techniques, and these assays can therefore be used to aid in diagnosis and monitoring (2).

Author Contributions: All authors confirmed they have contributed to the intellectual content of this paper and have met the following 3 requirements: (a) significant contributions to the conception and design, acquisition of data, or analysis and interpretation of data; (b) drafting or revising the article for intellectual content; and (c) final approval of the published article.

References

Plasma Abnormalities Following Overdose
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Case Description
A 62-year-old female with a history of schizophrenia was found unresponsive after ingesting supratherapeutic amounts of diltiazem and valsartan. At presentation to the emergency department, she was hypotensive and bradycardic. Eight hours later, a blood sample (Fig. 1A) was drawn for chemistry analysis and ultracentrifuged to clarify the turbidity (Fig. 1B). However, the lab was unable to assay the plasma sample. Multiple samples yielded similar findings. Plasma samples obtained the following day were appropriate for analysis.

Questions
1. What interfering substances are causing the plasma’s strawberry milk appearance?
2. What off-label medication was administered to this patient?
3. What drug(s) may be responsible for causing the abnormal appearance of her plasma?

The answers are below.

Answers
The combination of lipemia and hemolysis caused the plasma’s strawberry milk appearance. Lipid emulsion is designed to be infused slowly as part of a total parenteral nutrition regimen. However, this patient received a 120-mL IV bolus of lipid emulsion off-label for its “lipid sink” action against supratherapeutic levels of lipid soluble drugs, such as diltiazem (1). Both lipid emulsion and diltiazem can cause erythrocyte fragility, which may account for the in vivo hemolysis (2–5).

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References

News & Views

The P Value: Probable Does Not Mean Practical

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Nearly everyone is familiar with the literary detective Sherlock Holmes and his often-picked-on associate Dr. John Watson. In “A Scandal in Bohemia,” Holmes educates Watson on the difference between seeing and observing. That Watson is looking at the same information, yet deriving different (and more often incorrect) conclusions than Holmes, befuddles him. “I believe that my eyes are as good as yours,” Watson claims. To which Holmes answers “Quite so. You see, but you do not observe. The distinction is clear.”

The same holds true for the interpretation of scientific data. Researchers see data, but may fail to observe whether the data yield any meaningful results. Researchers reach conclusions, but may fail to observe whether the data support the conclusions. In doing so, they may miss important clues that the data provide.

Overreliance on statistical analyses of data is like seeing a snapshot of your data but not really observing the data. The P value is an excellent example of how researchers may over- or underinterpret data and thus fail to see the true picture. To illustrate this fact, let us start with what the P value really is.

In research, one can never state with 100% certainty that any change or difference is real. In fact, probability testing starts with the assumption that the difference between groups is zero (the null hypothesis). Therefore, all one can do is determine the probability (P value) that the null hypothesis is true. If the P value is small enough, it suggests, but does not prove, that the difference seen did not occur by chance and that the groups, therefore, may have come from different populations. However, the P value does not tell you anything about how large the difference is between 2 groups, or whether the statistical significance implies any clinical significance. Yet the misperception exists that the smaller the P value, the greater the importance.

As examples of how the P value is misleading, we have created a hypothetical study of patients with epilepsy being treated with phenytoin. Serum phenytoin concentrations were measured for 50 patients who remained seizure free and 50 patients who had a subsequent seizure. Two separate example data sets are provided.

Fig. 1 shows 1 data set. Bar graphs of mean with SD (Fig. 1, A and E); mean with SD plots (Fig. 1, B and F); median, interquartile range, and range plots (Fig. 1, C and G); and scatter plots of all data points (Fig. 1, D and H) are shown. The mean (SD) for the seizure-free group is 14.1 (4.3) vs 16.4 (6.0) μg/mL for the group.