We have discussed earlier the important role played by experience in the hypothesis generation phase of diagnosis (1). We have pointed out that if a physician has experience of encountering the widely varying presentations of a given disease in different patients, he is likely to suspect it and formulate it as a diagnostic hypothesis when its presentation is atypical.

In this paper, we shall discuss the equally important role played by experience in the hypothesis verification phase of diagnosis.

We have pointed out earlier that a disease as a diagnostic hypothesis is usually verified to be correct when a highly informative test result for it, usually with a likelihood ratio (LR) greater than 10, is observed in a patient (2).

The example of such verification we have often given is of verification of the diagnostic hypothesis of acute myocardial infarction (MI) by acute Q wave and ST elevation EKG changes (acute EKG changes) which have a likelihood ratio of 13 (3).

This verification occurs, as we have pointed out, in any patient regardless of prior probability, as we see in the common practice of EKG reading physicians diagnosing acute MI from acute EKG changes alone without any clinical information (4).

This method of hypothesis verification is obviously not Bayesian, as the likelihood ratio of 13 of acute EKG changes is not combined with prior probability of acute MI in a patient to generate a posterior probability from which acute MI would be diagnosed in the Bayesian method (5).

We have illustrated this point with the example of a real patient discussed in a clinical problem solving exercise who is a healthy 40 year old woman who presents with highly uncharacteristic chest pain and is found to have acute EKG changes (6).

In this patient, the estimated prior probability of 7 percent is combined with LR of 13 for acute EKG changes (3) to generate a posterior probability of 50 percent.
from which acute MI would be diagnosed to be indeterminate in the Bayesian method.

But this diagnosis is not made by the discussing physician in this exercise.

Instead, he correctly diagnoses acute MI definitively from the high LR of 13 for acute EKG changes alone.

We have pointed out this is done because the LR of 13 indicates a thirteenfold increase in odds of acute MI in this particular patient (7), which locates evidence due to acute EKG changes in this patient (Appendix).

We suggest that localization of evidence in a given patient is only part of the reason that acute MI is diagnosed from acute EKG changes in this manner.

The other important reason, as we shall now discuss, is that in this method, hypothesis verification is validated as being highly accurate by our experience.

It is reasonable to assume, we suggest, that acute MI, like any other disease, occurs with varying presentations and therefore with varying prior probabilities in different patients.

Thus our experience of the accuracy of diagnosis of acute MI from acute EKG changes would be gained from patients with varying prior probabilities.

As the diagnostic accuracy of acute MI from acute EKG changes across varying prior probabilities is known to be 85 percent (3), our experience would be that acute EKG changes would diagnose acute MI correctly in 8 to 9 out of 10 patients encountered by us.

It is this experience, we suggest, which validates our diagnosis of acute MI from acute EKG changes in a given patient such as in the 40 year old woman as being correct.

That the validating experience is gained from patients with prior probabilities which are different from those in the given patient is of no consequence, we believe, because the pathophysiology of acute MI is the same in all patients regardless of prior probability as far as we know.
This method of validating verification of a diagnostic hypothesis by a test result can be looked upon, as we have pointed out elsewhere, as an application of a confidence argument (8).

In this argument, we consider the patients with varying prior probabilities in whom we suspect acute MI to constitute a heterogenous population which is known to contain patients with acute MI.

If patients with acute EKG changes are repeatedly drawn from this heterogenous population, 85 percent of these patients will have acute MI.

Therefore, in a given patient with acute EKG changes such as in the 40 year old woman, we could say with a confidence level of 85 percent that this patient has acute MI.

We note that if the population from which patients with acute EKG changes are drawn were to be homogenous, for example, to contain patients with prior probability of 7 percent similar to that of the 40 year old woman, only 50 percent of patients with acute EKG changes will have acute MI.

This accuracy rate would correspond to the Bayesian posterior probability of 50 percent.

Thus if we only suspect acute MI in patients similar to the 40 year old woman in practice or are easily able to sort these patients from all other patients we see, our experience of 50 percent accuracy would be represented by the posterior probability of 50 percent.

This however does not happen in actual practice in which our experience of diagnostic accuracy of a test result is gained from a heterogenous population and is thus represented by a confidence and not by a Bayesian argument.

In conclusion, experience of diagnostic accuracy about a disease from a test result with LR greater than 10, gained from a heterogenous population of patients with varying prior probabilities, validates verification of a diagnostic hypothesis in a given patient in practice by a confidence and not by a Bayesian argument.
Appendix

In odds form of Bayes’ theorem,

Posterior odds = Prior odds x Likelihood ratio

Or Likelihood ratio = Posterior odds/Prior odds

Therefore, Likelihood ratio of 13 = Posterior odds/Prior odds = 13 = Thirteenfold increase in odds

References

2. Jain BP. Evidence from data is assessed by likelihood ratio during diagnosis. Posted online on Listserv May 1, 2018.