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*Conceptual Article*

# Beyond memorization: A study of problem-solving across math and medicine

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Mathematics and medicine are often portrayed as unrelated subjects, yet both disciplines rely on similar forms of conceptually driven problem-solving. This paper argues that high-level performance in each field depends less on memorizing large volumes of information and more on recognizing patterns, reasoning from core principles, and applying knowledge to unfamiliar situations. Drawing on cases from Biology Olympiad questions, organic chemistry, diagnostic testing, pharmacokinetics, and clinical decision-making, this paper shows how effective problem solvers integrate information across topics, evaluate alternative explanations, and justify their conclusions. Based on these examples, a cross-disciplinary framework is proposed with four shared aspects: (1) principle-based reasoning, (2) integration across systems/topics, (3) coordination of quantitative and qualitative data, and (4) transfer of understanding to novel contexts. This framework demonstrates parallels between mathematical thinking and clinical reasoning and challenges the misconception that biomedical learning is primarily rote learning. The paper concludes by outlining implications for STEM and pre-medical education, suggesting that curricula and assessments should cultivate 'big picture' reasoning and structured justification to better prepare students for both advanced mathematics and authentic medical practice.

Keywords: Biological Sciences; Clinical reasoning; Logic; Mathematics; Medicine; Problem-solving

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## 1. Introduction

There is a common misconception that problem-solving in the biological and medical sciences heavily relies on rote memorization of vast amounts of information (Eva, 2005; Schmidt et al., 1990; Schmidt & Mamede, 2015). In truth, effective problem solving in these fields, like in mathematics, depends on logical reasoning and conceptual integration. Mathematics combines abstract and theoretical frameworks that are widely applied to various fields: fluid dynamics uses calculus, macroeconomics relies on statistics, and probability theory underpins models of risk and uncertainty. Solving mathematical problems often involves a series of sequential, compound steps that build upon established procedures and principles. These challenges become even more complex when they demand creative insights or the recognition of unfamiliar patterns. In contrast, the biological sciences, such as biology, biochemistry, and biomedicine, are grounded in experimentation and the analysis of natural phenomena. Biological sciences demand the ability to synthesize principles across multiple topics such as physiology, genetics, and molecular biology to interpret complex systems. For example, developmental biology explores gene interactions to understand organismal growth, while neuroscience requires logical deduction to trace the effects of brain lesions.

Problems in these fields frequently involve applying intricate principles in counterintuitive ways. Despite their disciplinary differences, both mathematics and medicine reward individuals who grasp the understanding of logical connections and the 'big picture' when navigating complex and unfamiliar

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challenges rather than those who rote memorize formulas and facts. The purpose of this paper is to explore how problem-solving operates across mathematics and medicine, to highlight their shared cognitive structures, and to propose a framework for fostering a big-picture, multi-perspective approach in STEM and medical education.

Despite persistent stereotypes that biomedical success depends primarily on rote memorization, research on clinical reasoning consistently emphasizes the role of structured knowledge, hypothesis generation, and the flexible interplay of analytic and non-analytic processes in expert performance (Eva, 2005; Norman et al., 2007; Schmidt & Mamede, 2015). In parallel, the learning sciences literature on transfer argues that robust performance in new contexts depends on recognizing deep structural similarities across problems and applying governing principles beyond surface features (Barnett & Ceci, 2002). These perspectives suggest that high-level problem-solving in both mathematics and medicine can be understood through shared cognitive operations that privilege principled reasoning, integration, and adaptive use of evidence over recall of disconnected facts.

Building on these converging literatures, this paper makes three contributions. First, it advances a cross-disciplinary conceptual framework that specifies four shared dimensions of expert problem-solving across mathematics and medicine: (1) principle-based reasoning, (2) integration across systems/topics, (3) coordination of quantitative and qualitative data, and (4) transfer to novel contexts. Second, it illustrates how these dimensions manifest in representative tasks and decision situations drawn from mathematical problem-solving and clinical reasoning, aligning with established accounts of how clinicians generate and refine hypotheses under uncertainty rather than relying on undirected recall. Third, it derives implications for STEM and pre-medical education, arguing that curricula and assessment designs should more directly cultivate "big-picture" reasoning, justification, and transfer—competencies widely recognized as central to expertise but often underemphasized in routine instruction.

The next section synthesizes relevant scholarship on clinical reasoning and learning transfer to establish the conceptual foundations for the argument (Eva, 2005; Barnett & Ceci, 2002). The subsequent section presents the proposed framework and uses targeted illustrations to show how each dimension supports effective performance across domains. The paper concludes by discussing instructional and assessment implications and by outlining directions for empirical work that could test and refine the framework's claims.

## 2. Conceptual and Theoretical Foundations

### 2.1 The Interconnected Nature of Problem-Solving in Biological and Medical Sciences

In the biological sciences, particularly in fields like medicine and physiology, there is a common misconception that problem-solving relies heavily on memorizing vast amounts of facts. While memorization has its place, the essence of problem-solving in these fields, much like in mathematics, rests on logical connections and deductive reasoning. The challenges in biological sciences often span multiple topics, requiring more than just knowledge of isolated facts. For instance, a student diagnosing gas exchange failure in the lungs may need to consider epigenetic factors affecting the heart. Should they examine the relationship between alveoli and blood flow? Could the issue stem from a receptor malfunction or genetic factors? Or is it necessary to reassess all the available information? In some cases, gas exchange failure in the lungs can lead to hypoxia, inflammation, oxidative stress, and increased pulmonary pressure, which may alter gene expression in the heart's cardiac tissue (Barnes, 2009). These questions illustrate how a single problem can involve three or four seemingly unrelated subjects. The human body is an integrated system, and solving its complex problems requires understanding the intricate connections between its various components.

Beyond foundational topics, clinical diagnosis itself requires integrative reasoning. For instance, suppose there exists a woman with pleuritic chest pain, shortness of breath, and mild tachycardia. A memorized list of causes such as pneumonia, pulmonary embolism, pneumothorax, or anxiety does not provide guidance towards a correct diagnosis or a full clinical picture. The correct approach for problem-solving involves assessing risk factors (recent surgery, immobility, or oral contraceptive use), interpreting vital signs (body temperature, blood pressure, or respiratory rate), and choosing appropriate clinical tests (D-dimer or CT pulmonary angiography) in a logical sequence (Gulati et al., 2021). Diagnostic reasoning was originally characterized by Elstein et al. (1978) in *Medical Problem Solving: An Analysis of Clinical Reasoning* as a process in which clinicians generate a limited set of diagnostic hypotheses and then seek evidence to support or refute them. In stages, the clinician will update the likelihood of competing differential diagnoses rather than mechanically matching symptoms to a memorized pattern (Elstein et al., 1978; Schmidt & Mamede, 2015).

This clinical reasoning mirrors mathematical thinking where hypotheses can be created, tested against new information, and revised using rules. In the medical field, this reasoning can be described through frameworks that include illness scripts, hypothesis generation, and dual-process models of thinking with all of them emphasizing organized knowledge and evaluation over unstructured rote recall (Schmidt et al., 1990). These approaches towards learning and problem solving align with research on clinical expertise in medicine, showing that high-level performance depends on meaningful cognitive structures instead of volume of memorized facts (Yazdani & Abardeh, 2019).

### 2.2 The Big Picture Approach in Biomedical Problem-Solving

Problem-solving in the biological sciences relies heavily on a 'big picture' approach. In his workbook *Organic Chemistry as a Second Language*, Johns Hopkins professor David Klein likens organic chemistry to "one long story" that "make[s] sense in the grand scheme of the plot" - "if your attention wanders for too long, you could easily get lost" (Klein, 2004). He explains that just as someone understands a movie not by memorizing every line, but by grasping how the characters, plot, and scenes are interconnected, problem-solving in organic chemistry depends on understanding the overarching concepts. Klein emphasizes that asking "the right questions" tied to the core principles is key to this 'big picture' approach (Klein, 2004). While he acknowledges that basic rules, like nomenclature, require memorization, he sees these as merely tools for learning the language of organic chemistry rather than for true problem-solving. Ultimately, Klein's central point is clear: to solve complex problems, one must understand the guiding principles.

A similar big picture orientation is vital to effective clinical and biomedical reasoning (Eva, 2005; Norman et al., 2007). For example, a clinician who must interpret abnormal liver function tests, electrolyte disturbances, and endocrine profiles requires understanding of how organ systems interact with each other than recalling isolated thresholds for each system. Physicians must identify which core mechanisms - such as perfusion, obstruction, feedback regulation, or inflammation - could explain the observed findings, and then they should provide the proper pharmacology to treat a patient. This emphasis of organizing principles over disconnected details parallels Klein's views and reinforces that biomedical problem-solving is conceptual and not purely mnemonic.

### 2.3 The Big Picture Approach in Mathematical Problem-Solving

In mathematics, as in the biological sciences, individuals must rely on analytical and logical thought processes to solve problems effectively. Since mathematics is built upon a set of foundational rules (known as axioms), solving mathematical problems often requires understanding their subtleties and underlying principles. Like the biological sciences, mathematics demands familiarity with basic facts - such as formal definitions, rules, mathematical operators, and function types. However, the distinction is the same in both fields: while memory is important to some degree, true problem-solving comes from using these tools thoughtfully and grasping the broader concepts at play. Students who master this approach will thrive far more than those who misuse these tools.

Lehoczky and Rusczyk (2006) assert that mathematics is not about memorizing "facts, but approaches". He explains that math problems should teach students to logically work through any problem, where the memorizer can only solve familiar problems, but the problem solver can tackle unfamiliar ones. Such problems engage with how a single mathematical constraint or condition influences a larger set of established rules. They also emphasize that "formula sheets are not really math," comparing memorizing formulas to memorizing historical dates or spelling words (Lehoczky & Rusczyk, 2006). According to them, true mathematics is not about the rote application of facts, just as effective communication is not simply about reciting memorized vocabulary.

Similar to biology, problem-solving in mathematics relies on a 'big picture' approach. Lehoczky and Rusczyk (2006) encourages students not to memorize 'routine tricks' but to understand that these tricks are merely "extensions of a few basic principles". They emphasize that successful problem solvers and mathematicians "[possess] fewer tools," but they know "how to apply them" to a wide range of problems (Lehoczky & Rusczyk, 2006). This skill comes from adopting a 'big picture' mentality rather than following the "memorize-use-forget" method (Lehoczky & Rusczyk, 2006). Drawing from their own experience, Lehoczky and Rusczyk (2006) illustrates how organic chemistry parallels mathematics in problem-solving. In his Princeton Organic Chemistry class, he observed two diverging paths: one taken by memorizers, who saw each new concept as "coordinates" to be memorized, and another taken by problem solvers, who viewed "each new destination … as the result of a path from the building blocks" (Lehoczky & Rusczyk, 2006). He notes that while this class appeared to have no direct link to math, those who relied solely on memorization were ultimately "doomed" - though, in the end, they managed to get by (Lehoczky & Rusczyk, 2006). Like

Professor Klein, Rusczyk champions the 'big picture' as a key guiding principle, cautioning that an overemphasis on isolated details can lead to failure.

### 2.4 Gap and Need for a Cross-Disciplinary Framework

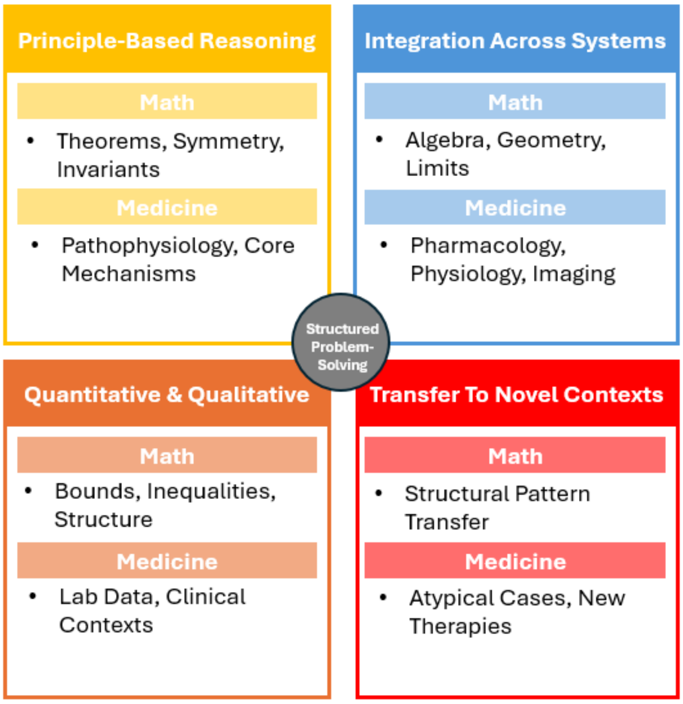
STEM and pre-medical education often emphasize procedural recall - memorizing steps, structures, or equations - over flexible reasoning (Bransford et al., 2000; Hmelo-Silver, 2004). While such memorization aids short-term performance, it hinders long-term adaptability, particularly in novel or interdisciplinary contexts. This gap is reflected in curricula and assessments that reward routine execution more than principled justification or transfer across contexts. Although prior work has examined problem-solving within individual domains, fewer approaches articulate a shared framework that spans both mathematical and clinical reasoning. This paper addresses this gap by proposing a unified framework for "big picture" problem-solving across mathematics and medicine.

## 3. Framework Development: Shared Dimensions of Expert Problem-Solving

### 3.1. A Cross-Disciplinary Framework for Problem-Solving

Figure 1 presents a cross-disciplinary framework that articulates shared phases of problem-solving in mathematics and medicine.

Figure 1
*A Cross-Disciplinary Framework for Problem-Solving in Mathematics and Medicine*




In Figure 1, each quadrant shows similar cognitive operations in mathematics and medicine, highlighting shared underlying structures of expert problem-solving. Building on the prior literature, this section describes a cross-disciplinary framework. This paper proposes four dimensions of effective problem solving in mathematics and medicine: 1) applying principle based reasoning which starts from core mechanisms and theorems rather than isolated facts 2) integrating topics across systems where multiple domains connect (e.g., physiology, pharmacology, and imaging; algebra, geometry, and limits) within a single problem 3) coordinating quantitative and qualitative data where numbers (lab values, risk scores, probabilities) are interpreted in light of mechanisms and rules, not treating them as free-floating or unconnected 4) transferring current knowledge to unfamiliar contexts where known structures are applied to novel tasks such as clinical presentations or interdisciplinary questions (Barnett & Ceci, 2002; Perkins & Salomon, 1992). The subsequent examples below from Biology Olympiad questions and peptide chemistry to diagnostic testing, SVD in bioinformatics, pharmacokinetic models, and clinical case analysis illustrate how these dimensions operate in practice across both fields.

### 3.2. Illustrative Applications of the Framework

*3.2.1. Problem-solving in Biology: Olympiad-style questions*

Building on my previous point, reasoning in biology is developed through critical thinking. Martyna Petrulyte, a trained competitor in the United States Biology Olympiad and International Biology Olympiad, emphasizes that biology is not just about "parrot learning" but about applying and truly understanding biological concepts (Petrulyte, 2018). Elaborating on this, Petrulyte (2018) explains that success in biology often involves navigating "unfamiliar situations" and drawing "reasonable conclusions" (Petrulyte, 2018). In these Olympiads, competitors frequently face multiple answer choices that seem plausible, creating a challenge. To determine the correct response, participants must rely on "higher cognitive skills" rather than rote recall, as these questions are deliberately designed to discourage mindless memorization (Petrulyte, 2018). A common piece of advice given to competitors is that 'there is always a best answer,' though it may not be an answer that fully addresses the question (Petrulyte, 2018). In other words, the best response is often determined by reasoning rather than simple fact recall. If a student merely memorizes answers to specific questions, they risk choosing the wrong answer when the context changes. Therefore, it's essential to understand the underlying concepts rather than relying on memorization. Additionally, questions often ask how blocking or inhibiting a step in a biological pathway might affect subsequent steps, pushing students to hypothesize and deduce outcomes. These types of questions not only require knowledge of the pathway but also demand careful judgment and critical thinking when faced with the unfamiliar. Consider two types of questions below: the first (example 1), which only requires rote memorization, and the second (example 2), which demands rote memorization and creative problem-solving. In the latter, students must go beyond simple recall and use logic to solve problems.

*Example 1*

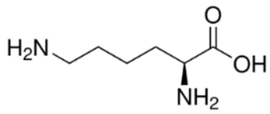
There are roughly 500 amino acids identified in nature, but just 20 amino acids make up the proteins found in the human body. Which of the following amino acids *generally* has the potential to form a covalent disulfide bond?

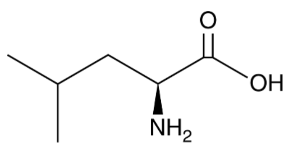
- **A. Cysteine**
- B. Valine
- C. Alanine
- D. Proline

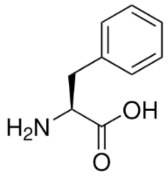
In example 1, rote recall tells us that *cysteine (option A)* contains a thiol (-SH) group, which can form disulfide bonds (S-S) through oxidation. This process results in the formation of covalent bonds between two cysteine residues, thereby strengthening protein stability and structure. In contrast, the other amino acids in this scenario are hydrophobic and lack the ability to form such bonds.

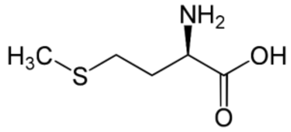
*Example 2*

There are roughly 500 amino acids identified in nature, but just 20 amino acids make up the proteins found in the human body. Which of the following amino acids more generally has the potential to form a covalent bond with a similar amino acid in another polypeptide chain:

**A.** 

B. 

C. 

D. 

In example 2, rote memorization only helps identify the structures as follows: option A (lysine), option B (leucine), option C (L-phenylalanine), and option D (D-methionine). Since both leucine and L-phenylalanine are hydrophobic, they cannot participate in disulfide bonding, narrowing the choices down to lysine and methionine. Under normal conditions, cysteine is typically responsible for forming covalent disulfide bonds, but cysteine is not one of the options. Lysine, however, can form covalent bonds in certain biological contexts, such as cross-linking with other lysine residues or during post-translational modifications.

Methionine, while containing sulfur like cysteine, is structurally different; its sulfur is part of a thioether group (-S-$CH_3$), which does not participate in disulfide bond formation.

Additionally, it's important to note that option D is D-methionine, the enantiomer of the naturally occurring L-form (Nelson & Cox, 2017). Most amino acids in proteins exist in the L-configuration, and D-amino acids are rare in biological systems, particularly in eukaryotes like humans (Nelson & Cox, 2017). D-methionine is unlikely to participate in the same biological processes as L-amino acids, making it an improbable choice. Therefore, option A, lysine, is the best answer. Lysine can form covalent bonds in specific biological contexts, such as protein cross-linking (e.g., in collagen) and post-translational modifications (like ubiquitination). Lysine's side chain properties make it highly reactive. It is a polar amino acid, positively charged, and water-soluble, which contrasts with methionine's hydrophobic side chain. More importantly, by carefully analyzing the structural properties of the amino acids, one can logically deduce that lysine is the correct answer, eliminating the need for memorizing isolated facts.

*3.2.2. Problem-solving in clinical assessment: Insights from USMLE step 2 CK*

USMLE STEP 2 CK questions are built to focus on structured clinical problem-solving rather than rote recall in most cases, and their recurring patterns make this clear. A large number of questions are multi-step vignettes that first require identifying the most likely diagnosis (often from incomplete or sometimes atypical presentations) and then identifying the single best next step in either evaluation or management based on disease severity, stability, and evidence-based algorithms. In terms of diagnosis, it is logical to have one diagnosis explain as many symptoms as possible and problems that a patient is having since many diseases have similar symptoms. In certain cases, a subset of questions separates best initial test from most accurate test, forcing students to weight invasiveness, cost, and safety rather than automatically choosing the gold standard test. Many questions probe exceptions and contradictions to default practice (e.g., how should one treat a patient with a true drug allergy, pregnancy, organ dysfunction, QT prolongation, or overlapping toxicities), rewarding attention to constraints and conditional logic. Other questions emphasize the importance of longitudinal and systems thinking, preventive care and screening thresholds, prognostic factors, hospital protocols, ethics, communication, quality improvement, and patient safety. Data-heavy items such as tables, EKGs, ABGs, imaging, growth charts, trial abstracts, 2x2 diagnostic tables require interpretation and integration, not just formula memorization (Schmidt & Mamede, 2015; United States Medical Licensing Examination, 2021).

Altogether, these patterns show that STEP 2 CK is an organized test of big-picture reasoning: examinees must filter noise in questions stems, apply core mechanisms, navigate decision trees, and justify one coherent choice among many plausible options. Although the USMLE STEP 2 CK does not have free response questions, some answer options can stem from A to K as to offer many possible options from many potentially partially correct options, eliminating guessing and thus making it difficult for mindless rehearsal. Examinees must navigate algorithms, weigh competing options, and recognize when standard approach fails due to contextual factors. In addition, question stems can often be imprecise by using vague language, paraphrasing canonical buzzwords with synonymous or indirect phrasing, and connecting familiar concepts in unfamiliar combinations (National Board of Medical Examiners [NBME], 2016). The NBME Item-Writing Manual emphasizes that clinical examinations are designed to assess the application of underlying concepts instead of isolated factual recall, where item writers are trained to create vignettes and stems that require interpretation of clinical information and avoidance of cues that favor superficial test-taking strategies (National Board of Medical Examiners [NBME], 2016). The NBME guidelines recommend clinical vignettes and one-best-answer item formats that assess reasoning and interpretation of information with clear stems and plausible distractors to reduce one's reliance on superficial cues (National Board of Medical Examiners [NBME], 2020). This design penalizes surface pattern-matching and rewards examinees who recognize underlying mechanisms and structures despite changes in wording or context. Successful problem-solvers must therefore map novel phrasing onto known conceptual schemas rather than search for memorized trigger words. Those who approach these questions as disconnected facts or checklist can miss the forest for the trees: individuals may recall guidelines or drug names but fail to recognize the overall pattern that makes one management step uniquely correct. This style of questioning can resemble mathematical problem-solving in which individuals are rewarded for identifying structures, applying general principles, handling exceptions, and justifying a single best solution with many possible routes.

The USMLE STEP 2CK has several vignettes with recurring decision patterns. Firstly, trends triumph over clinical snapshots. Normal vital signs can currently hide a dangerous trajectory (e.g., blood pressure sliding from 127 to 110 to 96 over hours, and respiratory rate trending from 16 to 22 to 30), which could cue one towards sepsis or hemorrhage pathways rather than simple reassurance (United States Medical Licensing Examination, 2021). Secondly, severe-sounding stems often demand basic first steps: reflux with "crushing" chest pain requires a PPI trial, postpartum fever without uterine tenderness but with focal breast findings can point to mastitis but not broad endometritis workups (United States Medical Licensing Examination, 2021). Thirdly, one is often confronted by having to select the earliest appropriate test instead of the fanciest, most accurate test (e.g., non-contrast head CT now before MRI; fourth-generation Ag/Ab or NAAT before older ELISA in early infection). The exam can place decoy labs that will not change care or management (e.g., mild hyponatremia in a psych admission; a small bilirubin bump in gallstone pancreatitis). When confronted with two competing diagnoses that fit, it is often helpful to choose one that changes immediate action (e.g., diffuse ST-elevation with normal troponin to treat pericarditis instead of catheterization for myocardial infarction). In certain cases, medical disposition is the importance - clinic versus emergency department versus admit versus telemetry - rather than the label itself (United States Medical Licensing Examination, 2021). The timestamps (postpartum hours, fever day ≥5, specific post-op day) at which illnesses occur are important as the same symptoms can imply different processes at different times (United States Medical Licensing Examination, 2021). Lastly, the examinee must switch between chronic to acute thinking when viewing clinical vignettes: a COPD flare needs steroids and bronchodilators now, not smoking cessation counseling; flash pulmonary edema needs diuretics/vasodilators, not long-term med optimization (United States Medical Licensing Examination, 2021). STEP 2CK allows the individual to see vignettes through lenses that convert thousands of elements into a small set of structured templates suited for the patient's best interest.

*3.2.3. Mathematical problem-solving beyond memorization*

Consider the two types of questions below: the first (example 3) requires only the rote application of mathematical tools, while the second (example 4) demands creative thinking that goes beyond simple recall.

*Example 3*

Evaluate if it exists (Dawkins, 2008).

$$\lim_{x\to 2}(8 - 3x + 12x^2)$$

The solution to this problem involves basic rules for computing limits, such as directly substituting the value to check if the limit can be determined (Stewart, 2015). A straightforward application of mathematical principles provides the solution with ease.

$$\lim_{x\to 2}(8 - 3x + 12x^2) = 8 - 3(2) + 12(4) = 50$$

*Example 4*

Suppose $a, b, x, y,$ are all positive and $a + b = 1$. Compute (Patrick, 2010).

$$\lim_{t\to 0^+} (ax^t + by^t)^{\frac{1}{t}}$$

The basic rule for computing limits fails in this case, as it leads to an undefined solution. Therefore, one must recognize the need for additional mathematical principles to solve the problem correctly. One useful approach is to apply logarithmic properties to transform the limit into a different form, such as an indeterminate one (Patrick, 2010).

$$\lim_{t\to 0^+} (ax^t + by^t)^{\frac{1}{t}}$$

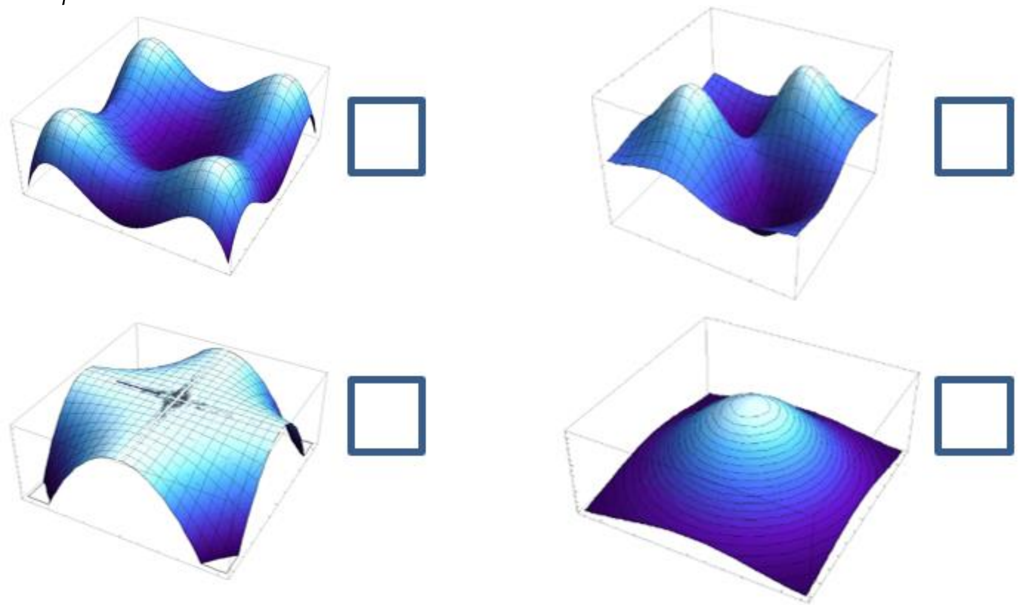
$$\lim_{t\to 0^+} \frac{log(ax^t + by^t)}{t}$$

Further evaluation requires using L'Hôpital's rule, which simplifies the process of evaluating limits in this form.

$$\lim_{t\to 0^+} (\ ax^t(log\ (x)\ ) + by^t(log\ (y)\ )\ ) = \ alog\ (x)\ + b\ log\ (y) = log(x^a y^b)$$

The final evaluation leads to $x^a y^b$ as the final solution. In this case, a simple rote application of mathematical principles is insufficient, as the problem requires more complex steps and the integration of multiple concepts to reach the correct solution.

*Example 5*



For each function label its graph from the options below, you may only use each function once, two of the graphs should remain unlabelled (Kludze, 2023).

$$A)\, f(x,y) = -\pi x^4 + 2\pi x^2 - \pi y^4 + 2\pi y^2 \qquad B)\, f(x,y) = \frac{1}{\pi} e^{-x^2-y^2}$$

For A, one can rewrite

$$f(x,y) = \pi(-x^4 + 2x^2 - y^4 + 2y^2) = \pi(2 - (x^2-1)^2 - (y^2-1)^2).$$

This rearrangement show that there are four symmetric maxima at $(\pm1, \pm1)$, a lower value at the origin, and rapid decay to large negative values away from this square - so the correct surface must have four equal hills surrounding a central valley. No pointwise computation is needed. They could also use quick traces:

$$f(x,0) = g(x), f(0,y) = g(y),$$

seeing a 1D quartic with a minimum at 0 and maxima at $\pm1$. This suggests a surface with a central valley and four surrounding peaks. Then one could use the second derivative test qualitatively while assessing the sign of $f_{xx}$ and $f_{yy}$. The answer is thus the first graph in the top left corner (e.g., row 1, column 1).
For B, the function

$$f(x,y) = \frac{1}{\pi} e^{-x^2-y^2}$$

is positive, radially symmetric, maximized at the origin, and decreases smoothly as $\sqrt{x^2+y^2}$ grows. Its graph must be the single, circular "Gaussian bump" among the options. Recognizing this comes from seeing the dependence on $x^2+y^2$, not grinding out derivatives. Here the key is spotting $x^2+y^2$. In polar coordinates,

$$f(r,\theta) = \frac{1}{\pi} e^{-r^2},$$

which is independent of θ. That immediately tells the big-picture student: perfect rotational symmetry about the origin, single maximum at $r = 0$, and smooth decay to 0 as r increases. The answer is thus the fourth graph in the bottom right corner (e.g., row 2, column 2).

In contrast, a formula-driven student can approach the task locally and mechanically. For $f(x,y) = -\pi x^4 + 2\pi x^2 - \pi y^4 + 2\pi y^2$, they plug in a few points or blindly compute $f_x, f_y, f_{xx}, f_{yy}$ at the origin without relating these to the overall shape. For $f(x,y) = \frac{1}{\pi} e^{-x^2-y^2}$, they may only think "exponentials go to zero" and choose any decaying surface, missing the decisive radial symmetry. In either case, the functions are treated as a black box for pointwise calculation, thus this method is slow and inefficient while never explaining why a particular surface must match a formula. More importantly, one could be misled by the scaling or orientation until they eventually stumble onto the correct match. The big-picture solver instead reorganizes the expressions (e.g., recognizing $x^2 + y^2$, spotting $(x^2 - 1)^2$ terms, identifying symmetry and repeated structure), then uses those global properties to eliminate incompatible graphs in a few decisive steps. The pedagogical point is that success relies on recognizing symmetry, rewriting expressions to expose geometry, locating critical points conceptually, and discarding incompatible graphs - a structured, global reading of information, not brute-force calculation (Marsden & Tromba, 2012).

*3.2.4. Intersections of mathematics and medicine*

Although medicine and mathematics are distinct fields, they often intersect in important ways. Both rely on formal models and structured reasoning that draw on shared habits of principled thinking, system-level integration, data interpretation, and transfer to new contexts. For example, biostatistics relies on complex formulas to design clinical trials, evaluate the effectiveness of treatments and vaccines, and assess health interventions within populations (Marchenko et al., 2020). These fields utilize statistical models and data analysis to interpret medical data and derive meaningful insights. Take, for instance, the question: How reliable is a urine hCG test compared to a blood test? (Altman, 1991; Marchenko et al., 2020). To answer this, one would need to use sensitivity and specificity, gold standards for evaluating diagnostic tests, both of which involve mathematical formulas to assess the accuracy and reliability of the test results (Altman, 1991; Marchenko et al., 2020). The logical outcomes of the urine hCG test based on condition/disease and test result are shown in Table 1. The equations are described below:

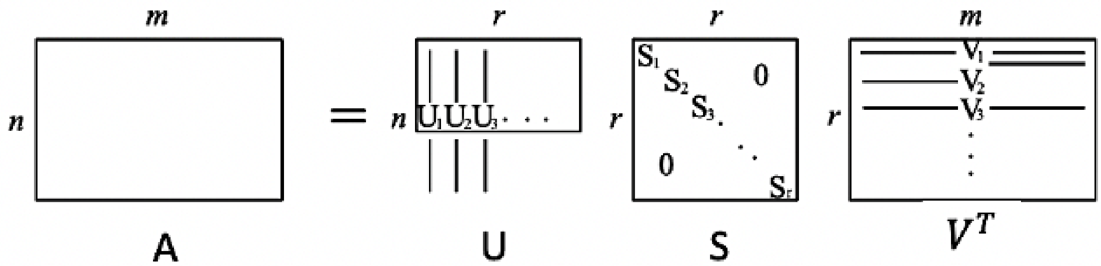
$$Sensitivity = \frac{TP}{TP + FN} \qquad Specificity = \frac{TN}{TN + FP}$$

Table 1
*Standard 2×2 contingency table illustrating sensitivity and specificity for a diagnostic test (created by the author)*

| | *Subject with Disease/Condition* | *Subject without Disease/Condition* |
|---|---|---|
| Positive Test | TP | FP |
| Negative Test | FN | TN |

This illustrates coordination of quantitative and qualitative data (dimension 3) and principle-based reasoning (dimension 1), where sensitivity and specificity act as constraints on diagnostic hypotheses rather than memorized facts. Bioinformatics and computational biology offer another example of the intersection between mathematics and biology, relying on algorithms and linear algebra concepts to analyze large datasets commonly found in genomics and proteomics. One such technique is Singular Value Decomposition (SVD), a matrix factorization method that breaks down a matrix into three simpler matrices (Alter et al., 2000). In bioinformatics, SVD is particularly useful for gene expression analysis and dimensionality reduction, helping to make sense of high-dimensional biological data that would otherwise be challenging to interpret (Alter et al., 2000). For instance, rows in a gene expression dataset often represent genes, columns represent different conditions (such as tissues or time points), and each matrix element corresponds to the expression level of a specific gene under a particular condition (Alter et al., 2000).

Figure 2
*Visualization of singular value decomposition (schematic)*




SVD can reduce the dimensionality of such datasets by filtering out noise, allowing the most relevant biological signals to emerge. This process, combined with gene clustering, helps uncover common biological and regulatory patterns, providing deeper insights into cellular processes. The gene matrix can be expressed mathematically as

$$A = USV^T$$

where A is matrix of gene expression data, U and V are orthogonal matrices, and S is a diagonal matrix containing the singular values. The visualization of the matrix decomposition is shown in Figure 2 (Zeybek et al., 2021). This reflects integration across systems/topics (dimension 2) and transfer to novel contexts (dimension 4), where abstract linear algebraic structures organize biological meaning across thousands of variables. Although adapted from a machine-learning paper, this schematic illustrates the domain-independent algebra of SVD used in bioinformatics (Zeybek et al., 2021).

Pharmacokinetics and pharmacodynamics commonly use differential equations to model the interactions of drugs within the human body. The compartment model is one approach used to measure how drugs are absorbed, distributed, metabolized, and eliminated (Shargel, 2012). A widely applied model in this field is the first-order kinetic model, which provides insights into how drug concentration in the bloodstream changes over time (Gabrielsson, 2016). This model simplifies the body into a single compartment and assumes that drug elimination is proportional to its concentration at any given moment. Using a first-order linear differential equation, it shows how drug concentration decreases exponentially over time. The equation for drug elimination is as follows:

$$\frac{dC(t)}{dt} = -k_e C(t)$$

where C(t) is the concentration of the drug in the bloodstream at time t, $k_e$ is the elimination rate constant, and $\frac{dC(t)}{dt}$ represents the rate of change of the drug concentration over time. This model is crucial for determining appropriate dosing schedules to prevent drug toxicity. This exemplifies principle-based reasoning and transfer, where a small number of differential equations govern diverse clinical dosing scenarios rather than memorized drug-specific rules. It also offers valuable insights into optimal dosing regimens and helps predict potential drug interactions across specific time intervals (Gabrielsson, 2016).

*3.2.5. Examples of problem-solving in interdisciplinary applications of medicine and mathematics*

Consider the following two examples of a problem that can be approached using both mathematical and biological methods.

*Example 6*

While studying meese, you find that the number of meese in two adjacent populations can be modeled using the following equations. Note that a(x) is the population of population A at x years and b(x) is the population of population B at x years (USABO-Center for Excellence in Education, 2020).

$$a(t+1) = 0.7a(t) + 0.3b(t)$$

$$b(t+1) = 0.3a(t) + 0.7b(t)$$

Currently, population A has 500 meeses, while population B has 5000 meeses. Which of the following is true? Select ONE.

A. The two populations will coexist with a higher population A
B. The two populations will coexist with a higher population B
**C. The two populations will coexist with equal populations**
D. Population A will disappear, leaving only population B
E. Population B will disappear, leaving only population A

The approach which uses mostly biology concepts still requires mathematical analysis to observe that the equations for $a(t+1)$ and $b(t+1)$ are symmetric, meaning that over time, populations A and B will influence each other at the same rate. Although population B starts larger than population A, the symmetry of the system ensures that both populations will eventually converge to the same value, resulting in equalized populations. Therefore, the two populations will coexist with equal populations.

A second approach involves using formulas and step-by-step problem-solving. First, the initial conditions can be identified as $a(0) = 500$ and $b(0) = 5000$ . To find equilibrium, one sets the equations $a(t+1) = a$ and $b(t+1) = b$, leading to the system of equations:

$$a = 0.7a + 0.3b$$

$$b = 0.3a + 0.7b$$

Solving for a and b, one finds that equilibrium occurs when a = b. The total population is the sum of the two initial populations:

$$a(0) + b(0) = 500 + 5000 = 5500$$

Since a = b at equilibrium, each population equals half of the total:

$$a = b = \frac{5500}{2} = 2750$$

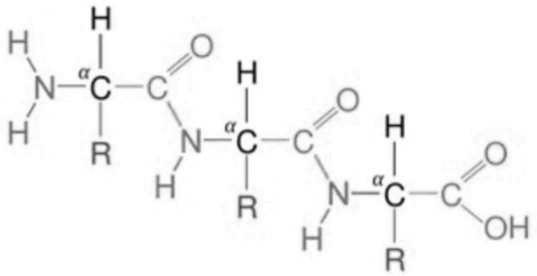
Thus, answer choice C is correct.

Lastly, consider this final example, which requires both mathematical reasoning and underlying biological concepts to solve the problem creatively.

*Example 7 adapted*

Figure 3

*Peptide bond formation and tripeptide structure with generic R groups. Image adapted from Wikimedia Commons (CC BY-SA 4.0)*



A small peptide with three peptide bonds consists of Gly-Ala-Gly-Ala (Bretscher, 2020). Given the subunit molecular weight of Ala is 89 and Gly is 75, what is the molecular weight of the oligopeptide (atomic weights are as follows: H, 1; O, 16; C, 12; N. 14)? An oligopeptide is shown in Figure 3 as a reference.

A. 382
B. 328
**C. 274**
D. 256
E. None of the above

To solve the problem, one must first calculate the molecular weight of the oligopeptide Gly-Ala-Gly-Ala by summing the molecular weights of all the amino acids and accounting for the loss of water molecules during peptide bond formation. The molecular weight of the glycine residues is:

$$GLY_{total} = 2 \times 75 = 150$$

and for the alanine residues:

$$ALA_{total} = 2 \times 89 = 178$$

The total molecular weight of the amino acids before peptide bond formation is:

$$150 + 178 = 328$$

Next, recall the biological principle that each peptide bond formation results in the loss of one water molecule ($H_2O$, molecular weight = 18). In this tetrapeptide, there are 3 peptide bonds, leading to a total weight loss of:

$$3 \times 18 = 54$$

Therefore, option 274 is the correct option as bolded, and the final molecular weight of the oligopeptide is:

$$328 - 54 = 274$$

If the water loss is not accounted for, the calculated molecular weight will be incorrect.

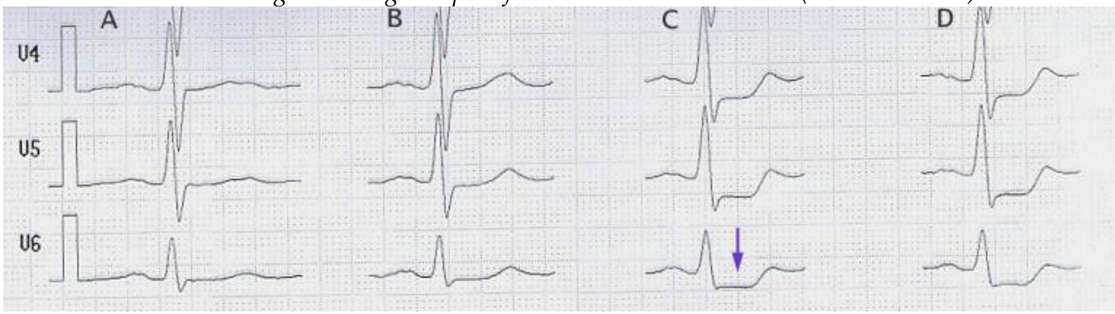
### *3.2.6. Clinical problem-solving examples*

A similar distinction between memorization and principled reasoning appears in clinical scenarios.

*Example 8 - Chest Pain Triage (author-created vignette, based on guideline-recommended evaluation of acute chest pain)*

Figure 4

*Twelve-lead electrocardiogram. Image adapted from Wikimedia Commons (CC BY-SA 3.0)*



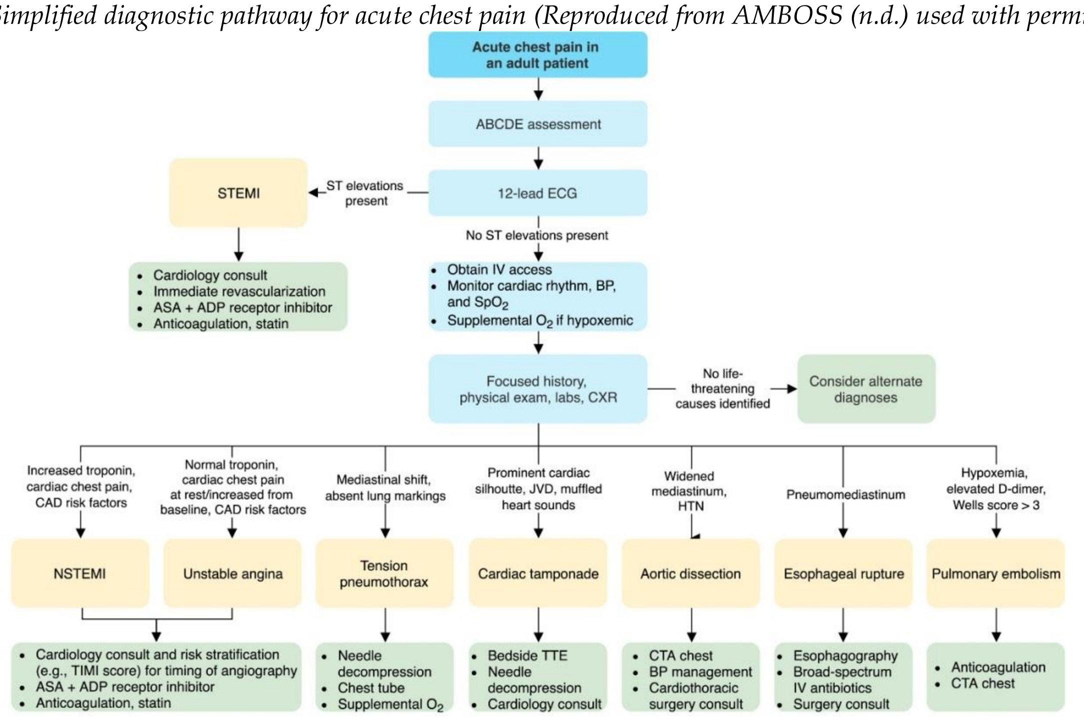

A 55-year-old man presents 40 minutes after exertional substernal pressure with diaphoresis. He has hypertension, hyperlipidemia, and a 30-pack-year smoking history. He is hemodynamically stable. An ECG is shown (Figure 4). What is the most appropriate next step in management?

A. Discharge with outpatient follow-up
B. Schedule outpatient stress test
**C. Admit for serial troponins and initiate therapy for non-ST-elevation ACS**
D. Give immediate fibrinolytic therapy
E. Reassure; no further evaluation

The correct answer is marked in bold. The patient's ischemic pain, risk factors, and ischemic ST changes define high-risk non-ST elevation acute coronary syndrome despite a normal initial troponin (Gulati et al., 2021). Big-picture reasoning requires one to integrate all the cues and mandates admission, serial biomarkers, monitoring, and guideline-directed therapy, rather than focusing on a single lab value or red flag. In terms of patient care, one could ask themselves what factors could lead to this patient's death within five minutes, an hour, or 24 hours while ruling out information and symptoms that do not align with the differential diagnoses.

Figure 5

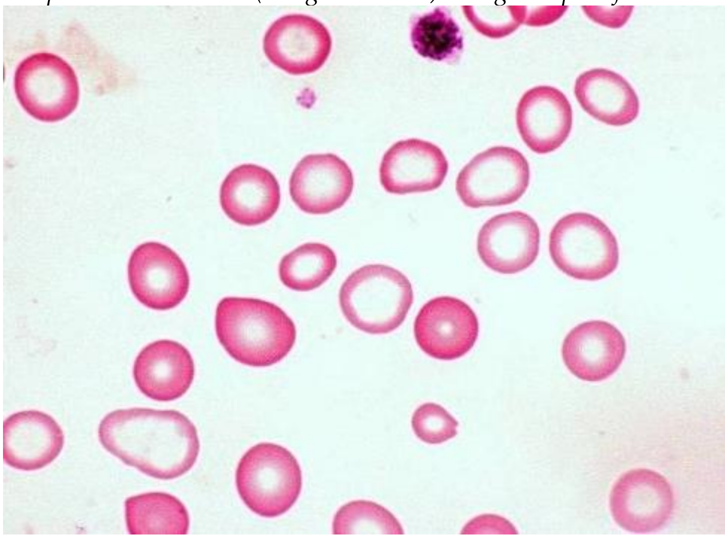
*Simplified diagnostic pathway for acute chest pain (Reproduced from AMBOSS (n.d.) used with permission)*



To make the logic more explicit, Figure 5 shows a simplified diagnostic pathway for acute chest pain. This pathway structures care into sequential decisions - initial stabilization, ECG-based stratification, evaluation for life-threatening causes, and risk-based testing, where each new data point (ECG, troponin, risk factors) updates the likelihood of competing diagnoses instead of a memorized list of symptoms (Gulati et al., 2021). This functions as a mathematical decision tree in which each new piece of data (ECG, troponin, imaging, risk scores, etc.) act as constraints that narrow the diagnostic search space, analogous to branch and bound algorithms in discrete mathematics. The clinician at each step implicitly performs Bayesian updating where one revises the probability of competing diagnoses based on incoming evidence rather than relying on static symptom disease associations (Elstein & Schwarz, 2002; Schmidt & Mamede, 2015). In this example, acute chest pain evaluation does not only require pattern recognition by itself, but rather an iterative constraint and probabilistic inference process which reflects how mathematical solution spaces are progressively reduced by constraints.

*Example 9 - Anemia Workup (author-created vignette, based on UCSF hospital handbook for anemia)*

Figure 6
*Peripheral blood smear (Wright-Giemsa). Image adapted from Wikimedia Commons (CC BY-SA 4.0)*

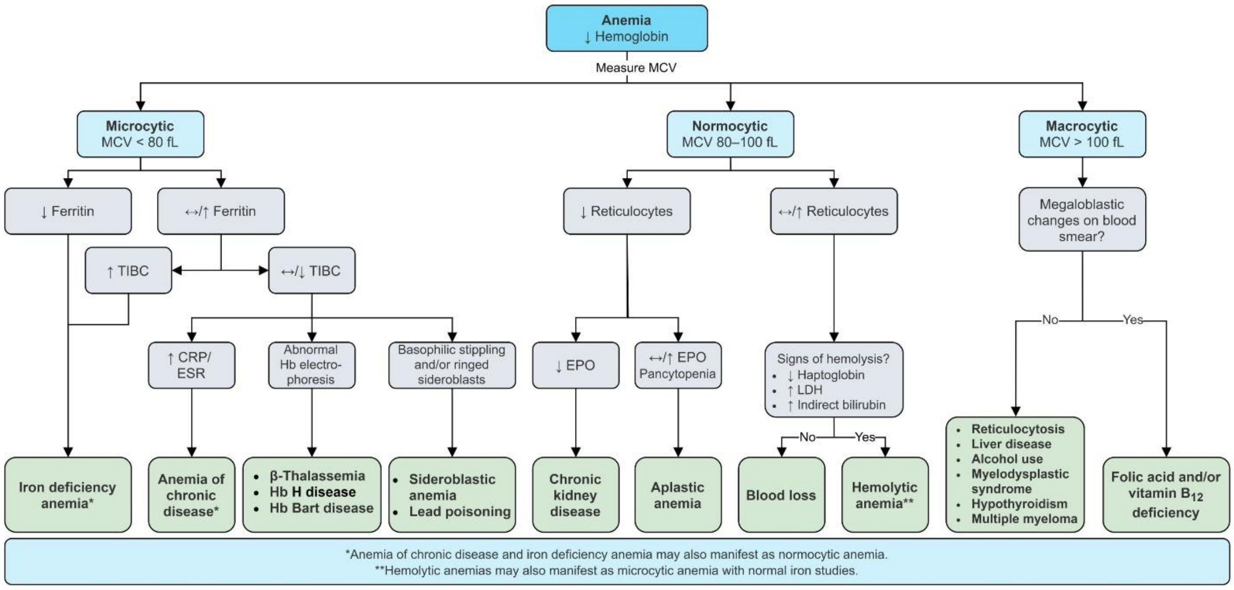


A 70-year-old woman has progressive fatigue and exertional dyspnea. She is postmenopausal and takes daily naproxen for osteoarthritis. Conjunctivae are pale; vitals are normal. Labs: Hb 9.0 g/dL, MCV 72 fL, ferritin 8 ng/mL, TIBC increased. A peripheral smear is shown (Figure 6). What is the most appropriate next step?

A. Start oral ferrous sulfate only and recheck in 3 months
B. Hemoglobin electrophoresis
C. Bone marrow biopsy
**D. Bidirectional endoscopy (colonoscopy and EGD) to evaluate occult GI blood loss**
E. Fecal immunochemical test (FIT) as sole next step

The correct answer choice is marked in bold (Walker & Cornett, 2025). In men and postmenopausal women, confirmed iron-deficiency anemia warrants endoscopic evaluation for occult gastrointestinal bleeding or malignancy (e.g., esophagogastroduodenoscopy, colonoscopy, or bidirectional endoscopy) instead of empiric iron therapy alone or noninvasive screening tests (American Gastroenterological Association [AGA], 2020). The figure provided is intentionally unlabeled as examinees must integrate the smear with quantitative data not only rely on a caption hint. When evaluating anemia, the act of simply memorizing iron deficiency versus B12 versus chronic disease is insufficient. A better approach uses a structured sequence - mean corpuscular volume, reticulocyte count, ferritin, inflammatory markers, hemolysis labs - to narrow possibilities (Walker & Cornett, 2025). Each result acts like a conditional in a proof where it either rules in or rules out branches of a diagnostic tree through logical consistency instead of rote recall alone. In both examples, clinical reasoning reflects the same habits shared in mathematics: defining the problem precisely, identifying relevant invariants, discarding incompatible options, and justifying conclusions with transparent logic.

Figure 7
*Simplified diagnostic pathway for anemia (Reproduced from AMBOSS (n.d.) used with permission)*




To demonstrate the structured reasoning, Figure 7 shows a simplified diagnostic pathway for anemia. The algorithm starts with confirmation of low hemoglobin, uses the mean corpuscular volume [MCV], reticulocyte count, and targeted laboratory tests (iron studies, markers of hemolysis, renal and liver function, vitamin $B_{12}$/folate levels) to narrow the differential. This encourages students not to memorize isolated disease labels, but instead it shows how each test rules in or rules out plausible categories - microcytic, normocytic, and macrocytic processes - and guides clinicians toward the most coherent explanation that satisfies the largest number of physiologic and laboratory constraints, which is similar to identifying feasible solutions in a constraint satisfaction or optimization problem. In addition, the algorithm reduces inconsistent diagnostic categories where each lab results function as a binary or ternary constraint. The diagnostic branching points serve as an implicit Bayesian update where the likelihood of a certain form of anemia is revised as new laboratory evidence is incorporated, reflecting probabilistic inference rather than sole pattern recognition. Therefore, the classification of anemia can be viewed as a multivariable interference problem where MCV, reticulocyte production, iron indices, and hemolysis markers serve as orthogonal dimensions that jointly define a feasible diagnostic region. As with a mathematical decision tree, each branch is determined by explicit criteria and logical consistency, not ad hoc recall.

## 4. Discussion

### 4.1. Theoretical Contribution (What the Framework Adds)

This paper advances a conceptual claim: high-level performance in both mathematics and medicine depends less on isolated recall and more on a shared set of cognitive operations that organize knowledge, constrain hypotheses, and support flexible transfer. Existing work in medical education describes how expert clinicians structure knowledge around mechanisms, generate hypotheses, and iteratively test them against incoming data rather than relying on undirected recall (Eva, 2005; Schmidt et al., 1990; Schmidt & Mamede, 2015). Likewise, research on learning transfer argues that effective performance in unfamiliar contexts requires sensitivity to deep structures and principled connections across problems rather than surface similarity (Barnett & Ceci, 2002; Perkins & Salomon, 1992). The cross-disciplinary framework proposed here integrates these lines of scholarship by specifying four shared dimensions of expert problem-solving—principle-based reasoning, integration across systems/topics, coordination of quantitative and qualitative data, and transfer to novel contexts—and by illustrating how they operate in representative tasks from mathematics and medicine.

Rather than presenting a new theory of cognition, the framework functions as an organizing synthesis that makes several established constructs more explicit and portable across domains. In clinical reasoning, dual-process accounts emphasize interactions between pattern recognition and analytic reasoning (Elstein & Schwarz, 2002; Schmidt & Mamede, 2015). The framework clarifies how analytic reasoning can be strengthened through principled constraints, explicit integration, and systematic interpretation of heterogeneous evidence (e.g., vitals, labs, imaging, risk factors) in ways analogous to mathematical reasoning with invariants and constraints (Lehoczky & Rusczyk, 2006; Marsden & Tromba, 2012). In mathematics education, expert-like performance has been associated with prioritizing structural features—symmetry, constraints, and underlying relationships—over procedural mimicry (Lehoczky & Rusczyk, 2006). The paper's examples (e.g., non-routine limits, surface identification via symmetry, decision pathways in acute chest pain and anemia) serve to demonstrate that these structural priorities can be articulated in a shared vocabulary that spans both mathematical and clinical contexts.

Importantly, the framework's contribution is not to claim that mathematics and medicine are identical, but to argue that their highest-level problem-solving can be described using comparable cognitive moves and designable learning demands. In this sense, the framework offers a conceptual bridge: it can help educators and researchers describe "big picture" reasoning with clearer components and use those components to design tasks, feedback, and assessments that reward justification, integration, and transfer.

### 4.2. Educational Implications (Curriculum, Instruction, Assessment)

The framework implies that STEM and pre-medical curricula should be intentionally designed to cultivate the four shared dimensions rather than assuming they will emerge automatically from content exposure. First, curriculum sequences can foreground principle-based reasoning by repeatedly anchoring new topics in a small set of governing mechanisms (e.g., conservation, equilibrium, feedback regulation, inflammation, perfusion) and asking students to derive predictions or management steps from those mechanisms rather than from memorized lists (Eva, 2005; Schmidt & Mamede, 2015). In mathematics, analogous emphasis can be placed on a small set of fundamental principles and reusable tools, consistent with the claim that mathematics is learned through approaches rather than formula accumulation (Lehoczky & Rusczyk, 2006).

Second, instruction can deliberately require integration across systems/topics by using problems that cannot be solved within a single compartment of knowledge. The paper's biology, pharmacokinetics, and diagnostic testing examples illustrate that expert performance often rests on linking concepts across domains (e.g., physiology with risk stratification and test selection; algebraic structure with geometric interpretation). This aligns with work suggesting that durable understanding is strengthened when learners must reconcile multiple representations and connect ideas across contexts (Bransford et al., 2000). In practice, instructors can use prompts such as "Which principle governs this situation?", "What information changes the decision?", and "What alternative explanations remain plausible?" to normalize cross-linking and hypothesis evaluation.

Third, assessment practices can be adjusted to reward coordination of quantitative and qualitative data and transparent justification. In clinical items, this means requiring students to use trends, risk factors, and test properties (e.g., sensitivity/specificity) as constraints on differential diagnoses and management choices rather than as separate facts (Altman, 1991; Gulati et al., 2021). In mathematics, it means valuing solutions that surface structure (symmetry, invariants, or transformations) and explain why a method works, not merely compute an answer. Rubrics can explicitly allocate credit to the selection of governing principles, the elimination of alternatives, and the coherence of the final justification. Even in multiple-choice contexts, item design can reduce superficial cueing by using plausible distractors that require principled discrimination (NBME, 2016, 2020).

Finally, the framework suggests that educators can use parallel problems across domains to foster transfer—for example, pairing a mathematical limit problem requiring transformation and constraint handling with a clinical test-selection problem requiring trade-offs among accuracy, invasiveness, and timing. Such pairing operationalizes the transfer literature's emphasis on structural alignment across contexts (Barnett & Ceci, 2002; Perkins & Salomon, 1992). Over time, repeated exposure to this kind of aligned reasoning demand may help learners internalize a portable problem-solving schema rather than a domain-bound checklist.

### 4.3. Boundary Conditions and Limitations

This paper is conceptual and illustrative. It synthesizes existing scholarship and uses representative examples to show how the proposed dimensions can illuminate problem-solving across mathematics and medicine; it does not provide new empirical data demonstrating that instruction aligned with the framework causes improved performance. Accordingly, the claims should be interpreted as a structured argument supported by prior theory and plausible illustrations rather than as a tested intervention effect.

Moreover, the framework is intended to characterize "high-level" or expert-like problem-solving demands, not all routine tasks in either domain. Some biomedical learning does require memorization (e.g., terminology, foundational facts, drug names), and some mathematical tasks rely on fluent recall of definitions and standard results. The claim is not that memory is irrelevant, but that memorized elements function as tools whose effective use depends on the four dimensions—especially principled reasoning and integration—when tasks become novel, complex, or high-stakes.

A further boundary condition concerns domain-specific knowledge structures. Clinical reasoning includes professional practices (e.g., ethical communication, patient safety, contextual constraints) that do not map neatly onto mathematics, while mathematics includes forms of proof and abstraction that are not identical to clinical justification. The framework therefore emphasizes shared cognitive operations without denying differences in epistemic goals, representations, and stakes. In addition, the examples in this paper are selected to be illustrative of the framework; other task types or specialties may foreground different constraints or require additional dimensions not captured here.

### 4.4. Directions for Empirical Research (Testable Propositions/Hypotheses)

The framework can be strengthened through empirical studies that test whether instruction and assessment aligned with its dimensions improve learning outcomes across contexts. Several testable propositions follow directly from the paper's claims:

- *Principle-based reasoning proposition:* Learners receiving instruction that consistently requires articulation of governing principles before solution attempts will show greater success on novel (non-routine) problems than learners trained primarily on routine procedures, controlling for baseline ability.
- *Integration proposition:* Tasks and curricula that require cross-topic integration (e.g., combining physiology with diagnostic test properties; linking algebraic form to geometric interpretation) will produce higher far-transfer performance than curricula organized as isolated topic blocks, even when near-transfer performance is similar.
- *Quant–qual coordination proposition:* Explicit training in interpreting quantitative indicators as constraints on qualitative hypotheses (e.g., risk scores, trends, likelihood updating) will improve diagnostic accuracy and reduce superficial cue-driven errors in clinical vignettes, compared to training focused on symptom–disease matching alone.
- *Justification proposition:* Assessments that allocate credit to justification quality (principle selection, alternative elimination, coherence) will better discriminate expert-like reasoning than assessments focused mainly on final answers, and may encourage deeper study strategies over rote rehearsal. This can be evaluated by comparing students' written rationales, error patterns, and retention across assessment formats.

Methodologically, future work could employ quasi-experimental course designs, cross-sectional comparisons of novices and advanced learners, or mixed-method studies analyzing students' reasoning traces (e.g., think-aloud protocols, written explanations, structured reflection prompts). In addition, it would be valuable to test whether the framework predicts performance similarly across different medical specialties and across different mathematical subfields, thereby evaluating its generality and boundary conditions.

## 5. Conclusion

This paper has argued that mathematics and medicine share a common problem-solving core grounded in principled reasoning, integration, coordinated interpretation of heterogeneous evidence, and transfer to unfamiliar contexts. Drawing on scholarship in clinical reasoning and learning transfer (Barnett & Ceci, 2002; Eva, 2005; Perkins & Salomon, 1992; Schmidt et al., 1990; Schmidt & Mamede, 2015), and using illustrative examples from Biology Olympiad-style questions, organic chemistry, diagnostic testing, pharmacokinetics, clinical case analysis, and mathematical tasks, the article proposes a four-dimension cross-disciplinary framework: (1) principle-based reasoning, (2) integration across systems/topics, (3) coordination of quantitative and qualitative data, and (4) transfer to novel contexts.

The framework challenges the misconception that biomedical learning is primarily rote memorization by making visible the structured reasoning demands that underlie competent clinical decision-making. At the same time, it clarifies what "big picture" thinking can mean in concrete instructional terms: selecting governing principles, linking information across domains, treating quantitative indicators as constraints on interpretation, and justifying conclusions in a transparent chain of logic. For educators, the practical implication is that course design and assessment can be intentionally aligned to elicit these dimensions—through integrated problems, prompts that foreground mechanisms, and rubrics that reward justification and alternative evaluation—rather than rewarding routine execution alone. For researchers, the framework offers a set of testable propositions that can guide empirical studies of transfer, diagnostic accuracy, and the development of expert-like reasoning across STEM and pre-medical education.

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## References

Alter, O., Brown, P. O., & Botstein, D. (2000). Singular value decomposition for genome-wide expression data. *Proceedings of the National Academy of Sciences, 97*(18), 10101-10106. https://doi.org/10.1073/pnas.97.18.10101

Altman, D. G. (1991). *Practical statistics for medical research*. CRC Press.

American Gastroenterological Association. (2020). *Gastrointestinal evaluation of iron deficiency anemia* [Clinical practice guideline]. https://gastro.org/clinical-guidance/gastrointestinal-evaluation-of-iron-deficiency-anemia/

AMBOSS. (n.d.). *Anemia*. https://next.amboss.com/us/article/6T0j72

AMBOSS. (n.d.). *Chest pain*. https://next.amboss.com/us/article/eo0xaS

Barnes, P. J. (2009). The cytokine network in chronic obstructive pulmonary disease. *American Journal of Respiratory Cell and Molecular Biology, 41*(6), 631-638. https://doi.org/10.1165/rcmb.2009-0220TR

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn? A taxonomy for far transfer. *Psychological Bulletin, 128*(4), 612-637. https://doi.org/10.1037/0033-2909.128.4.612

Bjork, R. A., & Bjork, E. L. (2011). Making things hard on yourself, but in a good way: Creating desirable difficulties to enhance learning. In M. A. Gernsbacher, R. W. Pew, L. M. Hough, & J. R. Pomerantz (Eds.), *Psychology and the real world: Essays illustrating fundamental contributions to society* (pp. 56-64). Worth.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (Eds.). (2000). *How people learn: Brain, mind, experience, and school*. National Academies Press. https://nap.nationalacademies.org/catalog/9853/how-people-learn-brain-mind-experience-and-school

Bretscher, A. (2020). *BioMG 1350: Introductory biology - Cells and development* [Practice exam]. Department of Molecular Biology and Genetics, Cornell University.

Dawkins, P. (2008). *Computing limits*. Paul's Online Math Notes. https://tutorial.math.lamar.edu/Problems/CalcI/ComputingLimits.aspx

Elstein, A. S., & Schwarz, A. (2002). Clinical problem solving and diagnostic decision making: A selective review. *BMJ, 324*(7339), 729-732. https://doi.org/10.1136/bmj.324.7339.729

Elstein, A. S., Shulman, L. S., & Sprafka, S. A. (1978). *Medical problem solving: An analysis of clinical reasoning*. Harvard University Press.

Eva, K. W. (2005). What every teacher needs to know about clinical reasoning. *Medical Education, 39*(1), 98-106. https://pubmed.ncbi.nlm.nih.gov/15612906/

Gabrielsson, J., & Weiner, D. (2016). *Pharmacokinetic and pharmacodynamic data analysis: Concepts and applications* (5th ed.). CRC Press.

Gulati, M., Levy, P. D., Mukherjee, D., Amsterdam, E., Bhatt, D. L., Birtcher, K. K., Blankstein, R., Boyd, J., Bullock-Palmer, R. P., Conejo, T., Diercks, D. B., Gentile, F., Greenwood, J. P., Hess, E. P., Hollenberg, S. M., Jaber, W. A., Jneid, H., Joglar, J. A., Morrow, D. A., O'Connor, R. E., Ross, M. A., & Shaw, L. J. (2021). 2021 AHA/ACC/ASE/CHEST/SAEM/SCCT/SCMR guideline for the evaluation and diagnosis of chest pain. *Circulation, 144*(22), e368-e454. https://doi.org/10.1161/CIR.0000000000001029

Hmelo-Silver, C. E. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*(3), 235-266. https://doi.org/10.1023/B:EDPR.0000034022.16470.f3

Klein, D. R. (2004). *Organic chemistry as a second language*. Wiley.

Kludze, A. (2023). *Calculus III: Complete notes* [PDF]. https://github.com/AKludze/Cornell-Math-1920-Academic-Excellence-Workshops-AEW/blob/main/Kludze%20-%20Calculus%20III%20Complete%20Notes.pdf

Lehoczky, S., & Rusczyk, R. (2006). *The art of problem solving, volume 1: The basics* (7th ed.). AoPS Incorporated.

Marchenko, O. V., LaVange, L. M. & Katenka, N. V. (2020). Biostatistics in clinical trials. In O. V. Marchenko & N. V. Katenka (Eds.), *Quantitative methods in pharmaceutical research and development* (pp. 1-70). Springer. https://doi.org/10.1007/978-3-030-48555-9_1

Marsden, J. E., & Tromba, A. J. (2012). *Vector calculus* (6th ed.). W. H. Freeman.

National Board of Medical Examiners. (2016). *Constructing written test questions for the basic and clinical sciences: A guide for faculty*. https://health.uconn.edu/faculty-development/wp-content/uploads/sites/69/2017/06/constructing_written_test_questions.pdf

National Board of Medical Examiners. (2020). *NBME item-writing guide*. https://www.nbme.org/sites/default/files/2021-02/NBME_Item%20Writing%20Guide_R_6.pdf

Nelson, D. L., & Cox, M. M. (2017). *Lehninger principles of biochemistry* (7th ed.). W. H. Freeman.

Norman, G. R., Young, M., & Brooks, L. (2007). Non-analytical models of clinical reasoning: The role of experience. *Medical Education, 41*(12), 1140-1145.

Patrick, D. (2010). *Calculus* (2nd ed.). AoPS.

Perkins, D. N., & Salomon, G. (1992). Transfer of learning. In T. Husén, & T. N. Postlethwaite (Eds.), *The International encyclopedia of education* (2nd ed., pp. 425-441). Pergamon.

Petrulyte, M. (2018). *How to prepare for the Biology Olympiad and science competitions*. Nielsen Book Services.

Schmidt, H. G., & Mamede, S. (2015). How to improve the teaching of clinical reasoning: A narrative review and a proposal. *Medical Education, 49*(10), 961-973. https://doi.org/10.1111/medu.12775

Schmidt, H. G., Norman, G. R., & Boshuizen, H. P. A. (1990). A cognitive perspective on medical expertise: Theory and implications. *Academic Medicine, 65*(10), 611-621. https://doi.org/10.1097/00001888-199010000-00001

Shargel, L., Wu-Pong, S., & Yu, A. B. C. (2012). *Applied biopharmaceutics & pharmacokinetics* (6th ed.). McGraw-Hill Education.

Stewart, J. (2015). *Calculus: Early transcendentals* (8th ed.). Cengage.

United States Medical Licensing Examination. (2021). *Step 2 Clinical Knowledge (CK): Sample test questions* [PDF]. Federation of State Medical Boards & National Board of Medical Examiners. https://www.usmle.org/sites/default/files/2021-10/Step2_CK_Sample_Questions.pdf

Walker, E., & Cornett, P. (2025). *Approach to anemia*. UCSF. https://hospitalhandbook.ucsf.edu/02-approach-anemia/02-approach-anemia

Yazdani, S., & Hoseini Abardeh, M. (2019). Five decades of research and theorization on clinical reasoning: A critical review. *Advances in Medical Education and Practice, 10*, 703-716. https://doi.org/10.2147/AMEP.S213492

Zeybek, S., Pham, D. T., Koc, E., & Secer, A. (2021). An improved bees algorithm for training deep recurrent networks for sentiment classification. *Symmetry, 13*(8), 1347. https://doi.org/10.3390/sym13081347