Using artificial intelligence in health-system pharmacy practice: Finding new patterns that matter

The CPO Perspectives section of *AJHP* features content of interest to Chief Pharmacy Officers and other decision-makers in health-system pharmacy. *AJHP* Contributing Editor Scott Knoer, M.S., Pharm.D., FASHP, coordinates the solicitation and review of articles for this series.

Am J Health-Syst Pharm. 2019; 76:622-627

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Keywords: artificial intelligence, data analytics, machine learning

DOI 10.1093/ajhp/zxz018

The technologies collectively referred to as artificial intelligence (AI) currently provoke hype and speculation about their increasingly powerful capabilities, while raising concerns that machines will soon be doing most of our jobs. Yet it is not true that AI will soon replace human expertise.[1,2] Instead, for the foreseeable future, if we are to realize value-based payment,[3] achieve the quadruple aim,[4] and establish learning health systems,[5] then pharmacists' expertise will have to be complemented by AI in ways that lead to more informed medication-use decisions and better outcomes.[6]

The challenge for chief pharmacy officers and other pharmacy leaders is to discover how to apply the technologies of AI in ways that reveal new patterns in health data that actually matter in practice. Can AI assist us to improve patient experiences and health outcomes, upgrade population health, reduce costs, and better inform pharmacists and other providers? These are the things that truly matter. Using AI to assist pharmacists will not be as easy as the hype about AI and its power suggest.[7]

Simply put, where AI is concerned, we have to be astute. Now is the time to set aside both pessimism and optimism about AI. Instead, we should remain skeptical but open-minded about its uses and impacts. It is certain that AI will help us analyze more data more rapidly, in more ways than ever before. As we apply AI to pharmacy data in attempts to find patterns that matter, we will experience fits and starts, ups and downs, challenges and benefits, wins and losses.[8]

AI in health-system pharmacy practice

This article discusses AI in the context of its anticipated use in health-system pharmacy practice, trying to avoid hype about AI while keeping a focus on how it could one day help pharmacists provide better care. The discussion covers a specific use of AI of interest to pharmacy—*prescription anomaly detection* for the purpose of calling out strange or unusual prescriptions. To uphold safety, attention is also paid to some known limits and real risks of AI.

What is AI? AI experts at MIT Sloan have developed a syllabus for an executive short course entitled "AI: Implications for Business Strategy."[9] It defines AI as the use of computer systems to analyze large quantities of data, then applying the results of those analyses programmatically to better inform decisions. As this definition makes clear, AI combines 2 processes. First, AI uses statistical methods to *learn about patterns* in large "training" datasets comprising data from many past cases. Next, AI *applies the previously identified patterns it has learned* to indicate something potentially helpful about new cases. This is why, in health-system pharmacy, our challenge is to use AI to find patterns that actually matter in practice. If AI can learn about useful patterns in large training datasets, then we can use it to apply what it has learned to new cases. In this manner, AI can guide people to make the best possible use of medications, so they ultimately gain better health. There is growing evidence that this is now possible in health-system pharmacy.[10]

Can AI actually learn? According to Adriaans,[11] AI exhibits a capability to compress data into recognizable patterns, which is one broad form of learning. People sometimes learn in a similar way. For example, when we are young, we are taught to recognize letters as patterns, like the pattern of the curved line that forms the letter *S*. Then, when we encounter new instances of this curved line pattern, as in the word *Smile*, we recognize the *S* at the beginning of that word when we see it. In contrast to this simple example, AI's potential value lies in the identification of highly complex patterns that people would otherwise miss. AI then generates further value by applying the highly complex patterns it learns systematically and automatically to case after case.

Is AI safe and effective? When it works well, AI enables machines to do things that seem very smart to us, like translating one human language into another.[12] It seems as if AI makes machines intelligent. The reality, though, is that, even with AI, machines are not intelligent in the ways that humans are.[13] Recognizing this, we must keep the safety and effectiveness of AI in mind.[2] Tutt[14] has proposed an "FDA for Algorithms" to ensure there is evidence to indicate various AI implementations are safe and effective before they are put into use in practice. Whether or not such an agency is established, pharmacists clearly have a critical role to play in helping to generate the evidence that is needed to inform decisions about how and when to implement AI on a widespread basis in routine pharmacy practice.

What is true about AI. AI makes it possible for machines to process natural human language *with only a few mistakes*, for robots to adapt to *many* new circumstances, and for algorithms based on learned patterns to give *highly accurate* predictions and automatically classify things correctly *most of the time*.[8] Yet not one of these AI capabilities rises to the level of perfection. Even when AI outperforms people on certain tasks, it does not, and cannot, entirely eliminate errors. There will always be some degree of noise or uncertainty—and some bias—within any AI-powered system. Noise and bias conspire to make AI errors inevitable.

Due to space constraints, this article now sets aside AI for natural language processing and AI-enabled adaptive robots, even though these are interesting uses of AI. From here on, the focus is exclusively on machine learning (ML), which is an increasingly common AI method. ML applies AI to large datasets and automatically either makes predictions or classifies things. ML is already being used in attempts to improve medication use safety.[10,15]

Using ML to identify strange electronic prescriptions. In our latest research, we have been exploring how a very simple ML approach might be used to tell pharmacists when a new electronic prescription is somehow strange or unusual, and why it is so.[16,17] The 2 sequential processes described above—learning patterns from data and applying learned patterns to classify new cases—are encompassed by our work.

We first examined prescription data to learn about local prescribing patterns, such as the real-world prescribing pattern for metformin 500 mg oral tablets (Table 1). Next, by applying this simple prescribing pattern to new electronic prescriptions for metformin 500-mg oral tablets, we can classify each new prescription as one with a common instruction (e.g., 500 mg 2 times daily with meals), as one with a rare instruction (e.g., 500 mg 4 times daily), or as one with an unprecedented instruction (e.g., 1,500 mg once daily). By first learning and then systematically applying real-world prescribing patterns to classify electronic prescriptions, we found that 6% of the electronic prescriptions we analyzed from 2017 had unprecedented instructions that were never seen during prior year.[16] A key next step in this research is to evaluate whether telling pharmacists when a new electronic prescription is written in a rare or unprecedented way enables them to foil more prescribing errors and improve the safety and quality of care.

ML is statistical learning

As the very simple prescribing pattern example of ML shows, ML always involves statistics. In fact, ML is essentially a growing set of methods for analyzing large quantities of data statistically to arrive at useful new patterns in the data; patterns that support automated

Table 1. Counts of Instructions in 307 Electronic Prescriptions for Metformin 500-mg Tablets[a]

Instruction on Electronic Prescription	Count
500 mg 2 times daily with meals	75
500 mg 2 times daily	72
1,000 mg 2 times daily with meals	47
1,000 mg 2 times daily	39
500 mg once daily	23
500 mg once daily with breakfast	19
1,000 mg once daily with breakfast	8
500 mg once daily with dinner	4
500 mg 3 times daily	4
250 mg 2 times daily	2
1,000 mg once daily	2
750 mg once daily	2
1,000 mg once daily with dinner	2
1,000 mg once	1
500 mg 2 times daily before meals	1
500–1,000 mg 2 times daily with meals	1
500 mg once	1
500 mg every morning	1
500 mg daily	1
1,000 mg every evening	1
500 mg 4 times daily	1

[a]The table constitutes a simple real-world prescribing pattern for this product as it was ordered for inpatients 75 years old or older at the University of Michigan Hospitals during 2016. Eight instructions only appear once.

prediction or classification.[8] ML's statistical methods give rise to new patterns, which can be expressed as algorithms using mathematical equations and numbers.[18] These algorithms, which are just as often called "models," are then used to calculate a prediction for some variable of interest or to classify something, such as a prescription, into one category instead of another.

Some of the statistical methods involved in ML are familiar to pharmacists. As one example, consider logistic regression, which is a method of predicting the value of a binary dependent variable by analyzing a group of independent variables. We can use logistic regression to create a model that enables us to predict whether an individual will or will not experience some adverse drug event (ADE).[19] By analyzing relevant data about independent variables (e.g., variables describing features of individual patients), we can identify a new pattern, in the form of a function or a model, to predict whether an ADE will or will not occur for a particular person over a set period of time. If our logistic regression model has a high enough accuracy,[20] it may be useful for predicting who will experience a particular ADE in pharmacy practice.

Logistic regression is one of several key statistical methods used for ML. Other key methods, like linear regression, may also be quite familiar. But some ML statistical methods are new to most pharmacists. These include the methods of support vector machines, nearest neighbors, decision trees, random forests, centroid clustering, neural networks, and deep learning.[8] ML uses all of these statistical methods, sometimes in combination, to analyze large quantities of data and learn new patterns. Then, if the new patterns learned are potentially helpful and not obvious to experts, spurious, or misleading, they can potentially be usefully applied in practice. An interesting recent example is how ML has been used to accurately classify whether or not images of the human retina show signs of retinopathy.[21]

ML experts are often explicit about the 2 interrelated steps involved in AI: learning new patterns, and then applying those patterns to new cases. ML work begins by using various statistical methods to analyze a *training dataset* to learn a new pattern that is represented as a statistical model. ML work then continues by applying the new pattern to an independent *test or validation dataset*. This second move is made to evaluate, using additional statistical tests, the degree to which the pattern learned from analyzing the training data also fits the test or validation data. When newly learned patterns are shown to fit well, and when they indicate differences that actually matter in practice—such as the difference between a person who is likely or unlikely to experience a particular ADE—then a ML model may be suitable for a trial implementation.

Critical requirements for ML

The scope of useful ML for health is evidently growing. Yet, a number of things are required to use ML effectively to learn patterns that matter in practice. Here are 6 things that are required to achieve useful ML for health:

1. A decision task that can potentially be better informed by analyzing relevant data,
2. A large quantity of high-quality data relevant to the decision task,
3. Statistical methods suitable to identify patterns that matter in the relevant data,
4. Computing resources sufficient to perform the required statistical data analyses,
5. Software tools that make it possible to deploy ML models effectively, and
6. Reliable outcome measures for judging ML performance on the decision task.

These requirements are critical for ML success but not easy to meet. This article next examines each in turn, keeping the practice of pharmacy in the forefront.

A decision task that can be better informed. There are many decision tasks in pharmacy that could potentially be better informed by using ML. These include drug treatment decisions, drug selection decisions, drug dosing decisions, and decisions about inventory par values, to name a few. It is not difficult to find decision tasks in pharmacy to which AI and ML could be applied.

A large quantity of high-quality data. This requirement can be hard to meet. How much data is needed to be successful with ML? As always with statistics, there is no single answer to this question. However, successful ML projects have used datasets comprising tens of thousands of records.[21] Can enough data be sourced to enable ML for drug treatment decisions, drug selection decisions, or dosing decisions? Can enough data be sourced to support ML for better inventory management? Even with electronic health records (EHRs) and inventory management software, many organizations will not generate enough data on their own to enable ML to better inform these decisions. Instead, organizations may need to combine the data they have with data from other organizations to enable useful ML for health-system pharmacy.[22]

Statistical methods. The number of workable statistical methods for ML is increasing.[8] There are 2 primary types of statistical methods for ML—parametric and nonparametric. Parametric methods, such as linear regression, apply statistical methods associated with known assumptions about the distribution of the underlying population (e.g., that the underlying population distribution is normal). Nonparametric methods, such as the method of nearest neighbors, do not make any assumptions about the distribution of the underlying population. Obviously, selecting appropriate ML methods is one key to success with ML.

Computing resources. Given the large amount of data that has to be analyzed, and the complexity of some of the statistical analyses, ML can require extraordinary computer processing power.[21] It may demand more computer processing power than a laptop or desktop computer can provide. While it is true that sufficient computer processing power can now be sourced online, it remains expensive. The cost of doing ML is another reason that pharmacy leaders will want to consider when thinking of pursuing it.

Software tools for ML. Software tools for performing ML analyses are readily available. Examples include open source tools like TensorFlow[23] and Torch.[24] Harder to find are software tools that make it easy to deploy ML functions or models within EHRs. What we need are straightforward mechanisms for implementing ML models in all types of medication use systems.[25] Our research team is working on new open source tools for this purpose.[26]

Reliable outcome measures. To evaluate the performance of ML, we must also have reliable outcome measures. This means we need to collect and review data on health and safety outcomes, and on financial outcomes, arising from applying ML models to better inform decision tasks in health-system pharmacy. This is not an easy requirement because reliable data on health and safety outcomes are often difficult to obtain.

We have just examined 6 critical requirements for ML, which is 1 use of data analytic AI approaches to generate predictions or classify things. While some of these ML requirements are easily met, others are not. In particular, the requirements for large quantities of high-quality data, for abundant computer processing power, for easy ways of deploying ML models within existing medication use systems, and for reliably measuring outcomes from applying ML models in practice are all very challenging at present.

Biases, rare events, and inadequate accuracy

Bias is guaranteed. One serious concern about ML, which again always involves statistical learning from limited data, is that bias is guaranteed.[8] The field of statistics, which is about generalizing based on sampled data, exists because it is often impossible to collect data from all individuals in a population. Bias occurs because our data samples are necessarily imperfect. Data samples often exclude members of important subgroups in a population while overrepresenting other subgroups. Due to bias, ML may wrongly learn a new pattern that then gets systematically applied in practice. Steps must be taken throughout the process of using ML to avoid this bad outcome. These steps include carefully analyzing the diversity of the datasets being used for ML and addressing apparent data gaps.[27] They also include limiting the application of ML models in practice to those cases where the historical data and new cases are reasonably well matched.

The startling frequency of rare events. Rushing to fully automate processes by using ML is another concern. While it is interesting to think of how ML is enabling self-driving cars to perform autonomously on public streets, in pharmacy practice we have to anticipate thousands of different types of rare events. The trouble is that rare events simply cannot be predicted from historical data.[28] Given the complexity of human health and the vast number of ways that individual people are unique, rare events and "exceptions to the rule" appear surprisingly commonly in practice. This is because there are so many different kinds of rare events and rare diseases. For this reason, instead of fully automating decision tasks in pharmacy using ML it is advisable, instead, to use ML to inform pharmacists about the patients and families they serve so that they can apply their experience and judgment.

Inadequate accuracy. Another serious concern about using ML models in practice is that they may not be sufficiently accurate. A related concern is that the accuracy of ML models can degrade over time as practice patterns and patient populations shift and change. This concern highlights the need to be able to evaluate the performance of ML models on an ongoing basis. Without this capability, it may not be appropriate to deploy ML models in ways that directly influence clinical decision-making.

Potential uses for ML in pharmacy over the next 5 years

So, can we use ML in pharmacy to discover and apply patterns that matter in practice and better inform our decisions? It seems likely that, yes, eventually we can and will do this. Here are a few examples in which, over the next 5 years or so, we may be able to meet all 6 of the requirements outlined above.

Drug product decisions using pharmacy-related images. One area in which a large quantity of high-quality data can be gathered and used for ML is image processing. Expect image processing using ML to be applied more widely within the pharmacy supply chain. This use of ML could help quickly and accurately identify drug products. This capability could possibly be used to detect and alert staff to mislabeled oral solids or to detect particulates in syringes or IV bags.

Decisions to treat. At least 1 vendor is already using ML to inform clinicians about the decision to treat patients with medications.[10] By using a large quantity of EHR data and ML to learn patterns about appropriate medication use, software is able to detect and alert in instances when a prescribed drug seems to deviate from the pattern of appropriate use for that drug.[15] There are likely to be other similar ML efforts targeted specifically at decisions of whether or not to treat a person with a particular medication.

Drug selection decisions. Once a decision has been made to use drugs to address a particular health problem, ML may be able to inform drug selection. As an example of this, ML capable of indicating, through automated classification, who is and who is not likely to experience particular adverse effects from a particular drug could be useful.

Dosing decisions. Because dosing is readily quantifiable in terms of dosage and frequency, for those drug treatments where the responses to therapy are also readily quantifiable, it seems likely that ML will eventually be used to help guide decisions on dosage. Here, responses to therapy include any physiological response that is measurable. ML to support dosing decisions may offer advantages, for example, when blood levels of drugs or related factors can be routinely assessed. Work using AI to achieve a closed-loop artificial pancreas is one example of this.[29]

Inventory management decisions. There is a natural desire to use ML to help set par values by more accurately predicting medication use in hospitals and health systems. One difficulty in applying ML to inventory management seems to be that sufficiently large quantities of data on drug use at the level of individual hospital units are not readily available. Better predictions of par values for inventory management may require mechanisms to combine and aggregate patient and medication-use data in new ways. This is an interesting area of further exploration towards being able to predict, for a given patient and day, what will be the medications that are required and used.

Preparing to explore the use of ML in health-system pharmacy

Having covered AI and ML, this discussion finishes by considering where the pharmacy profession needs to go next with respect to these technologies. Here is a "Top 5" list of things that pharmacy leaders can do to prepare for the use of ML and other AI in health-system pharmacy:

1. Engage. With an appropriate balance of skepticism and open-mindedness, chief pharmacy officers and other pharmacy leaders should engage the topic of AI in pharmacy practice. Now is the time to raise awareness about the many issues that pertain; especially the risks of using data that are of insufficient quantity or quality. In addition, leaders need to make opportunities available for pharmacists to increase their understanding of AI and its uses and especially ML.
2. Study. Because ML models are coming into use in health-system pharmacy, all pharmacists need to learn more about how ML works. In the future, pharmacists will be expected to analyze key aspects of medication-related ML models, just as we are expected to analyze scientific publications reporting studies involving medications.
3. Prioritize. Pharmacy leaders need to determine which medication-use decision tasks should receive priority for data-driven improvement using ML. The many requirements of ML, and concerns raised here about its safe use can inform a profession-wide discussion of AI priorities for health-system pharmacy.
4. Collaborate. Organizations will need to collaborate to aggregate enough reliable data, analyze it appropriately, and understand the effects and outcomes from applying ML models in practice. State-wide, regional or national-scale activities in this area should be considered given the requirements for large quantities of data, expert statistical know-how, large-scale computing resources, and ongoing evaluation of the impacts of AI.
5. Share. Pharmacy leaders also need to prepare the ground for effectively sharing the best ML and AI models so that these technologies do not end up further increasing health disparities.[27] For many years, the Cockcroft-Gault, Jelliffe, and Wright formulas have been used by pharmacists to estimate patients' glomerular filtration rates.[30] These formulas, and the science upon which they are based, have been accessible to all pharmacists. As ML and AI methods and models come into pharmacy practice, it will be important to continue to do research and share the methods and models we use, and the lessons we learn from using them, as widely as possible throughout our profession.

Conclusion

There is a lot of hype about AI in the popular press. It is likely that AI, and particularly ML, will be used to find and learn patterns in pharmacy data that, when applied in practice, will have both positive and negative consequences. To promote the best possible outcomes from using AI as a complement to pharmacists' expertise, chief pharmacy officers and other health-system pharmacy leaders should engage this topic, study it, prioritize the decision tasks in pharmacy in which these technologies can potentially do the most good, collaborate to make best use of these technologies, and share the results and lessons learned that come about by using them.

Disclosures

The author has declared no potential conflicts of interest.

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