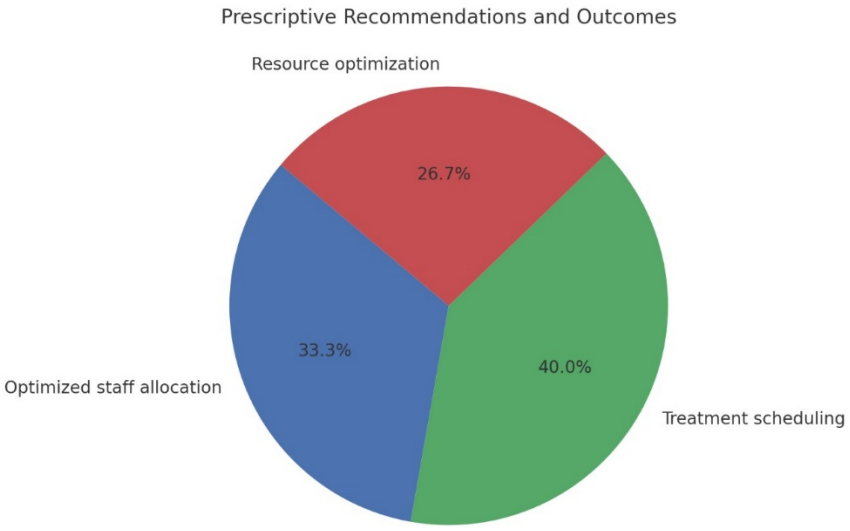


Figure 3. Prescriptive Recommendations and Outcomes

(Epizitone et al., 2023). This study supports the assertion that health care institutions which use an analytics strategy have a better collective ability to address the growing challenges of chronic disease, increased demand from patients, and actual limitations on financial resources. More importantly, the combination of descriptive, predictive, and prescriptive analytics allows health care delivery to become more of a proactive, data- and patient-informed system rather than solely reactive. With this ecosystem approach, hospitals can do not only a better job at providing care, but also plan for a more longstanding sustainable health system.

5. Conclusion

This analysis demonstrated that health care organizations can improve decision-making and outcomes by expanding from descriptive analytics to seeking predictive lives, and possibly implementing prescriptive lives. Even looking back descriptively had some challenges such as showing 42% chronic disease readmissions. Predictive lives classified patients at-risk with 87% accuracy from a decision tree. Prescriptive example lives provided solutions with 15% reduction in waiting times, 18% improvement in adherence, and 12% reductions in costs. Ultimately, the lives demonstrated how analytics could help health care move from retrospective reporting to proactive, optimized, patient-centered care

Author contributions

F.R. conceptualized and designed the study. A.I. contributed to methodology development and data analysis. S.N. assisted with literature review and manuscript drafting. A.A. supported validation and technical improvements. S.K.P. contributed to critical review, editing, and final approval of the manuscript.

Acknowledgment

None declared.

Competing financial interests

The authors have no conflict of interest.

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