Digital Decision Making: Computer Models and Antibiotic Prescribing in the Twenty-First Century

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(See the article by Daneman et al. on pages 1131–8)

Antibiotic selection has become complicated. Gone are the days when you only needed to search a small book, such as the Sanford Guide to Antimicrobial Therapy [1], to find the appropriate antibiotic. Today, the right antibiotic may depend on your patient, other patients in the vicinity of your patient, your patient’s insurance, your hospital, your hospital’s formulary, your city, the time of year, and many other factors [2–6]. Some antimicrobial decisions require one to serve as part physician, part epidemiologist, part economist, part pharmacist, part historian, and part sociologist. With limited time in which to see each patient and to make decisions, juggling all of these roles is challenging for even the most multitalented physicians.

When decisions are complicated and are subject to rapidly changing conditions, computer models can help. Many other industries have long used computer models to facilitate decision making. If automobile manufacturing, building construction, air traffic control, financial planning, and meteorological forecasting did not use computer simulation, we would surely see many more accidents, wasted investments, and other mishaps. Why should antimicrobial therapy decisions be different? The stakes are potentially very high. Improper choices can lead to morbidity, mortality, and significant costs and even have the potential to change the long-term infectious disease ecosystem [7, 8]. Why not use all of the techniques at our disposal?

Consequently, we need more computer decision models, such as the macrolide model presented by Daneman et al. [9] in this issue of Clinical Infectious Diseases. Their model analyzes how the local prevalence of macrolide resistance affects the choice of using a macrolide to treat community-acquired pneumonia. This represents an important advance, because most antibiotic prescribing mandates, to date, have been based on expert opinion [10–13]. Without computer models, even the most knowledgeable experts have limitations. Experts often rely on their personal experience and retrospective data review. Depending exclusively on past data and experience to understand the present and to predict the future is dangerous. A decade or two ago, how many could fully predict the economic and epidemiologic conditions that we face today?

Although computer models vary in complexity, generalizability, and applicability, general principles guide the construction, interpretation, and use of all antibiotic decision models. Understanding these principles precludes their misinterpretation and misuse. The relative strengths and flaws of the macrolide model help to illustrate the following general principles.

Perfection is not the goal. No antibiotic research study is perfect. Even a well-designed, randomized, controlled trial has many shortcomings. Similarly, every computer model simplifies real life situations and incorporates many assumptions. When considering a computer model, the temptation often is to discard the model completely once any flaws are identified. However, a flawed model is usually better than no model, as long as the flaws are understood, and the model still provides useful information. Daneman et al. [9] clearly acknowledge the limitations of their model. Nonetheless, their model remains superior to any other currently available model. Moreover, the model’s imperfections raise pertinent questions that can be used to guide future research and policymaking. For example, the model does not show how the availability of different alternative therapies may affect optimal macrolide use, which is an issue that future studies may explore. The model also exposes the general limitations of the data, which leads us to the next principle.

Consider but do not obsess over the
model’s data sources. Another tendency is to focus too heavily on the quality of a model’s input data. Critics often recite the mantra “garbage in, garbage out,” claiming that a model is only as good as the data that it examines [14, 15]. However, using the best available data is not always feasible or necessary. Most infectious disease surveillance and outcome data have numerous inherent flaws. Data quality depends heavily on reporting and testing procedures, as well as on the composition of the sample population. Surveillance data usually only include reported cases from selected surveillance sites. Many cases go unreported. Severe, unusual, and urban cases may be overrepresented. The sample population may lack appropriate patient diversity. Because catching and following all cases in the general community may be difficult, most infectious disease outcome data comes from special populations that tend to have worse outcomes (e.g., patients who present to emergency departments or hospitals).

As the macrolide model exhibits, computer models can overcome these data issues. By extrapolating, combining, completing, and transforming multiple data sets, computer models can be especially useful when data is weak or deficient. The macrolide study includes a good number of sensitivity analyses, which, in many ways, are the most valuable part of a model. Seeing how model results change when you vary key parameters along a range of input values can, first, identify the relative importance of each input parameter (if a parameter value has little impact on results, then it may be reasonable to disregard the parameter or even drop it from the model) and, second, show what might happen if input data were different or improved. Daneman et al. [9] present sensitivity analyses that demonstrate what would happen if certain values (e.g., probability of community-acquired pneumonia being due to pneumococcus) were higher or lower than the available data values.

Delineating relationships is more important than giving specific answers. Because the right antibiotic varies in different situations and times, an antibiotic decision model should not provide a single specific answer. Employing a static model (i.e., one that represents a single set of conditions) that generates a single answer is analogous to buying a single shirt size and expecting it to fit an entire population. The shirt will fit some people, but it will be too loose or too tight for most others. To their credit, Daneman et al. [9] avoid making specific decisions for clinicians, such as when a macrolide should be used and what level of macrolide resistance or risk of death is acceptable. Instead, they define the relationship between pneumococcal resistance rates and excess risk of death. Knowing this relationship allows each individual physician to tailor the optimal antibiotic choice to his or her specific situation and acceptance of risk [16]. Rather than dictate answers, a good model provides tools to arrive at answers.

Both simple and complex models have their roles. How complex should a model be? Simple models can elucidate general principles, isolate paramount factors, and be easily understood. However, they may neglect certain factors and overgeneralize certain situations. More-complex models can be more comprehensive, can identify subtle interactions, and may be more valid for specific situations, but they can also be unwieldy, costly to construct, too specifically tied to a given set of conditions, and difficult to alter in the future. When first exploring a problem, simple models, such as that proposed by Daneman et al. [9], should prevail. As our knowledge and understanding of antibiotic decision models progress, more-complex models should join the fold, but simple models may remain useful.

Antibiotic decision models should clearly define their audience and output. A prescribing physician, hospital epidemiologist, hospital administrator, insurance executive, policy maker, and other relevant parties can have very different perspectives and incentives. Therefore, vague model outcome terms, such as clinical impact, clinical outcome, and economic value, can have different meanings for different people. Instead, a model should have clear, relatively objective outcomes, such as risk of death.

In general, antibiotic decision models should not make value judgments or subjective assessments. The primary purpose of a decision model is to identify relationships that may not be clearly evident. Ultimately, humans should make decisions. Computer models should facilitate but not replace human decision making. If we understand and appreciate the role of computer decision models, physicians and computer decision models can tackle infectious diseases as partners, and antibiotic prescribing can then join other industries in the twenty-first century.

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References
7. Arda B, Sipahi OR, Yamazhan T, et al. Short-term effect of antibiotic control policy on the usage patterns and cost of antimicrobials,


