’19

前期日程

# 小論文

（医学部医学科）

**注　意　事　項**

1. 試験開始の合図があるまで，この問題冊子を開いてはいけません。

2. 問題冊子は１冊（７頁），解答用紙は３枚，下書用紙は２枚です。落丁，乱丁，印刷不鮮明の箇所等があった場合には申し出てください。

3. 氏名と受験番号は解答用紙の所定の欄に記入してください。

4. 解答は指定の解答用紙に記入してください。

　（１）文字はわかりやすく，横書きで，はっきり記入してください。

　（２）解答の字数に制限がある場合には，それを守ってください。

　（３）訂正，挿入の語句は余白に記入してください。

　（４）ローマ字，数字を使用するときは，マス目にとらわれなくてもかまいません。

5. 解答用紙は持ち帰ってはいけません。

6. 問題冊子と下書用紙は持ち帰ってください。

次の文章を読んで，問 1 〜11 に答えなさい。文末の訳注一覧に，*のついた単語の訳注があります。

In the good old days, clinicians thought in groups. “Rounding” was a chance for colleagues to work together on problems too difficult for any single mind to solve. Today, thinking looks very different: we do it alone, gazing at computer screens. Our knee-jerk* reaction is to blame the computer, but the roots of this shift run far deeper. (1)Medical thinking has become vastly more complex, mirroring changes in our patients, our health care system, and medical science. The complexity of medicine now exceeds the capacity of the human mind.

Computers, far from being the problem, are the solution. But using them to manage the complexity of 21st-century medicine will require (★)fundamental changes in the way we think about medical thinking and in the structure of medical education and research.

It’s ironic that just when clinicians feel that there’s no time in their daily routines for thinking, the need for deep thinking is more urgent than ever. Medical knowledge is expanding rapidly, with a widening of therapies and diagnostics promoted by immunology*, genetics*, and systems biology. Patients are older, with more coexisting illnesses and more medications. They see more specialists and undergo more diagnostic testing, which leads to exponential* accumulation of electronic health record (EHR) data. Every patient is now a “(2)big data” challenge, with vast amounts of information on past trajectories* and current states.

All this information strains our collective ability to think. Medical decision making has become maddeningly* complex. (3)Patients and clinicians want simple answers, but we know little about whom to refer for *BRCA** testing or whom to treat with PCSK9 inhibitors*. Common processes that were once straightforward — ruling out pulmonary embolism* or managing new atrial fibrillation* — now require numerous decisions.

So, it's not surprising that we get many of these decisions wrong. Most tests come back negative, yet misdiagnosis* remains common. Patients seeking emergency care are often admitted to the hospital unnecessarily, yet many also die suddenly soon after being sent home. Overall, we provide far less benefit to our patients than we hope. (4)These failures contribute to deep dissatisfaction and burnout among doctors and threaten the health care system's financial sustainability.

(5)If a root cause of our challenges is ( ア ), the solutions are unlikely to be ( イ ). Asking doctors to work harder or get smarter won't help. Calls to reduce "( ウ )" care fall flat*: we all know how difficult it's become to identify what care is ( エ ). Changing incentives is an appealing lever for policymakers, but that alone will not make decisions any easier: we can reward physicians for delivering less care, but the end result may simply be less care, not better care.

The first step toward a solution is acknowledging the profound mismatch between the human mind's abilities and medicine's complexity. Long ago, we realized that our inborn sensorium* was inadequate for scrutinizing* the body's inner workings — hence, we developed microscopes, stethoscopes*, electrocardiograms*, and radiographs*. Will our inborn cognition* alone solve the mysteries of health and disease in a new century? The state of our health care system offers little reason for optimism.

But there is hope. (6)The same computers that today torment us with never-ending checkboxes and forms will tomorrow be able to process and synthesize medical data in ways we could never do ourselves. Already, there are indications that data science can help us with critical problems.

Consider the challenge of reading electrocardiograms. Doctors look for a handful of features to diagnose ischemia* or rhythm disturbances — but can we ever truly "read" the waveforms in a 10-second tracing, let alone the multiple-day recording of a Holter monitor*? Algorithms, by contrast, can systematically analyze every heartbeat. There are early signs that such analyses can identify subtle microscopic variations linked to sudden cardiac* death. If validated, such algorithms could help us identify and treat thousands of people who might otherwise drop dead unexpectedly. And they could guide basic research on the mechanisms of newly discovered predictors.

Algorithms have also been deployed* for an analysis of massive amounts of EHR data whose results suggest that type 2 diabetes* has three subtypes, each with its own biologic signature and disease trajectory. Knowing which type of patients we're dealing with can help us deliver treatments to those who benefit most and may help us understand why some patients have complications and others don't.

(7) There is little doubt that algorithms will transform the thinking underlying medicine. The only question is whether this transformation will be driven by forces from within or outside the field. If medicine wishes to stay in control of its own future, physicians will not only have to embrace algorithms, they will also have to excel at developing and evaluating them, bringing machine-learning methods into the medical domain.

Machine learning has already promoted innovation in many fields ranging from astrophysics* to ecology. In these disciplines, the expert advice of computer scientists is sought when cutting-edge algorithms are needed for difficult problems, but experts in the field — astrophysicists or ecologists — set the research agenda and lead the day-to-day business of applying machine learning to relevant data.

In medicine, by contrast, clinical records are considered treasure troves* of data for researchers from nonclinical fields. Physicians are not needed to enroll patients — so they're consulted only occasionally, perhaps to suggest an interesting outcome to predict. They are far from the intellectual center of the work and rarely engage meaningfully in thinking about how algorithms are developed or what would happen if they were applied clinically.

But ignoring clinical thinking is dangerous. Imagine a highly accurate algorithm that uses HER data to predict which emergency department patients are at high risk for stroke*. It would learn to diagnose stroke by churning* through large sets of routinely collected data. Critically, all these data are the product of human decisions: a patient's decision to seek care, a doctor's decision to order a test, a diagnostician's decision to call the condition a stroke. Thus, rather than predicting the biologic phenomenon of cerebral* ischemia, the algorithm would predict the chain of human decisions leading to the coding of stroke.

Algorithms that learn from human decisions will also learn human mistakes, such as overtesting and overdiagnosis, failing to notice people who lack access to care, undertesting those who cannot pay, and mirroring race or gender biases. Ignoring (8) these facts will result in automating and even magnifying problems in our current health system. Noticing and undoing these problems requires a deep familiarity with clinical decisions and the data they produce — a reality that highlights the importance of viewing algorithms as thinking partners, rather than replacements, for doctors.

Ultimately, machine learning in medicine will be a team sport, like medicine itself. The team will need some new players: clinicians trained in statistics* and computer science, who can contribute meaningfully to algorithm development and evaluation. But today's medical education system is ill-prepared to meet these needs. Undergraduate premedical requirements are absurdly outdated. Medical education does little to train doctors in the data science, statistics, or behavioral science required to develop, evaluate, and apply algorithms in clinical practice.

The integration of data science and medicine is not as far away as it may seem: cell biology and genetics, once also foreign to medicine, are now at the core of medical research, and medical education has made all doctors into these fields. (9) Similar efforts in data science are urgently needed. If we lay the groundwork today, 21st-century clinicians can have the tools they need to process data, make decisions, and master the complexity of 21st-century patients.

（Obermeyer Z, Lee TH.  Lost in Thought - The Limits of the Human Mind and the Future of Medicine.  N Engl J Med. 2017; 377(13): 1209-1211.  より引用，改変）

＊　訳注一覧

knee-jerk：型にはまった　　immunology：免疫学　　genetics：遺伝学
exponential：急激な　　trajectory：軌跡　　maddeningly：猛烈に
*BRCA*：乳癌や卵巣癌の原因となる遺伝子の名称
PCSK9 inhibitors：高コレステロール血症の治療薬
pulmonary embolism：肺塞栓（肺の動脈が詰まる疾患）
atrial fibrillation：心房細動（不整脈の一種）　　misdiagnosis：誤診
fall flat：全くの失敗に終わる　　sensorium：感覚器
scrutinize：徹底的に調べる　　stethoscope：聴診器
electrocardiogram：心電図　　radiograph：レントゲン写真
cognition：認識力　　ischemia：虚血（血液供給が不足する状態）
Holter monitor：ホルター心電図（携行型心電図）　　cardiac：心臓の
deploy：展開する　　diabetes：糖尿病　　astrophysics：天体物理学
treasure trove：埋蔵物　　stroke：脳卒中　　churn：かき回す
cerebral：大脳の　　statistics：統計学

問 1　下線部(1)を日本語に訳せ。

問 2　下線部(2)が指していることを文脈に即して 40 字以内で説明せよ。

問 3　下線部(3)について，なぜそうなのか，あなたの考えを述べよ。解答欄(1)には医師側の見方を，解答欄(2)には患者側の見方をそれぞれ箇条書きで記しなさい。

問 4　下線部(4)が指していることを 60 字以内で説明せよ。

問 5　下線部(5)の空欄（　ア　）～（　エ　）に当てはまる最も適切な単語の組み合わせを，以下のＡ～Ｆの中から一つ選び，記号で答えよ。

Ａ：ア complexity, イ simple, ウ unnecessary, エ necessary

Ｂ：ア simplicity, イ complex, ウ unnecessary, エ necessary

Ｃ：ア necessity, イ complex, ウ simple, エ necessary

Ｄ：ア complexity, イ simple, ウ necessary, エ unnecessary

Ｅ：ア simplicity, イ complex, ウ necessary, エ unnecessary

Ｆ：ア necessity, イ simple, ウ complex, エ unnecessary

問 6　下線部(6)を日本語に訳せ。

問 7　下線部(7)は，アルゴリズムによる医学の変化について述べている。本文を参照し，医学領域の変化はどうあるべきか，あなたの考えを述べよ。

問 8　下線部(8)が指す内容を説明せよ。

問 9　下線部(9)が指す内容を説明せよ。

問10　下線部(★)について，本文全体を参照し，著者が必要と考えている “fundamental changes” とはどのようなことかを説明せよ。

問11　医学医療分野にコンピュータの導入が進められている現状について，課題や負の側面を挙げるとすれば，どのようなことが考えられるか，あなたの考えを述べよ。

（以下，余白）