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Human Cognition and Medical Error

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Abstract

Three quarters of all medical errors stem from cognitive error, rather than the systemic errors that most efforts address. This narrative/conceptual review posits that many clinicians are not fully aware of or sufficiently focused on the innate cognitive processes our brains use for clinical reasoning. References refer largely to standardized reviews or peer reviewed research: data that exceeds individual experience or opinion. Unsupervised, all humans revert to these ancient methods of estimation that were not selected for modern complex medical decision making. Clinicians must appreciate dual processing theory and the limitations of the various methods of clinical reasoning, in order to maximize our problem-solving skill and find ideal clinical outcomes. Our brains default inversely to more or less complex methods to process the amount of uncertainty they confront. We can utilize the most effective method, abductive reasoning, only by gathering as much data as possible, thereby reducing uncertainty to its lowest levels. Even expert clinicians not giving sufficient attention to reflection and feedback ultimately reinforce their error-laden processes. Overconfidence, intuition, reasoning across scales, and our innate preference for mechanistic explanations over clear outcome data add to cognitive error and diminished outcomes. We must strive to identify our method of reasoning at all times, form new clinical questions to fill information gaps, and utilize impasses as new sources of data to remodel our diagnoses and treatment plans, while developing and adding to our clinical and communication skills. Humbly seeking multilevel feedback, and learning from review of our own work are essential. Only by anticipating, recognizing, and countering these very human errors can we reduce treatment failure and suboptimal outcomes, and increase professional satisfaction.

Introduction

Medical error is most often presumed to result from systemic errors of commission and omission: e.g., interventions on the wrong limb, delivery of the wrong medication, failure to provide an ordered treatment, misinterpretation of orders. The Swiss Cheese Model (**Figure 1**), for example, is an oft applied method to ensure that redundancy and duplication in a large medical system will ultimately catch every error before it impacts a patient. Medical error, though, most commonly results not from systemic shortcomings, but from individual, very human cognitive mistakes that are unexpected, unrecognized, and therefore persist uncorrected. 75% of all medical errors are cognitive [1,2]. Knowledge of how our brains form concepts, assess, judge, and calculate will aid the medical professional in anticipating, assessing, and correcting the common cognitive errors that so easily derail desirable outcomes for our patients. This commentary offers a narrative/conceptual review of the topic. While such an approach may suffer from selection bias, and the lack of standardized method may make it difficult to reproduce or verify, the references selected refer largely to standardized reviews or peer reviewed research, and data that exceeds individual experience or opinion. The intention is to provide clinicians targeted tools to reduce poor adherence, treatment failure, suboptimal outcomes, and professional dissatisfaction.

Conceptual Structure and Brain Function

Our brains are not *tabula rasae*, blank slates upon which experience will write [3]. Rather, the study of language acquisition indicates that innate cognitive structures exist in our brains, composed of neural assemblages that that "learn" and create meaning as they *fit* to our experiences [4,5]. Events, i.e. *episodic memories*, are stored in the neocortex; when called upon, the hippocampus constructs and reconstructs a sequential order of these events for us to "recall" utilizing *time* and *place* cells [6]. Repetitive experiences of episodic memory, each recreated "anew" and more often influenced by significance, inference, and experience than original content

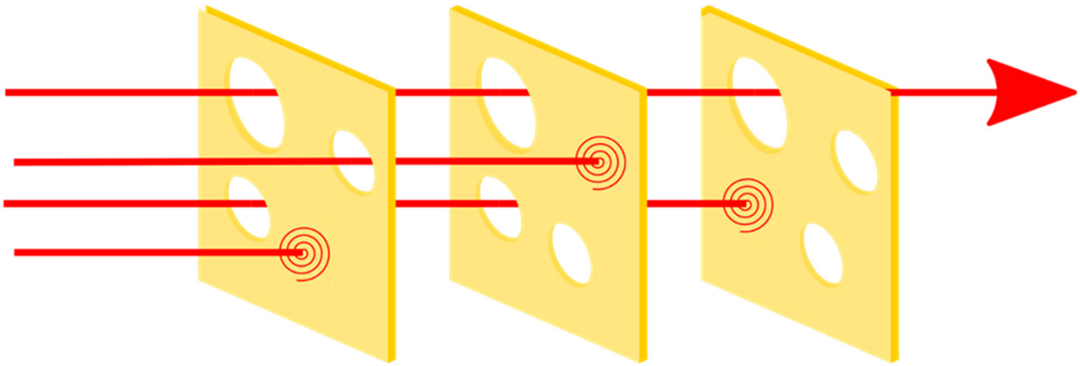

Figure 1. Swiss cheese model of human error trapping. The Swiss Cheese model of human error trapping attempts to block an error in one level of a system by adding safeguards at other levels. In this analogy, an arrow would theoretically not be able to travel through similarly placed holes in each slice of cheese as these would be blocked in at least one slice. The holes are not allowed to remain in the same location throughout the system. In practice, clinicians and administrators identify a shortcoming and install backup systems as multiple layers of defense in an effort to prevent it from affecting final clinical outcomes. Having each staff member confirm a patient's identity is one example. (By User: Ben Aveling - File:Swiss cheese model.svg, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=133912327).

and order, become "facts" for us. In other words, our memories are not fixed copies from an internal hard drive, but variable as they are irretrievably linked with imagination and social exigency [7]. As a result, our memories of "facts" have more *coherence* than *correspondence*, fitting with our concepts and images of ourselves more than accurately matching original events [8].

The data we gather from patients is manipulated into concepts we utilize to make judgements and predictions. Due to the "cognitive miser function," however, our brains exert the least cognitive effort possible to form these and solve problems [9]. Shortcut estimates, called heuristics [10], are automatically applied to project probable scenarios into the future. We remember these concepts, such as diagnoses, rather than raw data or events, so they are not often consciously confirmed [11]. Once a diagnosis has been made, we ignore symptoms that do not fit and "recall" ones that did not actually exist [12,13].

Dual Processing Theory

Popularized as *fast* (Type I) and *slow* (Type II) thinking, we can apply two types of cognitive processing to problem solving. Type I results from the innate cognitive mechanisms described above. It is ancient and may have evolved to help *homo sapiens* remove ourselves from danger and socialize, thus enhancing gene propagation [14]. Utilizing judgment based entirely on individual experience [15], this form of cognitive processing was not selected to solve the complex medical dilemmas we face today.

Type II has been developed through cultural, not biological evolution, and encompasses the *scientific method*: representing underlying principles, utilizing logic and providing abstract reasoning and hypothetical thinking. It *calculates* rather than *estimates*, considering the pooled experience of humankind (i.e., statistics) [9,14,16,17].

These two systems compete to control inference and our actions. While they may provide a check on each other's conclusions (e.g., ruling out an impossible body weight or lifespan calculation) [18], conscious use of Type II processing can temporarily suppress, but never eliminate, Type I conclusions [14,16]. As we humans have less capacity to utilize Type II, even the most intelligent, educated, and experienced clinicians most commonly default to Type I [9,19].

Type I processing often provides quicker answers, unless repetitively used Type II methods become encoded as Type I perceptual chunks, a process our brains use to extend their limited processing ability beyond serial attention [20]. Type I processing, unchecked by Type II, also results in a far greater number of cognitive errors [9]. The more trusted Type II, though, *must* rely on accurate data and validated methods or risk resulting in more serious consequences [18].

Success in modern medical practice requires analysis of decontextualized data, which Type I did not evolve to interpret: numerically presented information which exceeds the experience of a single provider [15]. Type II processing is required to manage this probabilistic information displayed in non-frequentist terms, e.g., making the best decisions about diagnosis and treatment selection, initially and over time [14].

Ambiguity and Uncertainty

Ambiguity, the multiple possible states of an event or medical presentation, is inherent in medicine; uncertainty, therefore can never be eliminated in clinical situations or decisions. Clinicians, as a group, however, discount unspecified probabilities and avoid both acknowledging and sharing our uncertainty, further increasing our cognitive error [21]. In all cases we must consider not only the amount of ambiguity in each case, but also our degree of *awareness* of our uncertainty in order to choose and employ the most error-free method of clinical reasoning [22,23].

When we face a high level of uncertainty about a diagnosis or effective treatment plan, our minds default to *eristic* reasoning. Hedonistic urges, including wishful thinking, loss aversion, a preference for the status quo, overconfidence, and the endowment effect (subjectively valuing our own possessions or ideas more highly than their objective worth), will direct our judgement and conclusions [24–27]. Ironically, in the absence of sufficient data to utilize higher level reasoning, this approach is even considered logical, as we have little else to guide us.

When we confront a case with moderate uncertainty, we unconsciously rely on heuristics, in-bred estimations linked to Type I reasoning. Again, these may well be faulty predictions as they rely solely on individual (and usually recent) experience without considering broader data. As only one example of these many shortcuts, when one patient has symptoms similar to another's, the *representativeness* heuristic [28] leads us to quickly apply the same diagnosis to both cases, inadequately considering a full differential diagnosis.

When we gather enough data to proceed with low uncertainty, we can then utilize the most effective method of clinical reasoning: *abductive*. This approach forms a hypothesis, tests it, then reformulates the original hypothesis in light of the information gathered from the test (e.g., treatment failure, new laboratory or physical data, poor treatment tolerance). This remodeling is key to preventing us from persisting with a diagnosis that defies response to our treatments. As Box and Draper wisely inform us "Essentially, all models are wrong, but some are useful…The practical question is how wrong do they have to be to not be useful" [29].

We can become more aware of which method of reasoning we have automatically turned to: eristic methods may be identified by what are usually considered non-logical approaches (e.g., beliefs, strong emotions, economic gain, prejudice); heuristics through cues (e.g., analogy, past performance), truth seeking attempts, and notable consideration of outcome consequence; and abductive reasoning by our utilization of broad data and stochastic, analytic methods, employing a creative, iterative hypothesis competition [27,30].

Changes in Medical Reasoning Across a Career

Medical practitioners often attempt various forms of reasoning as our careers evolve. Early on, we often struggle with hypothetical-deductive and inductive reasoning, finding it hard to form adequate hypotheses and to account for negative data. We also struggle to actively suppress incorrect information we learned alongside the correct [31–33]. After around six years of practice, we evolve into *expert* mode, utilizing *illness scripts* which link the conditions for a disorder (e.g., age, lifestyle, heredity, medical history, etc.) to the consequences of that illness (e.g., symptoms or functionality and their clinical course) [34,35].

The change unfortunately also represents a return to Type I pattern matching, in which unstructured, random, and atypical case information is poorly remembered. This reinforces a narrowing of our focus and promotion of *confirmation bias* – "seeing" mostly what we have seen before and expect to see again. Additionally, we develop a harmful bias towards positive feedback on our professional performance [36]. As a result, "expert" clinicians are as likely to make cognitive errors as more inexperienced practitioners [13,37,38]. While clinical experience can add to the reasoning powers of medical providers, without awareness of these processes, conscious reflection, and feedback it reinforces conceptual error and lowers our clinical performance [20].

Common Sources of Error

Overconfidence is a risk in all professions. In medicine, particularly, we overestimate our abilities and suppress awareness of our errors, leading to incomplete evaluations, fewer requests for consultation, and unrealistic acceptance of lower complexity thinking [39]. Errors often result from employing simpler, rather than more complex cognitive strategies [40]. In fact, our clinical encounters have become even more complex during the past few decades: more treatments have become available and medical comorbidities have increased as many patients live longer lives [41].

Intuition is commonly involved in expert decision making, as feelings become integrated into illness-scripts [42]. Decisions based on intuition carry a strong emotional impact for the clinician and easily compete with choices that rely less on it [43]; when intuitive answers come to us easily, this unfortunately bolsters overconfidence in our decisions [44]. Such bias gives providers a more personal sense of involvement than Type II processing might, resulting in more positive feelings when an intuitive choice is correct, than when a non-intuitive choice is confirmed [43]. As a group, we make diagnoses too quickly and then cherry-pick data to fit our initial impressions, instead of seeking explanations for the complete results of broad and thorough assessments.

Further, we prefer and usually restrict ourselves to observable scales in creating and employing our clinical narratives. This leads to error as we fail to allow for emergent properties (those that cannot be explained by lower levels of complexity; e.g., "life" from chemistry, or "mind" from neurons). We particularly exhibit this bias when we choose to follow presumed or even theoretical mechanistic explanations of disease, illness, and therapeutics over clear and undeniable outcome data [45,46]. We cannot predict response to an intervention based on its structure or plausibility, but only on demonstration of its clinical efficacy.

Methods That Reduce Cognitive Error

We will never be free from cognitive error, nor from uncertainty. With effort, though, we can reduce the impact of overconfidence and, conversely, indecision in our clinical problem solving [47,48]. Uncertainty is distinct from indecision – the former is inevitable, the latter misleading and harmful to patients. To strike the right cognitive balance, we must always identify the method of reasoning we are using, make sure it fits the amount of data we have, and always work to increase our volume of information so that we can eventually and effectively utilize abductive reasoning.

We must identify gaps in our data – in our own knowledge base, as well as in the clinical information we obtain from and about patients. We must help patients learn to be searchers alongside us, as we both try to find answers to well-framed, yet still outstanding, clinical questions. Improving our communications skills leads to enhanced adherence and outcomes [49,50]. We must be able to explain our uncertainty, while providing a well-reasoned method for reducing it. We need to take time to review our records of past and current cases, identifying mistakes, successful approaches, and developing new insights we can apply. We must utilize feedback from others: patients, staff, and peers, alike, by *listening* and *asking* for it. We must complete full semi-structured assessments at each patient contact in an effort to identify all comorbidities that so often derail full clinical responses, especially with long-term patients. Templates are often helpful. We must then preserve and account for all of our data. Electronic medical records make it too easy to copy previously obtained data; we must record all the details of new, thorough assessments at each visit in order to find the answers to ambiguous presentations, treatment failures, and suboptimal outcomes.

It is essential to adopt humility, recognizing and responding positively to clinical impasses, as new data from our iterative hypothesis competition help us remodel our clinical understanding of patients' situations. We must avoid rapid diagnosis whenever it is safe and reasonably possible, always developing a meaningful and useful differential diagnosis, and routinely make time for review and reflection. Whenever possible, we need to develop and add to our clinical skills, as we seldom recommend treatments we cannot provide, and may not adequately consider diagnoses that require them [51].

Conclusion

Unrecognized suboptimal cognitive acts lead to faults in diagnostic reasoning and mistakes, resulting in increased patient harm [52]. Treatment failure, failure to treat, and acceptance of suboptimal outcomes worsen prognosis, morbidity, and mortality. Our cognitive errors may result from knowledge gaps, faulty data gathering, or incorrect information processing [53]. We must improve our quality of care by learning our brains' default functions when not guided by conscious oversight: the innate mechanisms that distort our assessments and conclusions and misdirect the care we intend to provide. Given the high degree of cognitive error in our field, this is an ethical imperative. Research shows that application of the insights and methods described above results in better clinical outcomes and professional satisfaction. Future research to quantify the effect of each technique on treatment success may provide even greater motivation and justification for adoption by students and practicing clinicians.

Table 1. Steps to reduce the impact of cognitive errors on clinical practice.

• Utilize semi-structured interviews and templates
• Identify and fill information gaps
• Preserve and account for all data
• Avoid rapid diagnosis; always create a differential diagnosis
• Seek, acknowledge, and utilize multisource feedback
• Develop and add to clinical skills
• Recognize and positively respond to clinical impasses as new data
• Apply humility

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