

# The Promise and Peril of Healthcare Forecasting

J. Frank Wharam, MB, BCh, BAO, MPH; and Jonathan P. Weiner, DrPH

Health plans and physician groups increasingly use sophisticated tools to predict individual patient outcomes. Such analytics will accelerate as US medicine enters the digital age. Promising applications of forecasting include better targeting of disease management as well as innovative patient care approaches such as personalized health insurance and clinical decision support systems. In addition, stakeholders will use predictions to advance their organizational agendas, and unintended consequences could arise. Forecasting-based interventions might have uncertain effectiveness, focus on cost savings rather than long-term health, or specifically exclude disadvantaged populations. Policy makers, health plans, and method developers should adopt strategies that address these concerns in order to maximize the benefit of healthcare forecasting on the long-term health of patients.

*(Am J Manag Care. 2012;18(3):e82-e85)*

For author information and disclosures, see end of text.

The future is not what it used to be. Health plans and physician groups increasingly use sophisticated tools to predict individual patient outcomes,<sup>1,2</sup> and such analytics will rapidly expand as US medicine enters the digital age. Over the coming decade, the Affordable Care Act will spawn new healthcare organizations and existing ones will convert to electronic health records (EHRs). These stakeholders will dip into the burgeoning reservoir of health data to make predictions that advance their organizational agendas and financial well-being.

Despite widespread and increasing adoption,<sup>1,2</sup> the use of “healthcare forecasting” to predict outcomes of individual patients has received little attention in the health policy community. This commentary reviews potential unintended consequences of such profiling, outlines policies to maximize benefits, and suggests innovative uses.

Healthcare Managed Care & Communications, LLC

## INTRODUCTION

Three related fields—healthcare forecasting, risk adjustment, and actuarial science—use similar statistical techniques to predict the future behavior of patients, but for different reasons. Healthcare forecasting generally implies predicting an individual’s costs or healthcare utilization for interventional purposes such as proactive disease management, patient education, or surveillance to promote population health. Risk adjustment refers to determining comparability between patient populations based on current or predicted healthcare utilization or expenditures. It is most often used to compensate health plans or physician groups fairly based on their patients’ morbidity. Actuaries use similar statistical methods to set insurance premiums and to determine coverage eligibility.

Previous literature has explored the uses and pitfalls of actuarial techniques and risk adjustment<sup>3</sup>; this article instead focuses on the use of healthcare forecasting to intervene (eg, using disease management) with individual patients at risk of high costs or suboptimal outcomes.

## HEALTHCARE FORECASTING: BACKGROUND AND TRENDS

Healthcare forecasting of this type—often called “predictive modeling”—is used by all major health insurers, integrated delivery systems, and many other healthcare organizations (Table).<sup>1,2</sup> At present, these stakeholders are

**In this article**  
Take-Away Points / e83  
**Published as a Web exclusive**  
www.ajmc.com

primarily known to use predictive modeling for disease management—identifying and intervening with individuals likely to incur high costs.<sup>1,2,4,5</sup> For example, statistical tools might detect the diabetic patients with the highest probability of hospitalization in the following year based on age, coexisting chronic illnesses, medication adherence, and past patterns of care. Less common predicted end points include achievement of specific medical outcomes, process quality indicators, or patient behavior changes.<sup>2,6,7</sup>

The variables in statistical prediction models usually come from computerized medical and pharmacy insurance claims and other administrative sources. Data are less commonly drawn from surveys, laboratory results, or EHRs.

Healthcare reform is likely to increase the use of healthcare forecasting. The Affordable Care Act includes multiple provisions intended to accelerate quality improvement.<sup>8</sup> Medicare will expand performance-based physician compensation by 2014 and initiate pilot projects that bundle hospitalization and peri-hospitalization payments.<sup>8</sup> Physician groups will therefore have greater incentives to “know the future” (ie, determine how their patient populations will affect relevant outcomes and payments). The legislation also creates accountable care organizations that can receive substantial compensation based on attaining risk-adjusted cost and quality-of-care targets.<sup>8</sup> These groups will have incentives to anticipate and prevent high-cost events and nonadherence to evidence-based care.

## PITFALLS AND CHALLENGES

### Contributing to Adverse Selection and Increased Disparities

Some predictive model vendors openly acknowledge that their forecasting tools can be used to avoid high-risk patients or to identify those that will remain healthy.<sup>2,9,10</sup> Moreover, because forecasts are used to include patients in interventions, they can also be viewed as excluding the persons not identified. For example, using forecasting or other structured case-finding methods, some health plans explicitly exclude patients with mental health diagnoses, addictions, and language barriers from disease management, because these factors might “predict” a minimal impact of interventions.<sup>2</sup> More broadly, even in an environment where persons with preexisting conditions are guaranteed coverage and where performance monitoring and payment are risk adjusted, both insurers and physicians can benefit financially from selecting healthier patients to serve.

### Take-Away Points

Predicting patient outcomes using healthcare forecasting—frequently termed “predictive modeling”—will accelerate as US medicine enters the digital age.

- The potential benefit of forecasting is facilitation of innovative patient care improvement strategies.
- Possible pitfalls include the exacerbation of health disparities, the propagation of interventions that have little evidence of effectiveness, lack of transparency, and a short-sighted focus.
- Health plans, method developers, and policy makers should adopt strategies that address these concerns in order to maximize the benefits of healthcare forecasting for patients.

### Propagating Disease Management With Limited Effectiveness

There is little evidence regarding how or whether forecasting improves healthcare value.<sup>11</sup> This is due to both the modest level of research and what is termed the “impactibility” problem.<sup>2</sup> That is, even if prediction algorithms accurately identify at-risk patients, intervening to achieve desired outcomes is often inhibited by limitations of current disease management approaches or the general state of medical science.

### Lack of Transparency and Standardization

Private companies often develop and sell statistical prediction algorithms and therefore have strong incentives to keep “recipes” proprietary. Furthermore, standards do not exist for governing key forecasting realms such as appropriate patients and outcomes to target, risk factors that should be considered, appropriate structures of forecasting equations, and acceptable levels of accuracy. This lack of transparency is reminiscent of the 1990s, when insurers often treated criteria for medical necessity coverage as proprietary, likely contributing to the managed care backlash.

### Short-Term Focus

Because of the rapid turnover of insurance coverage and current rules allowing some high-risk individuals to be denied coverage, most health plans and employers have tended to forecast short-term, high-cost outcomes such as rehospitalization or next year’s utilization. But predictive techniques could also identify patients who need care that has longer-term benefits; for example, identifying persons especially in need of interventions such as cancer screening, obesity prevention, or cholesterol control.

## MAXIMIZING BENEFITS

Policy makers, tool developers, and health plans should consider strategies to enhance the benefits and minimize potential negative consequences of healthcare forecasting. Such strategies include the following 4 approaches.

■ **Table.** Overview of Healthcare Forecasting

<b>Users of Predictions</b>	<b>Input Data Used to Predict Outcomes</b>	<b>Outcomes Predicted</b>	<b>Uses/Interventions Based on Predictions</b>	<b>Goals of Interventions Based on Predictions</b>
Health plans	Health insurance claims and administrative data	Costs	Disease/care management	Reduce costs
Public insurers	Electronic health record data	Health services utilization	Patient education	Improve quality/health outcomes
Integrated healthcare delivery systems	Health questionnaire/patient self-assessment data	Behavior/utilization patterns	Healthcare systems/policy change	Enhance patient safety
Provider groups	Laboratory data	Quality/evidence-based care	Surveillance to promote population health	Determine optimal policies
Researchers		Health outcomes	Budget allocation	
Employers or coalitions		Likelihood of behavior change		

**Increased Transparency and Standardization**

Health insurers and physician groups should share key information about their use of healthcare forecasting such as data inputs, types of algorithms used, and predicted outcomes. This sharing would enable better understanding of the impact of predictions on their enrolled populations. Such data collection could be voluntary and added to existing quality reporting that occurs through the Centers for Medicare & Medicaid Services and the National Committee for Quality Assurance. As suggested by a recent article critiquing hospital readmission forecasting,<sup>12</sup> the scientific community should establish minimum accuracy benchmarks for models predicting various established outcomes. Additional standards should be developed for model development and deployment.

**Research**

In the future, key research priorities should include examining the impact of predictive models on quality, the contribution of new data sources on forecasting accuracy, and the degree to which forecast-based interventions contribute to disparities between targeted and excluded patients. Better understanding is needed regarding optimum predictive algorithms such as automated approaches that detect patterns and correlations (data mining and artificial intelligence) versus algorithms that incorporate investigator hypotheses and iterative feedback (structured and learning models). To improve the effectiveness of disease management, continuing research on how forecasting can best identify patients amenable to feasible interventions will be essential.

**Incentives for Long-Term Health Maintenance**

A full discussion of policies that encourage employers, physicians, and health plans to cultivate long-term account-

ability toward patients goes beyond the scope of this commentary. However, such policies could encourage stakeholders to expand the application of innovative forecasting tools that promote health among patients likely to experience adverse health events well into the future, rather than just those at short-term “risk.”

**Increased Oversight or Self-Regulation**

If negative effects as described above are in fact documented, increased external oversight or self-regulation by stakeholders might be needed. For example, regulations could address how long-term health should be added to forecasts. Although the Affordable Care Act proscribes bias against patients with high predicted morbidity, potential abuses such as dropping of vulnerable patients should be monitored.

**INNOVATIVE USES**

The increasing sophistication of predictive modeling and the changing health policy environment present opportunities for innovative forecasting applications that could enhance healthcare value and equity.

**Personalized Health Insurance Design to Reduce Disparities**

High cost sharing is a barrier to care for certain populations. High-deductible health plans are expanding at unprecedented rates, and health reform may further accelerate growth. Predictive modeling could facilitate targeted identification of at-risk populations and proactive interventions such as employer health savings account contributions or cost-sharing exclusions for relevant services. This type of forecasting application might be termed “personalized health insurance,” given that

coverage levels of individuals or populations could, to some degree, be calibrated to their forecasted characteristics.

### Clinical Decision Support Systems

The widespread adoption of EHRs and increasing interoperability between health information technology systems could enable advanced clinical decision support. Like the personalized health insurance described above, such electronically supported predictive modeling systems (e-PM systems for short) could provide tailored, real-time clinical recommendations for individual patients based on predictions about their health. If patient outcomes are captured by the EHR and linked to prediction metrics, this feedback loop could also add to the evidence base regarding the real-world impact of forecasts on clinical decisions and patient benefit.

### CONCLUSIONS

The growing use and increased sophistication of electronically mediated patient-level forecasting presents challenges for ethical use and opportunities for innovative applications. Health plans, method developers, and policy makers should adopt strategies that directly address these issues in order to maximize the benefit of healthcare forecasting on the long-term health of patients.

#### Acknowledgments

We gratefully acknowledge the insightful comments on this manuscript of Drs Jim Sabin and Richard Platt of Harvard Medical School and Harvard Pilgrim Healthcare Institute Department of Population Medicine.

**Author Affiliations:** From Department of Population Medicine (JFW), Harvard Medical School and Harvard Pilgrim Healthcare Institute, Boston, MA; Johns Hopkins Bloomberg School of Public Health (JPW), Baltimore, MD.

**Funding Source:** There was no funding for this project.

**Author Disclosures:** Dr Wharam reports that his salary was supported by Harvard Medical School and Harvard Pilgrim Healthcare Institute Department of Population Medicine. Dr Weiner reports that he is one of the devel-

opers of the Adjusted Clinical Groups (ACG) Case-Mix System, which is owned and copyrighted by The Johns Hopkins University. ACGs are used for risk adjustment and predictive modeling. The University receives royalties for commercial applications of the ACG system.

**Authorship Information:** Concept and design (JFW, JPW); drafting of the manuscript (JFW, JPW); and critical revision of the manuscript for important intellectual content (JFW, JPW).

**Address correspondence to:** J. Frank Wharam, MB, BCh, BAO, MPH, Department of Population Medicine, Harvard Medical School and Harvard Pilgrim Healthcare Institute (HPHCI), 133 Brookline Ave, 6th Fl, Boston, MA 02114. E-mail: jwharam@partners.org.

### REFERENCES

1. **Robinson JC, Yegian JM.** Medical management after managed care. *Health Aff (Millwood)*. 2004;Suppl Web Exclusives:W4-269-W4-280.
2. **Lewis GH.** "Impactability models": identifying the subgroup of high-risk patients most amenable to hospital-avoidance programs. *Milbank Q*. 2010;88(2):240-255.
3. **Iezzoni LI.** The risks of risk adjustment. *JAMA*. 1997;278(19):1600-1607.
4. **Forrest CB, Lemke KW, Bodycombe DP, Weiner JP.** Medication, diagnostic, and cost information as predictors of high-risk patients in need of care management. *Am J Manag Care*. 2009;15(1):41-48.
5. **Seymour CW, Kahn JM, Cooke CR, Watkins TR, Heckbert SR, Rea TD.** Prediction of critical illness during out-of-hospital emergency care. *JAMA*. 2010;304(7):747-754.
6. **Cousins MS, Shickle LM, Bander JA.** An introduction to predictive modeling for disease management risk stratification. *Dis Manage*. 2002;5(3):157-167.
7. **McCall CJ.** Improving outcomes and reducing cost: the role of predictive modeling. *Manag Care*. 2003;12(10)(suppl):12-16.
8. **One Hundred Eleventh Congress of the United States of America.** *The Patient Protection and Affordable Care Act*. <http://democrats.senate.gov/reform/patient-protection-affordable-care-act-as-passed.pdf>. Published 2010. Accessed July 28, 2010.
9. **Stehno C.** *The Future of Predictive Modeling—As Viewed From the P&C Marketplace*. Deloitte Development LLC; 2006-2007. [http://www.iirusa.com/upload/wysiwyg/P1219/Online%20Docs/IIR\\_P1219\\_Stehno,%20Chris.pdf](http://www.iirusa.com/upload/wysiwyg/P1219/Online%20Docs/IIR_P1219_Stehno,%20Chris.pdf). Accessed October 11, 2010.
10. **Verisk Analytics.** Speakers bureau. [http://www.verisk.com/index.php?option=com\\_bookmarks&Itemid=150&mode=0&catid=9&navstar=0&search=](http://www.verisk.com/index.php?option=com_bookmarks&Itemid=150&mode=0&catid=9&navstar=0&search=) . Accessed October 24, 2010.
11. **Goetzl RZ, Ozminkowski RJ, Villagra VG, Duffy J.** Return on investment in disease management: a review. *Health Care Financ Rev*. 2005;26(4):1-19.
12. **Kansagara D, Englander H, Salanitro A, et al.** Risk prediction models for hospital readmission: a systematic review. *JAMA*. 2011;306(15):1688-1698. ■