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Letter from the Editors

Dear reader,

We are pleased to welcome you to the second volume of the *University of Manitoba Journal of Medicine (UMJM)*.

UMJM is student-run, expert-reviewed periodical with a twofold mandate — to provide a forum for medical students across Canada to develop their ideas through scholarly writing, and to encourage us all to engage with current topics in medicine. Launching *UMJM* has been a fun and exciting challenge over the last three years. With this second volume we were delighted to receive twice the amount of submissions as for our first volume; meanwhile, our editorial team has also nearly doubled in size. We owe our extreme gratitude to all reviewers, supporters, and University of Manitoba faculty and staff whose invaluable contributions have helped support and advance *UMJM*. We further owe our deepest thanks to all contributing authors, the enthusiasm and dedication of whom has made *UMJM* possible.

The theme for volume 2, issue 1 is *"The Future of Medicine."* We chose this theme to highlight the rapid evolution that is occurring across the field of medicine, and in hopes to promote a definite optimism for the future. To these ends we present work exploring a diverse scope of topics in the future of medicine.

Articles found in this issue address several pertinent topics relating to medical education, healthcare policy, interprofessional collaboration, and the expanding scope of technology in healthcare. How should medical schools of the future evaluate their student doctors? Can mainstream medicine productively interface with increasing Canadian pursuit of complementary and alternative medicine? What will be the future of human physicians in a healthcare system increasingly augmented with artificially intelligent medical technology? These questions and many more are tackled head-on by the authors of this volume.

Amidst exciting advances in healthcare policy and medical technology, the future also calls for increased humanism in medicine. As scientific and technological advances increase the complexity of healthcare, providers must be increasingly deliberate to maintain artistic and humanistic aspects of care, protecting space for human connection. The humanities and the arts are some of the best ways to foster humanism in medicine. To this end we are pleased to present two reflective artistic pieces in this volume, which come in addition to the superb cover art provided by Frances Eichorn. We look forward to further expanding the artistic and reflective elements in future volumes of *UMJM*.

We are excited for what the future of medicine may bring, and we are thrilled to include you in these exciting conversations. On behalf of the whole team at UMJM, we hope you will enjoy this second volume.

Happy reading!

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Letter to the Editor

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To the Editor,

Lana Tennenhouse's article, A Star Trek Exploration into the Usage of Data Obtained from Unethical Medical Experiments, is a stellar comparison of science fiction and real-world events that highlights the dilemma of what to do with the products of unethical medical experimentation. We do not, however, need to look as far afield as Nazi Germany or futuristic universes to find examples of unethical medical experimentation and its consequences.

In the 1950s and 1960s at McGill's Allan Memorial Institute, Dr. D. Ewen Cameron experimented on patients with mental illness. His work caught the attention of, and was then secretly funded by, the CIA; the agency was covertly supporting research in behavioural modification in the service of American geopolitical interests.[1] Cameron's theory of "psychic driving" proposed that patients with mental illness could be cured by erasing their memories and then rebuilding their psyches. The CIA was interested in Dr. Cameron's theory that patients in an "amnestic state" were hypersensitive to suggestion — in other words, they could be brainwashed. The experimental treatment included intensive electroshock therapy, chemical agents (including LSD), sensory deprivation and extended drug-induced comas. Many patients never recovered from the effects of treatment. Most were never informed about its experimental nature, or the potential side effects.

The results of Dr. Cameron's experiments were published in prominent medical journals and presented at international conferences, without critique.[2,3] In fact, he was recognized and rewarded for his contributions, being elected president of the Canadian, American and World Psychiatric Associations. The patients, their families, and the Canadian public were not aware of the unethical experimentation, or its funding source, until the 1980s when several families came forward and journalists began to ask questions.[4]

There are grim similarities between the experiments at McGill and the Tuskegee syphilis study. Both involved vulnerable populations, unable to advocate for themselves. Data from both projects were presented at conferences and published in reputable journals, giving validation to the experimental methods and results. It was only when the nature of the experiments became known beyond the psychiatric fraternity, that public outrage led to changes in research ethics guidelines and practice. If the exposure of medical malfeasance led to public distrust of the medical community, it is hard to argue that, in these cases, it was a bad thing.

Unlike the Star Trek: Voyager episode there were no positive therapeutic insights gained from the psychic driving experiments. CIA interrogators may be the only ones still interested in Dr. Cameron's experimental data.

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Curtain Call (Emerg is Busy Tonight)

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No, I don't know the date or the place or the time,
but my gut is on fire and there ain't been a sign
of the doctor and they can't say when I'll be seen,
when out there I can hear someone starting to scream
about being on *FIRE*! and I want to see who,
but this goddamn blue curtain is blocking my view!
But then it's pulled back with a squeak and a jerk.
You are who? You are what? You're a *"clinical clerk"*?
psoas sign cecum slate surgery suppurate ...
lap-ar-o-scop-i-cal abdomen insufflate ...
In English please? Poking some holes in my belly ...
Have I noticed my urine's especially smelly?
Out of ten? My gut's nine, I'd say eight for my ass.
I poop, pee, and fart, drink some beer and smoke grass.
Yes, that hurts and that hurts, DAMN! that hurts a lot!
I consent to whatever the hell that you've got
to do, just get me past this awful blue curtain.
They're wheeling me out now and I'm not so certain ...
... then someone is saying I'm all done my surgery ...
... then staring at blue curtains down in Recovery.

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Collaboration for the Future

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My art piece, titled *Collaboration for the Future*, is intended to convey several key ideas surrounding the competitive, sometimes hostile field of medicine. The variety of podium heights is meant to convey a sense of competition, and the glorification of overworking oneself. The stooped posture of the figures on the lower podiums symbolizes burnout as an effect of that same competitive culture. The colours are stark and sterile; however, the red circle in the background symbolizes the fact that promoting further collaboration between medical professionals could help decrease burnout and increase quality of patient care.

Collaboration and team work are emphasized in medical school, yet the medical field is often still felt to be an adversarial work environment. It's important for us to closely examine our own behavior and consciously create a culture of teamwork that will change the future of medicine for the better.

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Above average, below expectations: shortfalls in using class averages to inform the education of medical students

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Abstract

In this paper, I argue that the release of cohort-specific class averages through the ExamplifyTM scoring reports do not adequately encourage development of the Scholar role within the CanMEDS framework. Specifically, I argue that the release of cohort-specific class averages in their current format encourages students to focus on more individual metrics, thus dissuading students from participating in more collaborative efforts to generate collective improvements in practice.

Keywords: CanMEDS, scholar role, medical school, class average, academic performance

"CanMEDS is, at its heart, an initiative to improve patient care by enhancing physician training." [1]

This paper aims to examine the role that cohort-specific class-average exam marks have in informing medical students of their performance. For this piece, when I refer to class averages, I am referring specifically to the use of cohort-specific class averages that are provided to medical students during their pre-clerkship years in the Max Rady College of Medicine at the University of Manitoba. Exam reports, providing these averages, are generated by the online test-taking software known as Examplify^{TM}, created by Examsoft Inc.

As a foundation for my discussion of class-average grades, I will be making specific use of the CanMEDS role of Scholar. A physician's role as a scholar is defined as demonstrating "a lifelong commitment to excellence in practice through continuous learning and by teaching others, evaluating evidence, and contributing to scholarship." [1] Within this role, I wish to place a particular emphasis on competencies 1.2 and 1.3, which are as follows:

> 1.2 Identify opportunities for learning and improvement by regularly reflecting on and assessing their performance using various internal and external data sources
>
> 1.3 Engage in collaborative learning to continuously improve personal practice and contribute to collective improvements in practice [1]

Following every computer examination written by pre-clerkship medical students, students receive a score report from Examplify^{TM}. The score report details the student's raw score, the class-average score, and the report lists the breakdown of the course material by unit and learning objectives. The report is further broken down into Session, Unit, and Objective, and each section provides colour-coded qualitative feedback based upon the student's performance relative to the class average. "Doing Well" (green) indicates that the student has scored significantly above class average, "Needs Review" (yellow) suggests that the student has neither scored considerably above or below average, and "Needs Improvement" (red) indicates that the student has scored significantly below the class average.

Even before opening the official exam report on the Examplify^{TM} website, students can view their raw exam score. The student's exam score is presented in green, yellow, or red, immediately informing the student of their exam performance in comparison to the performance of their peers. In addition to the objective feedback students receive regarding personal performance, this colour-coded system provides students with additional information informing them of their relative academic standing in the class. This value-laden feedback can help to guide students' efforts.

While I will argue that the provision of class averages can be beneficial in addressing CanMEDS Scholar Competency 1.2, it may be undesirable in adequately encouraging development in competencies 1.2 and 1.3.

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How a class average may encourage development in Competency 1.2

Anecdotally, medical students tend to learn new academic strategies during the pre-clerkship years of medical school as they adapt to various new demands, including a busy coursework schedule, a large number of examinations, high expectations for examination scores, and an overarching need to efficiently learn and apply complex information. Before entering medical school, many medical students will have previously received near-top marks in their respective undergraduate course programs. By releasing a cohort-specific class-average grade, medical schools provide their students with valuable information about how their results compare to the results of others in their new peer group. In addition to providing an initial comparison of how a student's efforts compare to those of their cohort, the large number of exams students write during pre-clerkship allows students to compare their performance to their peers over time. By continually evaluating their performance outcomes relative to those of their peers, students can gauge effectiveness of their study strategies, and modify their strategies as indicated.

Degree of difficulty can vary significantly from exam-to-exam. With a goal of optimally representing the course material, exam questions at the Max Rady College of Medicine are created with intent to widely canvas the course objectives. Once created, questions are subjected to a secondary review by an outside assessment team. Despite this standardized process, some questions are still inevitably more difficult than others. Each course is led by a course director who is in charge of organizing the course and ultimately selecting the questions that will appear on examinations. Due to the variability in teaching styles, and what one course director versus another may deem an appropriate exam question, exam difficulty and class performance can vary significantly throughout the year. In personal experience, during my first year of pre-clerkship, I have observed class-average scores range from 71%-84% on modular exams. Providing a class-average grade for each exam allows students to assess their performance relative to that of the class.

A high-achieving class can motivate individual students to study harder or more effectively. If the class-average score on an exam is high, students are aware that their peers have effectively learned the material. Desiring to compare favourably to their peers, students may choose to increase their study efforts, consequently increasing their knowledge base.

Measuring progress within a cohort — such as the Max Rady College of Medicine Class of 2022 —eliminates many confounding variables that may otherwise be present if measures from multiple cohorts were to be combined into a single measure (e.g., combining grades from the classes of 2022, 2021, 2020, 2019 etc.). Confounding variables may present as follows:

1) Different timing of holidays and notable events relative to the class exam schedule (e.g., one year, a class social event may occur before a final exam, whereas the next year the event may take place afterwards).

2) A stressful event, impacting the entire class, may occur in one year and not occur in the next (e.g., injury or death of a student in the class).

3) A modular course changes its course leader from one year to the next, which could impact the presentation of course materials and the types of questions selected to appear on examinations.

Presumably, holding all else equal, events such as these will produce observable differences in performance across cohorts.

How feedback relative to class averages might be undesirable in fostering development of Competency 1.2

Even though the class average is generally used as a barometer for individual performance, the class average is a relative measure. Examplify^{TM} score evaluations can change from one year to the next. Depending on the distribution of the normal curve for a class' exam scores, the exact same raw score on an identical exam can result in different qualitative feedback from year to year. It is theoretically possible that one year a raw score of 80% receives feedback stating the student "needs improvement" in many sections, while the next year the same examinations score is considered "doing well." Even if the questions appearing on the examinations were the same, each student receives feedback that is relative to the performance of the class.[1]

CanMEDS Scholar Competency 1.2 states that students should be engaged in the continuous enhancement of their learning using various internal and external data sources. However, with the current exam software, self-reflection is limited by unstandardized and relative data. If a class average is lower than that of a previous year, then the relative nature of this scoring system could provide lower-achieving students with positive feedback about their performance. Without including the data of the past year's performance, students may lack additional data in reference to which they would be motivated to improve their academic achievement.

How feedback relative to a class average may be undesirable in promoting Competency 1.3

Despite of some of the shortfalls associated with providing student feedback relative to the class average,

[1] This outcome depends on the exact parameters which Examplify^{TM} uses to differentiate above-average exam scores from below-average exam scores. This is an exaggerated, and statistically improbable, example.

this feedback can nonetheless be a significant motivator for individual student improvement. Class averages aid students by providing an objective data source (albeit within a relative framework) to continually monitor and identify the effectiveness of their learning strategies. Providing a class average can also be a useful tool to regularly inform students about how their classmates are performing and can encourage students to strive to meet the learning standards set by their peers.

Indeed, class averages can promote significant student development in line with Competency 1.2. However, where Competency 1.2 focuses on individual student development, Competency 1.3 places a focus on student engagement in a collaborative learning environment. For many students, competing against classmates in their undergraduate classes has become *de rigueur* to attain admission into medical school among increasingly competitive pools of applicants. In preclerkship, students are primarily evaluated on their exam performance. The way evaluations are structured, students are incentivized to maximize their own individual efforts. Consequently, little focus is placed on working towards collaborative efforts that can contribute to collective improvements in medical education.

Consider the earlier hypothetical example where the same raw score on an exam could generate two different qualitative exam reports. Assuming that each class wrote the identical exam, differing qualitative feedback could affect an individual's preference for joining one class versus the other. With the option of joining either: the class where receiving 80% on an exam would result in positive feedback, or joining the class where 80% would result in less favourable feedback, I personally suspect that many students would prefer to be placed in the class where they are told they have "done well" by receiving a mark of 80%. Rather than embrace membership in the high-achieving class, I believe some students may be unwilling to sacrifice a relatively high-achieving performance and ranking among their peers that could be achieved for a given level of effort. If this unwillingness were to exist, it would speak to a certain psychological mechanism running counter to the spirit of the CanMEDS Scholarship competencies, and would act in opposition to the goal of having individual learners working to contribute to collective improvements in practice.

Concluding Remarks

Providing a class average to individual students for feedback can have numerous benefits in helping the individual student assess their performance relative to their colleagues. By assessing their Examplify^{TM} exam reports, students can identify areas in which they are underachieving relative to their classmates. Moving forward, students can then take steps to address these shortcomings by reflecting on previous approaches and implementing new methods. However, I believe that by informing students of their qualitative standing relative to the raw class average we may be dissuading collaborative efforts. This qualitative feedback may serve as a mechanism which promotes individual efforts above collaborative efforts. Consequently, I believe that this form of evaluative feedback is not promoting development in Competency 1.3 and is falling short of the current CanMEDS Scholar framework.

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Research as a University of Manitoba medical student: a crash course

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Abstract

"Do you have research experience?", *"What are your plans for the summer?"*, and *"How important is research?"*. These are questions which many 1st and 2nd year medical students may come across. Already, medical students have a strong interest in research. A 2014 Canadian survey polled students at the Michael G. DeGroote School of Medicine, and discovered that 89% of students had previous research experience.[1] While student research participation may vary from school to school, perceived barriers to student involvement in research persist. These often include a lack of time, unfamiliarity with the research process and absence of knowledge related to seeking research opportunities.[2] This commentary will discuss what research in pre-clerkship can look like, tips on the research process, the importance of research for medical students, and how to boost student involvement in research.

Keywords: medical student, research, Manitoba

Why is research in medical school important?

Exposure to research during medical school can provide numerous benefits. Students can gain an appreciation for a medical specialty by learning about future directions or important issues within a field, and/or seeing what work is being conducted "behind the scenes" to improve patient outcomes. Students can also gain firsthand insight into how physicians coordinate ongoing research projects in addition to, or in parallel with, their own clinical practice (for information on typical research involvement for given specialties, see the *Canadian Specialty Profiles* compiled by the CMA).[3] Research also allows students to build connections within a research team and its network of academic researchers, clinician-scientists, and clinicians.

In addition to exposure benefits, taking part in research projects allows one to develop specific skills that will be broadly generalizable within medicine. For example, skills learned in clinical research, such as performing statistical analyses on data sets, provides the student with knowledge on data manipulation. This knowledge can be used for one's own future research projects, and (possibly more importantly) provides the student with an understanding of how to critically appraise statistical analyses performed in other studies. Furthermore, skills such as chairing lab meetings and giving presentations can be used not only in other research projects, but outside of research as well. Research experience also furthers skills in multitasking, communication, and scholarly writing.[4] These, along with the many other skills developed in research, can be used between different specialties, within and outside of research, and for the rest of one's career.

As future physicians, it is important for medical students to be think critically, and to be able to keep up with the dynamic field of medical research.[5] Research experience is one excellent way to develop these broad analytical skills. A recent survey asked medical, veterinary, and dental students in Britain what key skills and attributes they considered to be important for a professional career. Results from the survey demonstrated that students valued having critical appraisal skills and an inquisitive mind, skills which they felt they developed more by completing their final research project, rather than the degree programs themselves.[6] Such skills help students understand the results of relevant diagnostic, prognostic, and treatment trials, as well as how to apply these findings to clinical problems.[5]

Research may also contribute to medical students successfully matching to their desired residency programs. This is because many residency programs place at least some emphasis on prior research experience, or involvement in scholarly activities, which may or may not result in a peer-reviewed publication.[7] The Scholarly Activities and Research Experience section of the Canadian Residency Matching System (CaRMS) residency application states *"This section is for recording scholarly activities and research experiences, which may include* ***paid or unpaid work****. For the purposes of this application, scholarly activities are defined as op-*

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portunities to participate in ***research****, organized* ***clinical discussions, rounds, journal clubs****, and* ***conferences****. The research experiences you list here* ***do not have to be published works****, simply research in which you were an active participant."*[7] Thus, participation in extracurricular scholarly activities, regardless of whether it is strictly published material or not, can be included on an application and may benefit the student.

Lastly, research further provides students with mentorship opportunities which enable knowledge-sharing on various topics. Clinician-scientists can provide students with insight into medical school, residency applications, and establishing a career suited to their interests.[8] Furthermore, early-formed, long-standing relationships could facilitate reference-letter requests in the future.[8] Establishing rapport with a clinician can allow him/her to write a more personalized letter attesting to the student's traits and skill set.[8]

How to get involved

The Max Rady College of Medicine offers pre-clerkship students a number of formal research opportunities.[9] Options include the BSc(Med) program (in which students conduct a research project over two summers following first- and second-year medical school), the MED Summer Research program (similar to BSc(Med) but conducted over one summer only), as well as the MD/MSc and MD/PhD programs, which require that medical students take 1-4 years away from medical training to complete their graduate degree. Each of these programs provide students with stipends of varying amount, along with strong administrative support and guidance. Further details information on these program, including frequently asked questions, and contact information, can be found on the College's Graduate and Advanced Degree Education in Medicine webpage.[9] Students may also conduct research through the Standing Committee on Research Exchange (SCORE) international exchange program through a partnership between the Canadian Federation of Medical Students and the International Federation of Medical Students. Applications are completed in the fall for exchange occurring the following summer. More information can be found on the program's website.[10]

While research experience can be obtained through university-sanctioned programs, research opportunities are by no means limited to these programs. Other university faculty, hospital staff, and resident physicians are often open to student participation on their projects. Students can discuss their interest in research while shadowing a physician, or can simply raise the topic with physicians they already know. Anecdotally, it can be quite easy to get involved with projects that require less of a time commitment than, for example, a two-summer full-time BSc(Med) project. These projects can still provide an environment to build connections with physicians, learn about a medical field, and hone practical skills students can use in future projects.

Tips (adapted from Young *et al*)[4]

- Find a mentor that is interested in working with students and has (preferably) done so before
- Before getting started with a project, conduct a literature review on the topic to come up with new ideas, or do readings (e.g. textbooks, online resources) to establish a knowledge base
- Before committing to a project, discuss with the researcher how you will be acknowledged for your contribution and what your goals are. You may want to ask about time commitment, if the researcher plans on publishing the project, the predicted timeline for publication (i.e. will the project be published before residency application deadlines?), and if the researcher is open to including students as co-authors.
- Set deadlines – both for yourself and in coordination with your mentor/supervisor
- Start small! Smaller projects are more manageable and have a greater likelihood of being finished
- Ask around! Take initiative, be a "trailblazer", and find projects that interest you and suit your abilities and schedule. Some University of Manitoba residency programs even list resident contact information on the residency program information webpage.

Conclusion

Research can benefit medical students by providing experiences which can be useful for future residency applications, allow for mentorship opportunities, and enable the development of critical thinking skills which could be utilized as future clinician and researcher. The Max Rady College of Medicine offers organized programs for involvement in research at undergraduate level, but students should also be open to reaching out to healthcare professionals to initiate, or get involved with active, research projects. The privilege of contributing to medical advancement, the skills and experiences gained, and the connections built, mean medical student involvement in research is likely quite beneficial to the general education of an undergraduate medical student.

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Caring for the carer: a look at physician wellness

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Abstract

As many medical students, residents, and attending physicians can attest, medicine is a unique and challenging field. With all that medicine entails, the topic of physician health and wellness has emerged as an area of concern. Poor physician wellness has numerous effects, with implications reaching beyond lives of the affected physicians and their families. Although progress has been made to improve physician wellness, the process remains incomplete. Changes at every level — from individual physicians, all the way to medical regulators and government — may be necessary to establish satisfactory support for physicians going forward.

Keywords: physician wellness, burnout, resident duty hours

Physician health and welfare is an area of growing interest and concern within the medical profession, whether at the level of the student learner or the experienced physician.[1] The Canadian Medical Association (CMA) explains that physician wellness "encompasses [not just] the prevention and treatment of acute or chronic issues of individual physicians; [but also] the optimization of interconnected physical, mental and social factors to support health and wellness."[1] Therefore, physician well-being can include broad issues such as burnout, addiction, personal stressors and mental health concerns, among others.[2]

To gain a better understanding of the issue, the CMA conducted and published the results of their National Physician Health Survey (2017), which includes data on approximately 3000 attending physicians (attendings) and resident physicians.[1] The survey found levels of emotional, psychological and social well-being to be high in only 87%, 81% and 65% of respondents, respectively.[1] Areas noted to be of concern included rates of burnout, depression, and lifetime suicidal ideation, with significantly more residents reporting these experiences than attendings.[1] Specifically, 48% of residents and 32% of attendings screened positive for depression, while high levels of burnout were reported in 38% of residents and 29% of attendings.[1] Although there were no significant differences in overall mental health, burnout, depression or suicidal ideation between various medical disciplines, those whose main setting was a hospital had higher odds of lower emotional, social and psychological well-being, with surgical specialists and laboratory specialists having the highest odds compared to all other areas of practice (1.74 times and 2.44 times higher odds respectively).[1] Interestingly, more than 80% of respondents were aware of physician health programs that were available to them, yet only 15% reported having accessed them in the past five years.[1] The top barriers to accessing services included a belief that the situation was not sufficiently serious, feelings of shame, and a lack of awareness of the array of services that were available.[1] For those who did seek help, the CMA lists mental health and related concerns (e.g. depression, burnout), personal stressors (e.g. family and relationships), addictions and associated disorders as the leading reasons.[1]

Concerns surrounding physician wellness are not an isolated Canadian phenomenon. Recent studies from the United States (US) found burnout rates of 45.5% and 43.9% in 2011 and 2017 respectively, with an increase to 54.4% in 2014.[3] This temporary increase is speculated to be due to a combination of changes in organizational structure that occurred with hospitals and medical groups around that time, simultaneous changes in regulations, and a proliferation of administrative work that resulted.[3] Examining the 2017 results further, emergency medicine, obstetrics and gynecology, and family medicine were the specialties found to have the highest rates of burnout.[3] Regarding suicide, data suggests that American physicians have one of the highest rates compared to any other profession in the US, with suicide claiming the lives of 300-400 physicians every year,[4] a rate twice that of US non-physician men and two to three times that of US non-physician women.[5]

The impact of physician health and wellness is not isolated to the physicians themselves and their families and friends. Patients and the healthcare system at large can also be affected by the downstream effects of physi-

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cian burnout. For example, a recent meta-analysis published in 2018 found that burned-out physicians are two times more likely to provide care that is sub-optimal and three times more likely to have a patient give them a low satisfaction rating.[6] Building on this, the Canadian Medical Protective Association (CMPA) observes that burned-out physicians may be "taking short-cuts, failing to follow established procedures, not answering patient questions, not discussing treatment options, and making treatment or medication errors that cannot be attributed to a lack of knowledge."[7] They further warn that due to these factors, patients of these physicians are more likely to be non-compliant with treatment regimens, have an extended recovery period post-hospital discharge and even more concerningly, have a higher chance of mortality.[7] Physician absenteeism and early retirement are also possible consequences that can have downstream effects.[8] Both absenteeism and early retirement can lead to fewer available physicians, which can affect an institution's ability to admit and care for patients, interpret imaging that is ordered, or perform surgeries.[7] This can lead to a further need to prioritize urgent cases, reduced access and quality of care, and increased workload for remaining staff.[7] To provide a financial perspective, the University of Toronto estimated in a 2014 study that premature retirement and diminished work hours as a result of burnout is costing the healthcare system $213.1 million; money that can be better spent elsewhere.[7] The fact that burned-out physicians are more likely to be involved in lawsuits, and may also be more liberal when it comes to the ordering of tests (e.g. blood work, imaging) or requesting of referrals, only adds further to this number.[7]

Having established that physician wellness is a concern, understanding the factors affecting it is important. Like many things, physician wellness is affected by a multitude of factors – both intrinsic and extrinsic.[1] Intrinsic factors are characteristics and vulnerabilities associated with an individual, whereas extrinsic factors have to do with outside influences. For example, extrinsic factors include matters related to duty hours, training/practice standards, patient loads, supports available, administrative demands, workplace autonomy, and criticism by others.[7,8] Overall, contrary to how some physicians may feel, the literature consistently describes extrinsic factors as the primary contributors of burnout.[9,10] This supports the claim that the responsibility of physician wellness falls not just on physicians themselves, but on medical schools, medical organizations, regulators, institutional and hospital leaders, as well as on governments.[8,9]

Undoubtedly, the work environment, duty hours, and expectations of attendings and residents are better than years past. Nonetheless, there are no regulations regarding minimum or maximum duty hours in a fully trained physician's practice. Conversely, a typical schedule for a resident can involve regular days being 10 hours long, compounded with frequent weekday calls (14-17 hours long) and weekend/holiday on-call shifts (24 hours long plus the amount of time it takes to transfer care to another provider).[11] To specify, in-hospital call can be scheduled up to seven times on average over a four week period, and when combined with home call, can be up to 10 times over the same time period.[11] This may result in up to an average of 89 working hours per week over a four week period being allowed, which is double the average of many other professions.[11] Educational/academic activities that preclude a resident from patient care do not qualify as duty hours and are therefore not included in this number.[11] Preparation for examinations and participation in common activities such as mentorship, research, or journal clubs are additional external commitments not accounted for by duty hours.[11] Despite this, workloads can still increase further by an additional on-call shift per month if a co-resident on a service takes leave for any reason (e.g. educational, compassionate, maternity).[11] In attempt to not compromise patients and colleagues, rigid adherence to duty hours is not advised; although concerns should be raised, if present, in order to address them (e.g. feeling pressured to stay).[12]

As evident from the above, many concerns and factors impacting physician well-being exist and have been identified. Fortunately, some strategies have been implemented or proposed in order to address this growing concern as well. Like others, the CMA suggests changes from the individual level up to the governmental level.[8] The individual physician can benefit from having a personal family physician, making conscious efforts in helping create supportive work and training environments, and ensuring sufficient time-off for interests outside of medicine (including personal relationships).[8] By being supportive of colleagues booking time off work for vacation or important personal events, one can help foster a culture where work-life balance is seen more positively, rather than as a lack of commitment. Higher-level changes that are recommended include addressing barriers that currently exist for physicians in accessing resources, promoting wellness more than just focusing on harm reduction, conducting research on the effectiveness of various possible interventions, and governmental enforcement of standards related to health and wellness that are comparable to other professions.[8] Specific examples of change at this level can include the introduction of a widely-accessible yet comprehensive document outlining resources available for those who need them, and implementing a wellness program (e.g. mindfulness sessions and peer-support groups) with staff input. This can simultaneously help tackle the stigma that currently surrounds mental health. Having regular opportunities to learn how to effectively manage stress, critically analyze one's own cognitive processing, and recognizing the interconnections between different aspects of life (e.g. physical, emotional, and cognitive) can be beneficial in building resilience – an important factor when it comes to tackling burnout.[1] However, as the CMA emphasizes, changes at the individual and systems level need to be combined in order for there to be meaningful impacts that are sustainable.[8] Thus, collaborations are paramount.[8] This distributive model of responsibility and promotion of a culture of wellness is outlined in the CMA Code of Ethics and Professionalism further establishing its significance.[13]

Current projects and interventions already in place include the CMA Wellness Ambassador initiative as well as the hosting of conferences such as the International Conference on Physician Health (October 2018).[14] Both the initiative and the conferences are aimed at gaining more insight on the issue of physician welfare, being a platform for ideas, and acting as catalysts for change.[14] On a provincial level, Doctors Manitoba has a website detailing many resources including a 24-hour confidential physician and family support line to manage a wide variety of wellness concerns.[15] Doctors Manitoba also has a Physicians for Physicians program that helps connect physicians with doctors experienced in treating fellow healthcare providers.[15] Physicians at Risk, a peer assistance program available for a wide range of issues (e.g. marital and financial stress), and MD Care (a program that provides physicians and their families with comprehensive psychiatric care), are additional resources in Manitoba.[15] The United States is taking a similar approach, introducing programs such as Physician Health First (established in 2017), which includes a website outlining many resources and educational materials.[16] Other initiatives include organizing health and well-being conferences, and appointing Chief Wellness Officers at some academic medical centers to ensure staff well-being is a priority.[16,17] As an example, the Mayo Clinic made a conscious effort to tackle staff wellness by targeting nine organizational strategies, resulting in a decrease in burnout rates by 7%, despite an 11% national rise.[10] These strategies included recognizing the presence and extent of their problem by various means of communication (e.g. townhalls, letters, face-to-face), striving to create a sense of community within the workplace (e.g. celebrating achievements and encouraging peer support when needed), and offering reduced duty hours to promote work-life balance.[10] This is yet another example that demonstrates the benefits of change and how the medical profession can evolve for the better.

Notwithstanding the advancements already made in the profession, (i.e. improvements in the working environment, duty hours, and other factors), physician health and wellness remains a concern of today and a goal for tomorrow. Strategic changes, such as the introduction of positions specifically designed to address wellness in the workplace, and contracts limiting resident duty hours, are a start — and should be more widespread — but they are not the ultimate goal or solution. Physicians, other stakeholders, and even entire countries need to come together to learn from each other, make wellness a priority, create change, and lay the foundation for a better future for everyone — patients and physicians alike.

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Past and future developments of rural residency programs in Canada: a way forward for the Interlake-Eastern Region and rural Manitoba

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Abstract

18% of the Canadian population lives rurally, yet only 8.5% of physicians practice in rural communities. Over the past 20 years, the College of Family Physicians of Canada (CFPC) has strived to improve access to health care for rural Canadians through increased development of rural residency training programs. Rural training for residents and undergraduate medical students has been shown to increase the likelihood that students and/or residents choose to practice in rural areas. Since 2011, all Manitoba regional health authorities have had rural Family Medicine residency programs offered through the University of Manitoba, with the exception of the Interlake-Eastern Regional Health Authority (IERHA). In July 2019, the IERHA accepted its first cohort of rural Family Medicine residents. Through an interview with the Interlake Eastern Family Medicine program director, Dr. Ian Alexander, and a brief review of the history of rural Family Medicine residency programs, this paper examines how a rural residency program may impact the healthcare in the IERHA.

Keywords: rural residency, family medicine, interlake-eastern regional health authority

The history and development of rural residencies in Manitoba and Canada

While approximately 18% of the Canadian population lives rurally, only 8.5% of Canadian physicians practice clinical medicine in rural communities (communities with ¡10,000 people).[1] While there is no single common definition of "rural," Statistics Canada defines rural communities as "the population living in towns and municipalities outside the commuting zone of larger urban centres with populations greater than 10,000."[2] In regards to medicine, rural practice is considered "practice in nonurban areas, [whereby] most medical care is provided by a small number of general practitioners and/or family physicians [who have] limited or distant access to specialist resources and high technology health care facilities."[3] Rural populations are faced with unique health challenges; this is due to decreased access to health care, exposure to harsher weather conditions, as well as increased occupational hazards associated with farming and mining. Furthermore, rural populations also tend to be older, less educated, and have a lower household income as compared to than those living in urban centers, all of which characteristics are associated with worse health outcomes.[4]

The challenge of retaining rural physicians in Canada is not novel. Twenty years ago, The College of Family Physicians of Canada (CFPC) acknowledged this concern, and published a report on the postgraduate education in rural Family Medicine that focused on recommendations for boosting the number of rural family physicians in the new millennium.[5] At that time, the CFPC reported that 30.3% of Canadians lived in rural areas, yet only 9.9% of physicians practiced rurally. The CFPC report recommended increasing the number of rural Family Medicine training programs in order to deliver training that would prepare physicians for rural Family Medicine practice. Motivating the development of more rural residencies programs was the recognition that the conditions of rural practice — including decreased access to specialists, less available medical technology, and unique health concerns — required rural practitioners to obtain a specific skill set, knowledge base, and attitude to provide optimal care. The CFPC recommended that rural Family Medicine training positions be available for application through CaRMS, identify specific rural community needs, and reflect rural health care requirements. As no national standards regarding rural training existed at the time, it was stated that students entering rural Family Medicine residencies would spend a minimum of six months of their two years of training in a rural centre, including a minimum of four months in one site to foster continuity of care. Additionally, over time, programs were developed that allowed residents to choose to become a family physician with enhanced skills in areas including but not limited to anesthesia, obstetrics, emergency medicine, and

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geriatrics. The CFPC Working Group recommended that communities with rural Family Medicine programs had a working hospital, were able to offer extensive clinic experience, and a curriculum based on the clinical realities of rural practice.

By 2013, substantial changes had been made to increase options accross the country for rural Family Medicine residency positions.[6] The number of rural training sites for Family Medicine residents increased from 25 to 86 (between 1998 and 2008), and the number of rural Family Medicine residency positions increased from 36 to 365 (between 1989 and 2013). However, despite this ten-fold increase in the number of rural Family Medicine residency positions, as well as the numerous incentives implemented by universities, governments, and communities to recruit family physicians to rural regions, the medical education system was nonetheless still unable to produce an adequate number of rural family physicians to serve rural communities.[6]

Recruitment and retention of physicians in Manitoba's rural and remote communities reflects the struggle seen across Canada.[7] Health responsibilities in the province are divided among five regional health authorities: Winnipeg (including Churchill) Regional Health Authority (RHA), Southern Health, Prairie Mountain Health, Northern RHA, and Interlake-Eastern RHA. Prior to July 2019, the University of Manitoba offered two urban Family Medicine residency programs (both in Winnipeg), a northern-remote program (various locations), and five rural Family Medicine residency programs (Brandon, Boundary Trails [Winkler/Morden], Parkland [Dauphin], Portage la Prairie, Steinbach). Through these various programs, Family Medicine residency has been offered in all Manitoba health authorities except the Interlake-Eastern since 2011; In July 2019 the Interlake-Eastern welcomed their first residents to their new program.

The Interlake-Eastern Regional Health Authority (IERHA) has a permanent population of 129,000 residents, and substantially grows beyond this in the summer months as tourists visit the lakes and beaches in the region. There are 10 hospitals in the region, 16 personal care homes, and 19 EMS stations throughout the 61,000km^2,[2,8]. The largest community in the IERHA is Selkirk, a town of nearly 10,000 people.[9] A new regional health centre was opened in Selkirk in 2017, and in June 2019 the region will accept the first two rural Family Medicine residents to be trained in the Interlake region. The IERHA reports that in other Manitoba regions, residents training in Manitoban rural residency programs develop connections to the community they are working in and often decide to practice as an attending family physician in the region. Other regions have and continue to see return rates of 70 to 80% because of the attachment doctors make to the community throughout two years of rural Family Medicine training.[10]

The future of medicine in the IERHA: An interview with Dr. Ian Alexander, MD, CFPC

Dr. Ian Alexander is a family physician who practices as part of the Selkirk Medical Associates group in the Selkirk Medical Centre and Selkirk Regional Health Center. Dr. Alexander graduated from the University of Manitoba, Max Rady College of Medicine in 2012. He completed his Family Medicine residency training in Dauphin, Manitoba prior to returning to his home community of Selkirk, Manitoba to practice medicine. Throughout his career, Dr. Alexander has demonstrated his passion towards medical education, as has acted as a preceptor for numerous students for exposures and electives in rural Family Medicine. His dedications towards medical education led him to become the Physician Lead in developing the new Family Medicine residency program in Selkirk, Manitoba. I have been fortunate to learn from Dr. Alexander throughout my undergraduate medical education and recently interviewed him regarding the future residency program in Selkirk.

Why did you want to start a residency program in Selkirk?

It was clear that no formal connection to the U of M existed in the IERHA when I started practice in 2014. I enjoy teaching and knew that I wanted to include that as part of my medical practice. In Selkirk there were occasional clerks, Rural Week students, and very few Home for The Summer students. It became clear that students wanted to spend time in our region, and that extrapolated well to expect that residents would be interested in our region. We know that residents and students help build a good environment for physicians and patients, and as a group we felt that having learners would help us. Not only would these learners help our day to day practice by challenging us and ensuring that we're up to date, but of course we hope to show the great opportunities that exist within our community and hopefully some of our learners will decide to join a local practice when they complete their training.

Is there a physician shortage in the Interlake? If so, how do you expect the introduction of a residency program to affect this?

Definitely. We are short physicians in all areas within in the Interlake Eastern Regional Health Authority. We see this with patients travelling long distances with the region, and potentially outside of the region to meet their primary care needs.

We are hopeful that the introduction of a residency program will help us recruit locally trained physicians to help meet the needs of our communities. While there is no formal return-of-service agreement, we are hopeful that the experience of working within the IERHA will encourage our residents and those trained in other Family Medicine programs to consider setting up practice in our region.

Why should students considering Family Medicine consider residency in the Interlake program?

We remain a great untapped resource for medical learners and subsequently offer the opportunity for excellent hands-on experiences for medical students and residents alike. Like many rural training programs, we offer excellent clinical learning without our students competing with large volumes of learners like in Winnipeg. We offer a great opportunity for students to experience the full variety of rural practice without having to be hours and hours away from the city.

How do you expect the rural residency program to change the way health care is delivered in Selkirk and the surrounding Interlake?

I strongly believe that a rural residency program will make the physicians more engaged, more team oriented, and more up to date in Selkirk and throughout the IERHA. This is a win-win-win for physicians, the community, and learners. Given that learners are trained in multi-disciplinary teams, the addition of a residency program will ensure that our practices grow in a collaborative, inter professional manner that can only help our physician colleagues, and our patients.

As our residents will be in Selkirk and throughout our health region we hope to have these changes impact Selkirk and all other communities that provide primary care. Within our region each community practices in a way that is most appropriate for its providers and population, and I hope that we can amplify what makes each community exceptional for its community members, and by this show our great region and what it can offer to any student who is interested!

The effect of rural exposure on rural recruitment

The physician recruiter for the IERHA, Ms. Lorri Beer, reports that to keep the emergency departments (EDs) within the IERHA open 24 hours a day and 7 days a week, the region would need to recruit over 20 physicians. She is confident that the new residency program will have a positive impact on recruitment to the region in the coming years, stating that "[by] offering our own program, we're integrating new doctors into our region earlier in their careers. Once they become fully licensed, they are already familiar with the region and its health concerns and internal processes. In essence, they have already established their own practice and they have the comfort of knowing what that practice looks like."[10] However, while increasing the number of rural residency positions provides more students with the option to train rurally, multiple studies have demonstrated that several factors influence the likelihood of rural practice prior to a medical student receiving their medical doctorate.

A recent study in New Zealand sought to determine factors that maintained medical student interested in working rurally by having students complete questionnaires upon entry into medical school and at time of graduation. The questionnaires focusing on demographics, career aspirations, and influencing factors.[11] Results of the study suggested the women raised in rural areas were the most likely to have rural intentions at entry to and exit from medical school. Furthermore, the study showed that the extent of interest in helping people, work culture typical of a discipline, and experiences during medical school are all factors that influence students' career decisions. Interestingly, students considering rural practice at both matriculation and graduation were comparatively less influenced by factors such as mentor influence, intellectual content of a specialty, and job security.[11]

A Canadian study of medical students matriculating between 2002 and 2004 found a strong positive relationship between career interest in rural Family Medicine at entry to medical school and post-residency rural practice as a family physician.[12] A recently published study involving cohorts of Manitoba medical students from a similar time period examined associations among current location of rural practice and frequency of access to rural-focused professional learning, finding that greater exposure to rural medicine predicted greater likelihood of rural practice.[13] Together, results of these studies suggest that students' perceptions of rural practice at the outset of medical school can influence the likelihood of eventually practicing in a rural area.

The Interlake Eastern Region of Manitoba continues to struggle to staff EDs and offer primary care to all residents. In offering a residency program the region hopes to recruit young physicians who will develop a positive relationship with the communities within, and consider continuing to work in the region following residency. Currently, many of the rural residency programs in Manitoba are relatively new, making is difficult to determine their long-term effectiveness in retaining rural doctors. The longest running program is the Parkland program. In this region the communities have become significantly better staffed when compared to two decades ago. In the future, the CFPC and Society of Rural Physicians of Canada should re-evaluate the growth of rural residency programs and determine their effectiveness at training adequate numbers of rural family physicians and improving rural health, particularly in smaller, understaffed communities such as those in rural and Northern Manitoba.

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Interprofessional collaboration and healthcare costs: a brief literature review

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Abstract

Rising healthcare costs are unsustainable for a publicly funded healthcare system such as Manitoba's, necessitating a search for cost-effective solutions. This article presents a brief literature review on the cost-effectiveness of interprofessional collaboration (IPC), which is one potential solution to rising healthcare costs. The review demonstrates that IPC is a cost-effective method of managing acute and chronic health conditions, and could lead to reduced emergency department visits and shorter hospital stays.

Keywords: interprofessional collaboration, healthcare costs, joint practice

Introduction

In 2017, the Manitoba government asked healthcare authorities to find cost savings, which led to a major revamp of the Manitoba healthcare system, including emergency rooms converted to urgent care; nursing job cutbacks and scheduling changes; funding cuts to some programs; and emergency medical services closure.[1,2,3,4,5,6] During the resulting assessment, interprofessional collaboration (IPC) emerged as a cost-effective, patient-centred solution to rising healthcare costs. This article presents a brief review of the literature on the cost-effectiveness of IPC.

IPC is a "partnership between a team of health providers and a client in a participatory, collaborative and coordinated approach to shared decision-making around health and social issues," involving individuals from at least two different professions.[7] As part of the CanMEDS framework, medical professionals are expected to collaborate with other healthcare team members.[8] Despite this expectation, IPC is not always the norm in current healthcare settings.[9] Studies of Canadian family physicians found that collaboration between physicians and non-physician healthcare providers is not very common.[10,11]

Literature Review

Relevant studies published within the last 10 years were identified with CINAHL using the subject headings (joint practice OR interprofessional relations) AND (cost benefit analysis OR health care costs OR costs and cost analysis OR cost savings). A study was included in this review if it identified an interprofessional team consisting of at least two different health professions and presented data related to healthcare costs. Studies were excluded if the team members discussed were not members of a healthcare profession, or if the study was comparing different IPC care delivery methods (e.g., in-person versus telephone-based). Thirty-four studies were reviewed and after application of the inclusion and exclusion criteria, nine articles were selected for inclusion.

Results

IPC in managing chronic conditions

A review on physician-pharmacist collaboration reported a 43-89% improvement in blood pressure control in individuals that were seen by both a physician and a pharmacist.[12] The same review also reported that physician-pharmacist collaborations reduced the average HbA1c by 1.2% and led to 24% more individuals having an HbA1c <7% compared to physician-only care. Additional studies on physician-pharmacist collaboration have reported a lower provider visit cost per patient and no significant cost differences between the collaborative care model and usual care – even though the IPC model provided greater hypertension and diabetes control.[12,13]

Cancer patients are another group of chronically ill individuals that benefit from IPC. Up to 35% (range: 4 – 35%) of patients with cancer discussed during multidisciplinary team meetings received changes in their diagnostic reports.[14] Furthermore, a review found that compared to a comparison group not discussed in multidisciplinary team meetings, those patients discussed in team meetings were more likely to receive appropri-

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ate staging and adjuvant treatment.[14] Individuals with cancer also benefit from collaboration between breast care nurses and physicians through reduced hospital readmissions, emergency department visits and mental health costs.[15]

IPC has been reported to lead to cost-reductions in managing patients with chronic pancreatitis and chronic kidney disease. In a review of 2-years of healthcare costs in a large medical center, applying an IPC model of healthcare to the treatment of individuals with chronic pancreatitis led to reduced length of hospital stays and an estimated overall savings of $670,750.27 USD (N=311).[16] Savings of $1931 USD annually per patient were reported in patients with chronic kidney disease treated using an IPC model involving nurses, physicians, pharmacists and dieticians.[17] The model led to better renal survival and fewer patients requiring transplant.[17]

IPC in managing acute conditions and in surgical settings

In a program addressing depression and anxiety secondary to acute cardiac illness, a psychiatry and social work IPC intervention was found to involve higher costs but resulted in more quality-adjusted life-years, depression-free days and fewer emergency department visits.[18]

A 2008 study showed that within a cardiac surgical unit, IPC involving nursing, medicine, pharmacy and physiotherapy reduced cancellations, postoperative clinical incidents, and the length of postoperative stays leading to cost savings worth $508,845 USD (n=260).[19] An economic analysis study found that IPC involving physicians, therapists and social work was more cost-effective compared to traditional perioperative hip surgery management if n>54 patients and resulted in cost savings if greater than 318 patients were treated annually.[20]

The Institute of Healthcare Improvement outlined the Quadruple Aim as a compass to direct the health care system's future. The Quadruple Aim lists improved experience of care, improved population health, improved provider well-being and reduced healthcare costs as potential targets for improving the overall health system.[21,22] The current literature suggests that IPC can be used as a tool to reduce long-term healthcare costs across a variety of healthcare settings, and in the treatment of various chronic and acute health conditions. In this review, most studies indicate a non-statistically significant slightly higher initial cost as the IPC model includes more healthcare professionals providing care to each patient. However, cost reductions to the healthcare system came from reduced emergency department visits, reduced length of hospital stays and better patient management (i.e. better assessment and treatment). These cost reduction measures are especially important for the Manitoba healthcare system as the system is undergoing a transformation resulting in emergency department closures while also experiencing a bed shortage.[23]

While the literature included in this article was reviewed specifically for outcomes related to reduced healthcare costs, the Canadian Interprofessional Health Collaboration also reports that IPC can enhance practice and service delivery, and may also enhance patient care.[24] Locally, the Winnipeg Regional Health Authority endorses collaborative care as it creates better health outcomes, enhances satisfaction with care, improves patient safety, increases providers' health and job satisfaction, and is cost-effective and cost-efficient.[25]

The articles included in this review have several limitations. First, most of the articles are from foreign healthcare systems. The differences between Canadian and foreign health systems limit the generalizability of the findings. Second, the number of articles involved in this brief literature review may not be representative of the entire knowledge base around the topic. Despite these limitations, Canadian healthcare systems are highly likely to benefit from enhanced IPC to promote cost-efficiencies and cost-reductions. As the current Manitoba healthcare system is undergoing transformation, policy makers and health leaders should investigate IPC as an evidence-based tool that offers opportunities for improved cost-effective care to be delivered within the healthcare system.

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Alternative Medicine in the Canadian Context: An Overview

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Abstract

Complementary and alternative medicine (CAM) refers to approaches to health care that falls outside of the medical mainstream. CAM modalities are experiencing growing popularity and use across Canadian society. This article explores the implications of this trend, examining why patients opt for CAM, the status of CAM in the public health care system, and what this may mean for health care practitioners.

Keywords: complementary and alternative medicine, review, canada, therapeutic relationship

Complementary and alternative medicine (CAM) describes a variety of health care approaches that fall outside the scientific and medical mainstream such as homeopathy, acupuncture, and naturopathy.[1] Users of CAM represent a significant and growing segment of Canadian society. A 2016 survey of Canadian adults, conducted by the Fraser Institute, found that nearly 80% of Canadians have used a CAM treatment at some point in their lives, with 56% reporting use of CAM within the past year.[2] This represents an increase from prior survey data collected in 1997 finding 73% lifetime use and 50% recent use of CAM.[1] These data indicate that CAM is a growing part of how Canadians approach health and their health care.[1] This article will examine why some patients elect for CAM therapies, the role of CAM in the Canadian health care system, and how physicians may constructively respond to patients who use CAM.

While a common narrative has been that the growth of CAM use is driven by increasing societal distrust of medicine and doctors, the evidence to support this is weak. This is especially true in a Canadian context, as recent survey data indicates that doctors remain one of the most trusted professions amongst Canadians.[3] Further, a number of studies have found that a patient's attitude towards their doctors was not a predictor of CAM use.[4,5] Given the evidence suggesting mistrust is not the driver of CAM use, one must consider other contributing factors. Other studies have indicated that patients elect for CAM treatments due to their "natural" presentation, to increase their healthcare options, and because they seek to be more engaged in their care.[5,6,7] These studies indicate that CAM is used by a diverse patient population for diverse reasons.[6,7] Further, the evidence indicates that patients see CAM as a supplement to, rather than a replacement for, mainstream Western medicine. The majority of those who see CAM providers do so to fill perceived gaps in their care and continue to visit physicians for their health concerns, especially significant ones.[6,8] There is also evidence that CAM use in Indigenous communities is linked to community relationships and a sense of personal empowerment after treatment.[7]

Although CAM therapies lie outside of the scientific mainstream by definition, some CAM therapies have greater or lesser levels of governmental and societal acceptance. Ontario is currently the only province to designate homeopathy as a registered health profession, but acupuncture, naturopathy, and chiropractic providers are designated in four, five, and ten provinces respectively.[9,10,11,12] Where these regulations exist, they are similar to those for other registered health professions, setting limits of practice and conferring the right to use the title of doctor in the context of their field.

While many CAM therapies are covered by private health insurance plans, the only CAM therapy covered by provincial health insurance plans is chiropractic. Chiropractic, a form of alternative medicine that purports to fix health problems by manipulating the musculoskeletal (MSK) system, has some degree of public health care coverage in British Columbia, Alberta, and Manitoba, with Manitoba being the only province to offer universal coverage.[13,14,15] This is in spite of limited and weak evidence in the literature to support chiropractic as a method for MSK related issues. The lack of evidence surrounding chiropractic may be responsible for a significant reduction in chiropractic health coverage in recent years;[16] notably, Ontario and Saskatchewan historically covered chiropractic treatments, but stopped doing so in 2004 and 2017, respectively.[17,18] Chiropractic is one of the most

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commonly used CAM treatments in Canada, with 42% of Canadian adults reporting at least one chiropractic visit in their lifetime.[2] Its popularity may partially attribute to its unique status among CAM treatments in its receipt of provincial coverage.

Despite growing popularity,[1]naturopathy and acupuncture have so far operated independent of the Canadian public healthcare system, with one notable exception. Since 2013, the Canadian College of Naturopathic Medicine (CCNM) has operated a naturopathic clinic out of a wing of the Brampton Civic Hospital in Brampton, Ontario.[19] This site operates as a training site for students of naturopathy. Although the cost of patient visits are underwritten by the CCNM and appointments are free at the point of access for patients, the recommended treatments must be paid directly by the patient.[19] Although the clinic reports high patient interest with 700 patient visits per month in 2016, the clinic's opening has attracted some controversy.[20] Proponents of the clinic hope that fostering links between evidence-based medicine and naturopathy will expand health care options and allow naturopathy to be tested in a more rigorous setting. Although most CAM therapies have not been rigorously tested, there is systematic evidence to support the use of acupuncture for some forms of pain relief, including migraine, osteoarthritis, and chronic musculoskeletal pain.[21,22] While some CAM therapies, such as acupuncture, have been adopted by some physicians, many health care practitioners remain skeptical. Some physicians have expressed concerns that alternative medicine practices put patients at risk, and that CAM providers weaken the credibility of physicians.[23] However, it is important to note that alternative medicine is an umbrella term describing a wide variety of services ranging from acupuncture to colonic irrigation to spiritual care, and including reiki and meditation. As these practices have a wide range of possible adverse effects and varying level of evidence to support (or contraindicate) them, it is important that physicians (1) know what CAM services their patients are accessing, (2) advise their patients accordingly (with respect to the patient's best interest in view of available evidence), and (3) do so while respecting patient autonomy.

CAM is accessed by a significant majority of Canadians in their lifetime and, although it remains largely outside the public health system, is *de facto* an established part of Canadian health care. As the utilization of CAM rises, it is prudent for family physicians and specialists to be aware that patients may seek CAM in parallel to conventional medical care. Research demonstrates that respecting patients' treatment choices helps physicians build stronger relationships with their patients, increasing compliance with physician recommendations and improving health outcomes.[24,25] Thus, despite physician biases towards or against CAM, it is crucial to foster open dialogue and support patient autonomy, which may increasingly include pursuit of CAM.

While CAM services mostly lie outside the public health care system and are accessed privately, chiropractic is covered in three provinces and naturopaths are working to develop relationships with mainstream physicians. Evidence also suggests that many patients who use CAM do so to complement, rather than replace mainstream medical therapies. Being aware of CAM's place in the health care system and staying informed about which forms of CAM Canadians utilize, can guide the discussions physicians have with their patients and help build and maintain the therapeutic relationship.

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CMDS v CPSO: Conscience-Based Objections to MAID and Ontario's Effective Referral Policy

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Abstract

Medical regulators across Canada have responded to the challenge of conscience-based objections to medical assistance in dying (MAID) with divergent approaches. In Ontario, the College of Physicians and Surgeons (CPSO) has decided that physicians with a conscience-based objection to MAID must provide an "effective referral" for any patient who requests one. In the recent case of *CMDS v CPSO*, the Christian Medical and Dental Society challenged this policy, arguing that it violates their members' rights to freedom of religion and equality. The court dismissed the constitutional challenge, holding that although the policy did infringe freedom of religion, it was justified because of the need to ensure equitable access to healthcare. This paper will briefly outline the court's reasons in the case and discuss some of the implications for affected physicians.

Keywords: medical assistance in dying, MAID, conscience-based objection, effective referral

In 2015, in *Carter v Canada (Attorney General)*, the Supreme Court struck down the prohibition on medical assistance in dying (MAID)[1]. Even at that time, it was already apparent that the degree to which healthcare providers could be compelled to participate in MAID would be a significant issue going forward. The Court in *Carter* was careful to say that nothing in their decision compelled any physicians to provide MAID and observed that "the *Charter* rights of patients and physicians will need to be reconciled."[2] However, the Court also declined to "pre-empt the legislative and regulatory response" by giving more concrete guidance on the rights and responsibilities of physicians with conscience-based objections to MAID.[3] Instead, the challenge was left for another day.

The legislative and regulatory response that the Court predicted has since arrived. Across the country, different medical regulators have crafted their own approaches to the difficult question of conscience-based objections to MAID. Here in Manitoba, policy of the College of Physicians and Surgeons of Manitoba (CPSM) requires a physician with a conscience-based objection to MAID to provide patients requesting MAID with "timely access to a *resource* [emphasis added]," which will "provide accurate information about MAID."[4] The CPSM is explicit in that an objecting physician is not required to refer a patient to another physician who will provide MAID.[5] Moreover, "resource" is defined broadly, encompassing not just other healthcare providers, but also "publicly available resources" that "provide reliable information about MAID."[6] This policy greatly attenuates the role that a physician with a conscience-based objection to MAID must play in providing access to care. In contrast, the College of Physicians and Surgeons of Ontario (CPSO) has mandated that physicians with a conscience-based objection to MAID must provide an "effective referral" for any patient that requests it.[7] The CPSO defines an effective referral as one that is made "to a non-objecting, available, and accessible physician, nurse practitioner or agency."[8] This requires a physician to play a more direct role in the delivery of MAID than in Manitoba.

In this article, I will briefly discuss a recent court challenge by the Christian Medical and Dental Society (CMDS), and some of its members in Ontario (collectively, the "applicants"), to the CPSO's effective referral policy. In *CMDS v CPSO*, the applicants challenged the Ontario MAID policy by arguing that it unjustifiably infringed their rights to freedom of conscience

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[1] 2015 SCC 5, [2015] 1 SCR 331 *[Carter]*.

[2] *Ibid* at para 132.

[3] *Ibid.*

[4] College of Physicians and Surgeons of Manitoba; "Medical Assistance in Dying", online: https://cpsm.mb.ca/cjj39alckF30a/wp-content/uploads/PAD/MAIDschm.pdf

[5] *Ibid.*

[6] *Ibid.*

[7] *CMDS v CPSO*, 2018 ONSC 579 at para 12.

[8] *Ibid.*

[9] *Ibid* at para 1.

and religion as well as their equality rights.[9] The Divisional Court held that, although the policy did infringe on the applicants' freedom of religion, the infringement was justifiable given the need to ensure equitable access to healthcare services.[10] The Court also rejected the equality rights claim.[11] This decision represents an attempt to balance the competing interests of physicians with conscience-based objections and patients requesting MAID. The decision has since been upheld at the Court of Appeal for Ontario, and it is possible that it has sufficient national importance to eventually reach the Supreme Court. Nonetheless, it is still worthwhile to examine the reasoning of the Divisional Court because this case has significant implications for the constitutional protections for conscience-based objections to providing MAID across Canada. While only the Ontario policy is being challenged, if the CMDS is successful, it could lead to new constitutional limits on the power of all Canadian medical regulators in this area.

I will begin with the Court's analysis on the issue of freedom of religion. The applicants, CMDS and some individual physicians, argued that an "effective referral" would require them to be complicit in acts that they viewed as immoral or sinful, and therefore the MAID policy violated their rights to freedom of religion.[12] The CPSO argued that the policy did not impose significant burdens on the applicants for several reasons, including the fact that the act of a referral is not akin to participating in MAID and a referral does not guarantee that MAID will ultimately be performed.[13] Nonetheless, the Court agreed with the applicants and found a violation of their freedom of religion. A key theme in the Court's reasoning was a reluctance to make judicial determinations of the precise requirements of religious doctrine.[14] Although a referral may appear to be quite removed from participation from MAID to an external observer, it is difficult for courts to objectively assess the impact of even indirect participation in MAID on a person with sincerely and deeply held religious beliefs. The upshot is that courts (and presumably regulators) will not extensively scrutinize the beliefs of physicians who assert a conscience-based objection to providing a given medical treatment.

However, in Canadian constitutional law, a law is not struck down simply because the applicants establish an infringement of one of their constitutional rights. There is a subsequent analysis wherein the government has an opportunity to argue that the infringement is justified.[15] In this case, the CPSO argued that the infringement of the applicants' freedom of religion was justified because of the need to provide equitable access to health services for Ontarians. The Court accepted this objective and upheld the MAID policy despite the infringement of the applicants' freedom of religion.

There are two points in this analysis that are of more significant interest to physicians. Firstly, the applicants argued that medical regulators in other provinces have chosen to adopt less stringent policies despite their equivalent mandates to regulate the medical profession in the public interest and ensure access to health care.[16] I have already discussed the Manitoba policy above. The applicants suggested that the existence of alternative regimes meant that the Ontario policy was not minimally impairing of their right to freedom of religion. The Court rejected this argument, holding that the CPSO is not bound to adopt the least intrusive policy so long as its choices fall within a "range of reasonable alternatives."[17] This reasoning is significant for physicians because, if upheld by the appellate courts, it will mean that protections for conscience-based objections will remain province-dependent for the foreseeable future. This may also ultimately affect where physicians with conscience-based objections choose to live and practice medicine.

Secondly, the Court attached significance to the fact that, for affected physicians with the most stringent religious beliefs, the ultimate cost would be a need to change their area of practice as opposed to leaving medicine entirely.[18] The Court described these effects as "not trivial" but "less serious than an effective exclusion from the practice of medicine."[19] The Court stated:

> for these physicians, the principal, if not the only, means of addressing their concerns would be a change in the nature of their practice ... In short, they would have to focus their practice in a specialty or sub-specialty that would not present circumstances in which the Policies would contemplate an obligation of "effective referral" of patients in respect of medical services to which they object. [20]

These burdens could potentially be of significance to the narrow subset of physicians who are affected. Given the novelty of the effective referral policy and MAID, it is difficult to go much beyond speculation at this point. That said, it is one thing for medical

[10] *Ibid* at para 230.
[11] *Ibid* at para 134.
[12] *Ibid* at para 86.
[13] *Ibid* at paras 102-103.
[14] See e.g. *Ibid* at para 108.
[15] There must be a pressing and substantial objective for the law, the means chosen in the law must be rationally connected to that objective, the means chosen must be minimally impairing of the right, and there must be proportionality between the salutary and deleterious effects of the law. See *R v Oakes*, [1986] 1 SCR 103 at paras 69-71.
[16] *Supra*, note 7 at para 172.
[17] *Ibid* at para 174.
[18] *Ibid* at para 207.
[19] *Ibid* at para 209.
[20] *Ibid* at para 207.

students to adjust their career plans because of these policies. However, a switch in specialty or subspecialty late in a physician's career, if even possible at all, could be a highly onerous undertaking. Moreover, for some physicians, a switch in practice area might also require other significant lifestyle changes. A rural family physician, for instance, would likely also have to relocate to a larger centre in addition to changing the nature of their practice.

In conclusion, the issue of conscience-based objections to MAID requires a consideration of competing interests. On the one hand, many physicians have deeply held beliefs that prevent them from participating, however indirectly, in the provision of MAID. On the other hand, patients seeking MAID require support from their physicians to achieve equitable access to the healthcare system. Balancing between these considerations is a difficult challenge that regulators, courts, and physicians will face for years to come.

Artificial intelligence and physicians in the future of medicine: a meeting of minds?

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Abstract

Artificial intelligence (AI) is one of today's most powerful technologies. Having already transformed the business world, AI may be poised to transform healthcare next. Current AI systems demonstrate impressive competency in certain tasks of clinical medicine. Machine learning approaches to creating AI are of particular relevance in healthcare, given the ability of modern machine learning algorithms to work with large amounts of complex data and generate intelligent predictions therefrom. Here we propose that much of what physicians do can be modelled as information processing and thus can be performed by AI. We further propose that whereas certain AI systems may adopt approaches based on novel pattern extraction and interpretation, and thus diverge from human physician cognition, AI is well-positioned to assist physicians by operating in parallel alongside them. Navigating the intersection of physician and AI competence will be a tremendous and complex challenge, but may return high rewards in improving patient outcomes and lead to transformative gains in medical knowledge. Advances in AI will have tremendous and complex impact on the future of medicine.

Keywords: artificial intelligence, machine learning, information theory, computer science, healthcare, medicine

1. Introduction

Artificial intelligence (AI) may be the most transformative technology of the 21st century. Any non-human machine system performing intelligent behaviour — behaviour that is proficient with respect to a complex goal — falls under the rubric of AI.[1] Recent years have brought tremendous advances in AI, with certain AI systems now capable of human-level speech recognition,[2,3] human-level language translation,[4] superhuman image recognition,[5] and superhuman performance in numerous complex games such as poker,[6,7] Go,[8] and Capture the Flag.[9]

Alongside development of enhanced capabilities, use of and interest in AI is also growing. The 2018 AI Index Report, prepared by the Human-Centered AI Institute at Stanford University, documents manifold aspects of progress, including huge increase in the number of AI papers published per year, increased number of AI startups and patents, and growing widespread adoption of AI in industry.[10] In some sectors, as of 2018, as many as 75% of companies had trialed AI or were currently using AI for certain functions of their business.[10] AI is currently used by diverse collections of companies in various industries including technology (Google, Samsung, Apple), social media (Twitter, Facebook, Instagram), entertainment media (Spotify, Netflix, Walt Disney), consumer goods (Amazon, Walmart), food and beverage (e.g. Starbucks, Coca-Cola, McDonald's), transportation (Hopper, Uber), and automotive (Tesla, BMW, Volvo).[11]

In view of increasing capabilities of AI systems and simultaneous transformative benefits of AI in diverse industries, many have suggested that AI may next transform healthcare.[12,13,14,15,16] Specialized AI systems have already been deployed into healthcare in various regions worldwide. In the US, the FDA has already approved specific AI algorithms for tasks including interpretation of magnetic resonance (MR) and computed tomography (CT) images of the brain,[17] heart,[18] liver, and lungs,[19] with some degree of autonomy.[20,21] Moreover, the FDA is fast-tracking approval of further AI algorithms.[22] In Japan, IBM's Watson now assists in diagnosing leukemia via genome sequencing, with some notable success, including possibly having saved lives.[23] In India, AI is widely used to interpret urgent ECGs to rule out or diagnose myocardial infarctions[24] and to detect cervical cancer in pathologic samples.[25] One hospital in Guangzhou, China is using AI to suggest diagnoses for hundreds of diseases, interpret computed tomography (CT) scans, and organize patient files via facial recognition.[26] Meanwhile, software by Beijing-based AI start-up, Infervision, assists with interpretation of CT scans in a majority of Chinese hospitals, as

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well as select additional hospitals outside of China.[27] In Europe, Google DeepMind is partnered with UK's National Health Service as of 2015, and has since been receiving patient data for the purpose of developing AI systems for healthcare.[28] At St. Michael's Hospital in Toronto, Canada, the Vector Research Institute is testing the application of AI to improve interpretations of radiographic imaging studies[29] and to predict when hospitalized patients require transfer to the intensive care unit.[30] These initial examples form what is likely just the beginning of AI's involvement in healthcare.

Within the roles of clinical medicine, the competencies of AI seem particularly well-suited to certain tasks, such as image classification. Much has been discussed about the possibility of AI replacing diagnostic radiologists.[31,32,33,34] Notably, many of the above examples of AI's deployment into healthcare are in diagnostic imaging. However, deployments for broader purposes have already begun and are likely to continue. As we will see, given extreme broadness of certain principles of AI and of computation more generally, the growing competency of AI applications may expand to cover extensive aspects of clinical medicine. Recent research indicates AI competence in diverse tasks such as predicting treatment response to medications,[35,36] predicting cardiovascular risk from routine laboratory data,[37] and diagnosing rheumatoid arthritis via automatic analysis of patients' electronic health records.[38]

Given broad and increasing capabilities of medical AI, some have wondered if AI of the future could render human physicians obsolete. Silicon Valley investor Vinod Khosla suggests that AI will replace 80% of doctors, possibly even on the timescale of a couple decades (written in 2012).[39] Notably, an AI-powered robot named Xiaoyi recently passed the Chinese medical licensing exam.[40] Although it is possible that advanced future AI systems will someday usurp certain roles of physicians, healthcare will first be faced with increasing competency of AI in an increasing number of medical applications, with specialized medical AI systems performing at levels of competency approaching, equalizing, and/or ultimately surpassing the competency of human physicians. Thus, rather than focusing attention on the possibility of physician replacement by AI, the more pressing question of today is *"what should the healthcare system do with AI systems that are as good as or better than physicians?"*

To adequately discuss these crucial matters, and to be prepared for what future technological advances will bring, physicians and healthcare policymakers must attain a working knowledge of the possibilities of AI in medicine. This will require some understanding of computational principles. Despite increasing adoption rates and ubiquity, AI and computers can be highly counterintuitive. For example, researchers at the University of Wisconsin-Madison recently created an AI system in a "nanophotonic medium" — essentially, a piece of glass, with no electricity required for its operations — that classified handwritten digits.[41] Even within standard modern electronic computers, AI is a diverse and immense category, subsections of which may defy intuitions. Thus, understanding AI's conceptual underpinnings in terms of computer science and information theory is prerequisite to understanding possible broad futures of AI in medicine.

In this paper we discuss physical and philosophical underpinnings of how AI systems may achieve competence in the complex goals of healthcare, noting certain similarities between information processing performed by AI and by human physicians. We also discuss certain capabilities of medically-focused AI systems, highlighting multi-faceted ways in which AI and physician competence will intersect, and how this will benefit patient outcomes and advance medical knowledge. To make the most of the future, healthcare must place a high priority on capturing value and mitigating risks of AI in the future of medicine.

2. Computation and artificial intelligence: brief primer for a medical audience

This section describes fundamentals of computation and AI in order to see how they may be relevant to medicine. We will see that computers are physical systems that store and transform information, and, notably, how this abstract framework can map much of what occurs in medicine. Transforming information in certain ways earns a computational system the designation of "intelligence", and machine learning approaches are one effective route by which contemporary computing systems achieve intelligence. We will also discuss certain advantages conferred by different types of AI. Readers familiar with computation and AI should advance to Section 3.

2.1 Information: modeling the world

A computer is a mechanical device that stores and transforms information via physical processes. Thus, the extent to which realms of medicine can be accessed by computers and AI is wholly dependent on the extent to which medicine can be modelled in terms of information. We will consider information generally before advancing to specifically consider information in medicine in Section 3.

Information has various technical definitions relating to divergent subcultures in the philosophy of information.[42] For our purposes, a sufficiently philosophically-neutral definition will be "what is conveyed or represented by a particular arrangement or sequence of things".[43] For example, a geographic map carries information about the physical environment of earth, in that multicolored patterns of shapes and their word-labels (the particular arrangement of things) convey and represent the earth. In carrying information about the earth (or a portion thereof), it can be said that the map *models* the earth (or its portion thereof). Whereas a map models the world via apparent physical likeness (e.g. water on a map may be coloured blue, mountains may appear raised), other technologies achieve modelling by means that are highly abstract.

For example, certain modern technologies encode information via etching microscopic pits into CDs, magnetizing surface points on computer hard drives, and using electrons to influence the charge of a capacitor.[44] Although it may be counterintuitive, these highly abstract modes of instantiating information can render extremely faithful models of systems in the outside world. A map stored on a CD or in a computer hard drive can model the outside system of interest (in this case, a particular geographic region) with the same arbitrary closeness that can be achieved by a paper map (i.e. bounded only by storage capacity, namely the size of the paper or the size of the hard drive's memory).

As another example of abstract information storage, consider a photographic image. It can be stored digitally on a smartphone device and represented in solid-state storage (a type of computer memory that uses electrical circuits and lacks moving parts), stored on a desktop computer represented in hard disk drives (a type of computer memory utilizing spinning electromagnetic rotating disks), or printed physically onto a piece of paper and represented via molecules of ink. Some "likeness" of the image, expressed via abstract electrical, magnetic, and molecular patterns, is translated across mediums, despite distinct modes of physical instantiation. The information "has a life of its own."[44] The ability of information to flow from model to model in this way may appear peculiar, but information itself ("that which is conveyed or represented") is *substrate-independent*, meaning that it does not change according to the way in which it is stored.[45] Another interesting property of information is that there is no apparent physical constraint on what can be represented by information.[46] Thus, to model any system, one need only possess information about that system, and possess a means of instantiating that information into a device such as a computer. As a result of these properties, information stored in a computer can represent diverse and complex features of the world such as images,[47] earthquakes,[48] and quasars.[49]

2.2 Computation: transforming the model

Although all computers store information, this alone is not sufficient to achieve their designation as computer. A *computer* is a device that not only stores information in memory, but utilizes functions to transform information.[44] *Functions* are mathematical equations that accept a set of data and output a paired set of data in one-to-one correspondence. Essentially, information enters a function, is acted upon by the function, and emerges transformed. The particular transformation that occurs is specified by the particular function. For example, a function may transform its input information by a two-fold factor of multiplication, as in the simple function "y = 2x". But functions can also perform transformations of much greater complexity. Physicist Max Tegmark gives the further examples of a function transforming input information that represents current positions of chess pieces on a chessboard into information representing best next move for Black, or transforming information representing all the world's financial data into lucrative stock market purchases.[44] (Functions of this kind illustrate, in outline, how a computational algorithm can be "intelligent." Section 2.3 considers this in detail.) The process of implementing a series of arithmetic functions alongside non-arithmetic functions to retrieve an output set of data is called an *algorithm*. The process of implementing such algorithms are called *computations*; thus, circularly, a *computer* designates a device that implements algorithms.

Like information, computation is also substrate-independent. What matters for computation is the transformation of information, not the physical substrate that implements the transformation. Thus, a wide variety of mechanical systems can function as computers. This insight, in general form, appears to have been first arrived at by Spanish polymath Ramon Llull (deceased 1316), who realized that mechanical artifacts could perform "useful reasoning".[1] Thereafter, in the 1500-1700s, various simple devices were built to perform mathematical calculations.[1] Modern computers use *bits*, simple two-state storage devices, to store and transform information. Like a power switch, a single bit can be off (represented as 0), or on (represented as 1), but not in-between. ("On" and "off" correspond to mutually exclusive physical states, such as whether electrical current flows through a given wire or not, whether a given area is magnetized or not, etc.) With a large enough number of bits stored in large and complex arrays, *any amount* of information can be stored and transformed in a computer's memory,[50] giving modern computers tremendous reach.

Modern computing is generally agreed to have begun with Alan Turing's seminal 1936 paper, "On Computable Numbers, with an Application to the Entscheidungs problem", in which Turing demonstrates that if a computer can perform a minimum set of basic operations, then it is a *universal computer*, meaning it can compute anything that any other computer can compute.[1,51] Notabbly, modern electronic computers, including smartphones and laptops, are universal.[44] Given that a computer is simply a physical system that transforms information, and given the possibility of information to represent any complex and interesting feature of the world, there is no obvious limit to the kinds of interesting and useful transformations of information that potential future computers can accomplish, other than the limits imposed by the laws of physics themselves — i.e. laws regarding the kinds of systems that can instantiate information and can perform a given physical transformation, how fast a given transformation can be performed, etc.[52] In creating universal computers, humanity may have initiated what physicist David Deutsch calls "a beginning of infinity".[46]

To whatever extent the conceptual future of computation is limitless, likewise, the application of computation to solve problems in medicine may be correspondingly limitless. The next section will discuss specifically how certain computational systems achieve "intelligence".

2.3 Intelligent computation in machines and in medicine

How can a computer achieve intelligence? The answer may be implied by the previous sections, but is worth elaborating in further detail. *Intelligence* has no single standard definition, but in regards to AI may be thought of as proficiency with respect to a complex goal.[44] (What exactly constitutes "complex" is itself difficult to define. A working definition put forth by biologist Richard Dawkins proposes that something is complex if it has "some quality, specifiable in advance, that is highly unlikely to have been acquired by random chance alone".[53]) A complex goal might then be "one that is unlikely to be reached by chance alone." An example of a complex goal might be winning a game of chess. If an AI system receives input information representing the positions of chess pieces on a chess board and successfully outputs moves for Black that are better than a random move generator, then it may be said to have some degree of intelligence with respect to chess. The better the moves, the more intelligent the system. Likewise, if an AI system receives input information representing all the world's financial data and successfully outputs lucrative stock market purchases, then it may be said to have some degree of intelligence with respect to the stock market.

In addition to the complex goals of winning chess or succeeding on the stock market, AI systems can also be intelligent with respect to the goals of medicine. If an AI system receives input of pixels representing a chest x-ray and outputs correct diagnoses therefrom, the system is intelligent with respect to interpreting chest x-rays. If an AI system receives input representing vital signs and bloodwork results and outputs accurate predictions of two-week mortality therefrom, the system is intelligent with respect to predicting mortality. If an AI system receives input representing history of presenting illness, physical exam findings, and laboratory data, and outputs a correct diagnosis therefrom, the system is intelligent with respect to diagnostics.

In their capacity for modeling and transforming information about the world, computers may succeed with respect to a complex goal, medical or otherwise, and thus achieve intelligence.

2.4 Machine learning to achieve artificial intelligence

We have seen that a computational system will be designated as AI if it has the proper algorithms to transform information in a way that is of benefit towards a complex goal. But where do these intelligent algorithms come from? Early approaches to AI entailed manually inputting pre-determined rules that would enable intelligent computation.[1] However, recent successful approaches to achieving AI mostly capitalize on machine learning principles. In machine learning, a computational algorithm is designed in a way that allows it to acquire intelligent behaviour – essentially, to learn. Compared to manually inputting putatively intelligent algorithms, machine learning has generally been a more efficient approach to achieving AI. A popular and effective form of machine learning is *deep learning*. Many applications of AI in medicine are AIs that are the product of deep learning. Deep learning algorithms excel at working with complex information, uncovering useful patterns hidden within the data. Yoshua Bengio of the Université de Montréal recently gave the following description:[54]

> "Deep learning algorithms seek to exploit the unknown structure in the input distribution in order to discover good representations, often at multiple levels, with higher-level learned features defined in terms of lower-level features."

Deep learning systems are intelligent with respect to the complex goal of generating good representations of complex data. A "good representation" is one that closely maps the topography of the input data, even when the topography is very complex. Good representation tames the complexity of the input data, allowing useful patterns to be discovered in the data, and allowing the system's output to be relatively simple and easy to work with, yet faithfully representing the original complex input data. In taming complexity to arrive at simple outputs, the system may acquire intelligence with respect to certain goals pertaining to the complex input information it received.

Deep learning generally occurs in *neural networks*, a computational strategy modelled after biological brains, in which information is passed through several successive layers of computational "neurons", with each neuron transforming its information via a function. The first layer of neurons receives the input data, generally representing the data exactly as received, with the number of neurons in the first layer usually in a one-to-one ratio with the number of variables in the input data (e.g. in image classification, this may be a one-to-one neuron-to-pixel ratio). Beyond that, information is passed to a smaller number of neurons at each successive layer, each layer performing computations, mapping "features" of the data as it passes through. A given layer processes in parallel; successive layers process in series. These feature maps pass through layers until ultimately, in the final layer of neurons, the system outputs a final pattern of information. That is the general scheme, but some neural networks employ more complicated connectomes. For example, a convolutional network generates successively smaller layers until it arrives at a small enough subset to output a result. For excellent comprehensive review of neural networks, please see LeCun et al. 2015.[55]

In general, deep learning systems refine their representations on "training sets" of data, datasets in which all outputs are already known and given to the system. (For example, a deep learning system for classifying images as "cat" versus "dog" will be trained on a large number of images of cats and dogs, both labelled as such. These labels are the "ground truths" of the training stage.) The system then moves to a "validation set", in which the deep learning system creators know the output, but the system does not. This step verifies the system's ability to output a correct result within some satisfactory margin of error. Finally, the system graduates to encounter the "test set" — the data of true interest, where the output results are unknown to both the system and its creators.

How do deep learning systems learn to adopt good representations? During training, in order to successfully transform input information into the desired (known) output information, individual neurons are empowered to adjust the functions they implement via a sophisticated mathematical technique known as backpropagation. Backpropagation achieves automatic error correction by moving backwards through the deep learning algorithm to adjust the system parameters to best suit the use-case.[56] This technique essentially reverse engineers how to represent the input data across layers so as to ultimately reach the desired (known) output. Returning to the example of classifying images as cat versus dog, such a deep learning system would receive input of pixels representing cats or dogs, and from these pixelated inputs, would be tasked with generating one of two output states: one representing "cat", the other representing "dog". In training, pixelated cat images (input) are paired with the known labelled output "cat". By backpropagation, the deep learning system is slowly taught to refine its representation of cat pixels such that, with increasing success, cat pixels will flow through layers of computation in such a way that ultimately and naturally leads to the output "cat" (and likewise for dogs and dog pixels). In this way, deep learning systems are designed to learn from the data themselves, thus they are well-suited to complex information.

The above training framework, in which training set materials are labelled with ground truths, is known as *supervised learning*. The counterpart to supervised learning is *unsupervised learning*, in which the deep learning system is not provided with ground truth outputs to serve as desired endpoints. Perhaps surprisingly, even without supervised human guidance, well-designed deep learning systems can achieve very good representations of complex data, reaching high levels of competence in performing challenging feats. For example, in 2017, AlphaGo Zero learned to play Go after starting as a "blank slate" without any human data or human knowledge.8 The system did not receive ground truth labels constituting winning strategies, high score optimization, or other direct supervision; it was only provided with the rules of the game. Learning only from unsupervised iterated self-play, AlphaGo Zero went on to become the top Go player in the world, better than any human player, and defeating the previous reigning-champion AI system by a score of 100-0.[8] As deep learning systems with greater and greater learning proficiency are engineered, the complexity of problems they can solve — with minimal subsequent human input — may increase to tremendous heights.

2.5 Advantages of intelligent computers

We have defined an AI system as any computational system that transforms information in such a way as to be of use towards a complex goal. Various AI systems collectively allow at least three great general advantages to their users. First, AI may tend to achieve superhuman proficiency at certain types of information processing, such as implementing mathematical transformations quickly and reliably (as in a pocket calculator). For such tasks, a computer can function as an external cognitive prosthetic device. The scope of this advantage is widened in modern electronic computers, which can perform wide-ranging tasks quickly and reliably.

Second, by modelling the outside world (or a portion thereof), computers can provide valuable predictions about likely future events in the modelled system, such as NASA's EO-1 satellite presciently alerting human researchers of natural events before they themselves detected anything.[57] Predictive power of computational models has led to their widespread adoption in other fields such as geology (predicting earthquakes)[48] and space exploration (trajectory and payload optimizations)[58].

Third, computational models themselves can be interesting objects of study, especially those arising from unsupervised deep learning methods, which may generate models that are conceptually divergent from human knowledge and human-preprogrammed models. Thus, the AI resulting from unsupervised deep learning systems can appear foreign and other-worldly to humans. Moves made by AlphaGo Zero, the Go-winning AI generated by unsupervised machine learning algorithms, were described by champion Go players as "alien" and "from an alternate dimension".[59] Alien or not, to the extent an AI system achieves real-world success, its model likely contains representations of real-world variables and parameters that are of interest. Therefore, in examining the model of Go within which AlphaGo Zero derived its alien hyper-successful moves, a path of new insight towards the game of Go may be charted. Further, the above-mentioned EO-1 satellite AI, which alerted human scientists of events of which they had been up to then unaware, was also generated by unsupervised machine learning approaches.[57] In studying AI models such as these, we may gain new understandings of the modelled systems themselves.

The extent to which the advantages of AI will be useful in medicine depends on the extent to which that which is useful about medicine can be abstracted in terms of information and its transformations. Section 3 will briefly consider the intersection between the transformation of information and the complex goals of healthcare.

3. Information processing is central to clinical medicine

AI transforms information in ways deemed intelligent with respect to a complex goal. To what extent does this pertain to medicine?

All medicine deals with information about a patient's body. From diagnosing a disease, to recommending a medication, to forecasting the likelihood of a particular outcome within the next ten years, most of what physicians do relates to an abstract information state of their patients' bodies. Ultimately, all useful medicine is useful only in so far as it relates to information about patients' bodies. Put the other way round, there may be little use in a physician whose medical advisements *do not* correspond to any information about his or her patients' bodies.

Certain aspects of medicine such as laboratory investigations, diagnostic imaging studies, and electrophysiological studies deal directly and overtly with bodily information. Referring specifically to radiologists and pathologists, Jha and Topol went as far as to coin the term "information specialist", writing:[60]

> The primary purpose of radiologists is the provision of medical information; the image is only a means to information. Radiologists are more aptly considered "information specialists" specializing in medical imaging. This is similar to pathologists, who are also information specialists. Pathologists and radiologists are fundamentally similar because both extract medical information from images.

We propose that, in a broader and more abstract sense, all physicians are information specialists. Across medical disciplines, it may be argued that the value of physicians is to receive complex input information, process and sort it into patterns that are meaningful and actionable, and prescribe an appropriate action on the patient's behalf. Jha and Topol's information specialists provide the clearest examples — a radiologist transforms two-dimensional pixelated greyscale information into a radiographic diagnosis; a pathologist transforms complex microscopic histological information into a pathologic diagnosis. But much else of what physicians do also relates to transforming information. A typical clinical physician receives complex input — history of entrance complaint, physical examination findings, current medications, laboratory findings, other investigative findings — recognizes patterns amidst the complexity, and thereby produces comparatively simple outputs such as diagnoses, risk assessments, and prescriptions. This scenario can be modelled as information flowing through the physician and emerging transformed. There is no obvious reason why a model accomplishing an identical transformation of information cannot be programmed into a modern electronic computer. (Given the substrate-independence of information and computation, this will be possible even with modern electronic computers using computational strategies that are dissimilar to the activities of the brains of human physician.) But beyond merely modelling such a transformation of information performed in vivo by a human physician, is it conceivable that, provided with sufficient memory and processing power, a well-designed deep learning neural network could be trained to accomplish a large set of similar such transformations, much like a physician, for a large set of incoming potential patients? This would be an extraordinarily challenging feat; nonetheless, we cannot identify a law of physics or principle of computer science that would preclude this possibility. As we will see in Section 4, many pieces of the above scenario — interpreting laboratory findings, interpreting diagnostic imaging, interpreting broad clinical data as stored in electronic medical records (EMRs), etc. — have already been captured by AI models. Thus, it appears that physicians and AI alike can bring their competencies to bear on the same problems within medicine. In this general sense, physicians and AI may undergo a "meeting of minds".

Interestingly, research indicates that physician diagnostic facility depends on pattern recognition to a far greater extent than it depends on systematic reasoning from first principles.[61] Thus, both physicians and certain AI systems such as deep learning neural networks share the common feature of undergoing training on large sets of data to hone their pattern recognition abilities. In the case of physicians, data comes in the form of patients, both real (in hospital) and hypothetical (on examinations, in study materials, and human actors serving as standardized patients). Whatever patterns are recognized by physicians can likely be recognized by AI, too. Additionally, as discussed above in Sections 2.4 and 2.5, certain AI systems (in particular, those utilizing unsupervised machine learning) excel at uncovering hidden patterns. We can likely expect such systems to uncover new patterns hidden in medical information, which may have exciting implications for the future of medical knowledge. This possibility is explored further in Section 4.3.

So far we have focused heavily on the scientific aspects of medicine, discussing the extent to which these can be modelled. Narrative, humanistic, artistic aspects of medicine must be considered separately. We leave this topic as a future direction for further discussion elsewhere.

4. AI and physicians: a meeting of minds?

We have seen that AI and physicians share certain commonalities. AI transforms information in ways that are intelligent; doctors transform medical information in ways that are intelligent. Medical information can be abstractly modelled and therefore instantiated into computers, where it can easily be made available to AI systems for transformation. Therefore, from first principles, we should expect that AI can intelligently transform medical information. Further, both physicians and deep learning systems achieve their utility via a heavy reliance on pattern recognition. Deep learning, and AI generally, are active areas of research. Sophisticated machine learning algorithms of the near future, able to self-learn from staggeringly complex data and programmed into universal computers with large storage capacity and processing power, may have no near limit to the competence they can achieve. Taken collectively, these considerations persuade us that the potential for AI to succeed in the future of medicine is likely broad and extensive.

The differences between AI and physicians will be equally important as similarities. Certain AI systems are likely to form representations based on novel pattern extraction and interpretation, thus diverging from human physician cognition and models. Additionally, differences in the characteristics of models used by physicians and AI may instate accordingly different competencies across medical use cases, which may in fact be complementary. For example, AI's pixel-by-pixel analysis of diagnostic imaging studies will have higher acuity for adjacent shades of grey,[16] complementary to human physicians' generally superior capabilities of lateral thinking and broad differential diagnoses.[62,63] Thus, physicians and AI may be well-suited to augment one another in collaborative clinical practice. Collaborating to interpret diagnostic investigations and offer clinical predictions is a kind of "meeting of minds" that is already underway. Sections 4.1 and 4.2 further explore possibilities in this area.

Further, in as much as AI's models of medicine are conceptually different but nonetheless accurate and useful, examining the details of the AI models may chart a course to new insight about the body. AI systems may float free of historical biases and schemas in medicine — for example, if they begin as an agnostic deep-learning neural network, as did AlphaGo Zero. If this is the case, examining the representational models employed by medical AI systems may reveal new insights about intra-body phenomena, leading the way to paradigm shifts in medical knowledge and allowing discontinuous, transformative, and rapid advancement. The possibility that physicians may learn about medicine from AI is a second way in which a "meeting of minds" may occur. This possibility is further explored in section 4.3

The intersection of AI and physician competence is clearly complex and multi-faceted. Thus, the question "what to do with medical AI that is as good or better than doctors?" cannot be answered without specifically considering what medical AI can in fact accomplish. Having advanced a detailed physical and philosophical argument in Sections 2 and 3 that the future reach of AI in medicine may be quite broad, we will now turn attention to discussing the *current possible reach* of AI in medicine, as demonstrated by recent active research.

4.1 AI can collaborate with physicians in the information specialties

Certain tasks in medicine have received plentiful attention of early AI research. Given specific competence of certain AI systems in recognizing and classifying images,[47] a natural early step for AI in medicine has been recognizing and classifying diagnostic images. The benefits of accurate image classification will be significant. For example, if AI can successfully classify diagnostic imaging studies, it may be able to serve as a cognitive prosthetic for radiologists, leading to gains in accuracy and efficiency. Alternatively, in geographic regions underserved by radiologists, some AI systems may be accurate enough to act in lieu of radiologists. The authors of a study reporting a deep learning system for classifying pulmonary tuberculosis on chest x-ray noted that such a system could be of particular value given a relative paucity of radiologists in certain TB-endemic areas of the world.[64] Many AI systems have demonstrated competency in transforming medical imaging information, pathological information, and electrophysiological information into accurate diagnostic and predictive information. We will consider representative examples in the information specialties of AI systems with capabilities to augment or enhance the abilities of physicians.

Chest x-ray is a widely-used imaging modality that has received a plenitude of AI research attention early on. Various AI systems have demonstrated the ability to perform similarly to radiologists at interpreting chest x-rays. In a recent notable study, a deep learning system was trained to detect fourteen different pathologies as demonstrated on chest x-ray.[65] Following training on over 100,000 disease-labelled chest-x-rays, the system was found to perform radiologist-level or better on classifying eleven of fourteen pathologies. Other work has also specifically demonstrated efficacy of an AI radiologist collaboration. In a multi-centre collaboration based out of South Korea which developed a deep learning system for classifying chest x-rays with varying degrees of accuracy for various pathologies; when assisted by the deep learning system, radiologists benefited from a significant increase in sensitivity.63 The authors suggested this may be due to the AI alerting radiologists to the possibility of the presence of major thoracic disease, and to localizing the area of possible lesions to mark spots needing further attention by radiologists.[63] Researchers at Thomas Jefferson University created a radiologist-AI collaboration achieving 97.3% sensitivity and 100% specificity in classifying pulmonary tuberculosis on chest x-ray.[64] AI-radiologist collaborations may be a natural fit due to AI's pixel-by-pixel analysis allowing computation thorough approach greater acuity for adjacent shades of grey,[16] but relative inferiority at lateral thinking62 and generating a differential diagnosis.[63]

Beyond chest x-rays, deep learning systems have demonstrated early success on other imaging studies as well. A collaboration based in Australia recently reported a deep learning system that, following training and validation on nearly 50,000 frontal pelvis x-rays, achieved 97% accuracy in diagnosing hip fractures.[66] Research conducted in Budapest demonstrates a deep learning system for diagnosis breast cancer on mammography that achieved 90% sensitivity and 70% specificity (a performance considered to be on par with some physicians, but not necessarily as accurate as specialized radiologists).[67] Researchers at the University of California developed a deep learning system for classifying echocardiogram views that achieved 97.8% accuracy of classification, and when tested against electrocardiographers on single low-resolution images, achieved 91.7% accuracy versus the electrocardiographers' 70.2-84.0% accuracy.[68] Notably, the US's FDA has already approved AI algorithms for interpreting certain diagnostic imaging studies,[20] including analyzing heart hemodynamics via cardiac MR images,[18] interpreting hyperacute stroke CT brain images,[17] and evaluating liver and lung lesions evident on MR and CT images.[19]

Outside diagnostic imaging, image classifying AI systems have also achieved success in histopathological examinations. Cancer is a common indication for histopathological investigation, thus many studies have concentrated here. Google recently reported the development of "LYmph Node Assistant" (LYNA), which outperformed pathologists in diagnosing metastatic breast cancer from pathological samples,[69] and, when applied to assist pathologists, made their job of diagnosing breast cancer "easier".[70] Google also recently reported a deep-learning system which outperformed general pathologists at grading prostate cancer, achieving an overall accuracy of 70% compared the pathologists' average accuracy of 61%.[71]

Image classification techniques and other deep learning systems may also be of use in interpreting "images" of electrophysiologic tracings such as ECGs and EEGs. Regarding ECG, evidence demonstrates utility of AI to interpret ECGs to identify arrhythmias and cardiac contractile dysfunction with approximately the same accuracy as cardiologists.[72,73,74] Regarding EEG, in long-term ambulatory EEG-monitored patients, AI may be able to predict seizure onset. A recent study reports a deep learning system achieving seizure prediction accuracy of 99.6% with a prediction time of one hour ore-ictal, and a low false alarm rate of one false alarm generated every 250 hours.[75] Applied to invasive intracranial EEG, deep learning systems may have some utility in helping classify seizure onset zone.[76] Additionally, there is promising evidence regarding the utility of AI systems to monitor against seizures in the intensive care unit, with accuracy approximately as good as electroencephalographers, in less time needed to review the EEGs.[77]

These above works demonstrate AI performing certain tasks at levels of competence similar to radiologists, pathologists, and electrophysiologists. On these narrow, information-heavy tasks, the "meeting of minds" has already begun. AI in cooperation with radiologists may improve sensitivity and accuracy,[63,64] and may provide similar such advantages to pathologists.[70] In collaboration with information specialists, AI could take many roles, perhaps screening all images and alerting physicians to the likely presence of major disease, or perhaps providing a useful consultant second opinion on an as-needed basis. As noted, AI may see things differently than humans, conferring an advantage in the spirit of "two sets of eyes are better than one".

Faster interpretation times achieved by AI will be of specific use as well. The FDA-approved algorithm for interpreting hyperacute stroke CT brain images automatically summons an interventionist if a large vessel occlusion is detected (since large vessel occlusions may be amenable to thrombectomy).[19] A human radiologist also interprets the CT images, however, the AI typically finishes first, allowing faster access to morbidity-reducing interventional treatment. AI systems in the information specialties may soon gain sufficient competence to act autonomously in broader clinical settings, which will be highly advantageous for regions underserved by radiologists and other information specialist physicians.

AI interpretative assistants also hold certain other advantages over their human physician collaborators, such as being present and available on hospital networks 24/7 without the need for rests or breaks. Further, whereas physician thoroughness may unfortunately decline throughout the day,[78,79] AI systems perform consistently at their given levels of accuracy. In fact, if programmed to continue learning from incoming contemporaneous patients, an AI system's level of accuracy will likely increase over time.

One downside of incorporating AI interpretative assistants is that physicians may come to depend too heavily on the AI in situations where it is inappropriate. Please see Section 6 for further discussion of this possibility, and discussion of other limitations of AI's entrance into healthcare.

4.2 AI can predict important clinical outcomes from various sources

In the information specialties, AI begins with a narrow model of the patient, a model that is already contained in the investigative study. However, outside the information specialties, medically-oriented AI systems have tended to intake broader, various data sources, forming broader models of the patient (rather than working exclusively with a chest x-ray-generated model of the thorax, for example). Abstract models resulting from these broad inputs have proved useful for prediction. Similar to the pixel-by-pixel approach to medical image interpretation, AI systems in broader aspects of medicine can likewise analyze data iota-by-iota. EMRs are one excellent source of such broad data. A recent survey found that 80.5% of US hospitals were using at least a basic EMR system.[80] AI can roam freely through a patient's EMR, automatically detecting patterns and predicting things with a high degree of accuracy. For example, a 2013 study reported a deep learning system which could sift through patients' EMRs and automatically predict diagnoses of rheumatoid arthritis with moderate accuracy.[38] We will consider representative further examples of the power of AI to predict diverse clinical outcomes from transformations of broad, often routine clinical information.

A recent international collaboration used multiple machine learning strategies (including some deep learning strategies) to construct an "early warning system" for predicting mortality amongst inpatients.[81] The system extracted patterns amongst variables including certain diagnoses such as congestive heart failure and acute cerebrovascular disease, and in patients' presentation to care histories in the months prior to admission. The system was tested prospectively on a set of 11,765 patients, of whom 255 passed away. Of these, for the 69 patients (13.3%) who had been at the highest risk of passing away, the AI system accurately predicted their death 40.8 hours in advance.[81] Similar to the notion that an AI system for chest x-ray could serve to notify radiologists of the possibility of major thoracic disease,[63] the study authors of the early warning system for mortality noted that such a system could be of use to automatically notify physicians and other healthcare professionals whenever a patient exceeded a given high-risk threshold.[81]

Other work has focused on what important outcomes can be predicted from hidden patterns in routine lab data. Recent work out of the Swedish Karolinska Institutet applied various machine learning models to routine laboratory data in effort to predict outcome following traumatic brain injury.[82] Study results identified increased serum creatinine, serum glucose, and plasma osmolarity, as well as decreased serum albumin, as factors predicting a worse outcome. Other work conducted out of the University of Nottingham exposed machine learning algorithms to routine lab data for the purpose of predicting adverse cardiovascular events.[37] Compared against standard-of-care American Cardiology guidelines in a retrospective test set of 378,256 patients, the machine learning system predicted 355 more events of cardiovascular disease than did current standard of care.[37] Greater predictive accuracy will be invaluable for forecasting important outcomes such as recovery from traumatic brain injury and risk of myocardial infarction.

In addition to predicting event outcomes, routine laboratory data may also be useful for diagnosing disease. Referencing previous work demonstrating underdiagnoses of primary hyperparathyroidism,[83] Somnay et al. devised a machine learning system based on routinely available clinical data that could diagnose primary hyperparathyroidism with accuracy superior to 95%.[84] Similar to other works on early warning systems81 and alerts of possible major disease,[63] Somnay et al. suggested that their primary hyperparathyroidism-detecting system could be incorporated into EMR software to create a "best practice alert" recommending parathyroid work-up in high-risk patients.[84]

Other work has applied AI to predict response to medications. A US multicenter collaboration used a variety of machine learning approaches to make treatment recommendations for choice of antidepressant for patients with major depressive disorder, identifying a subset of patients expected to benefit from sertraline therapy relative to placebo. This benefit was observed in study results, although the sertraline-receiving patients who had been identified as optimally suited to this treatment did not experience significantly different outcomes from the other, less-optimally-suited patients receiving the same treatment.[35] Beyond antidepressants, other work employed a variety of machine learning methods to predict optimal warfarin dose, a challenging task due to its narrow therapeutic range.[36] The AI in this study had some success, and the authors concluded it could be of benefit in determining optimal dosing, especially for patients needing low maintenance doses.[36]

This research collectively demonstrates competency of various AI systems in predicting diverse clinical outcomes including mortality, adverse events, diagnosis of disease, and response to treatment. In some cases, AI prediction algorithms may be superior to existing clinical prediction guidelines, such as the widely used Framingham risk score.[37] As suggested by some, AI prediction algorithms could run alongside physicians and flash warnings when deemed relevant. In as much as competency of such systems has been demonstrated and is likely to increase, healthcare policymakers and physicians should be correspondingly enthusiastic to obtain access to AI predictive powers. AI's predictions may arise from different variables than from clinicians, and may predict different things than physicians, thus, rather than necessarily usurp physicians as lead predictors and decision-makers, AI warning systems may more likely constitute a useful and complementary second opinion. With incorporation into healthcare and exposure to high volumes of patient data, predictive machine learning algorithms will attain greater and greater accuracies. Such predictive systems may also help close the gap in care existing between areas underserved by physicians (such as Northern and remote Canada, developing countries, etc.) compared to areas with relatively abundant access to physicians. This will be a highly important outcome, since whereas information specialty tasks such as interpretation of diagnostic imaging can often be outsourced to a nearby tertiary centre, the more intimate tasks of clinical prediction, such as "which patients on my ward are at high risk of two-week mortality?" cannot be systematically outsourced in the same way. As AI systems gain increasing predictive competency, a desire for utilizing this competency should compel physicians and policymakers to consider incorporating predictive AI algorithms into healthcare.

4.3 Could physicians working alongside AI gain new insights into physiology and pathophysiology?

In receiving broad information representing a patient, such as by roaming through their EMR, AI generates a novel model of the patient that is correspondingly broader than the model contained in a diagnostic imaging study. New, AI-generated models will be interesting objects of study. In particular, models resulting from unsupervised machine learning algorithms are likely to be highly creative relative to contemporaneous human-designed models. But regardless of how an AI model is generated, physicians and policymakers will be behooved to understand its salient features. If the medical community is to sanction the adoption of a particular

AI system, it will be important for purposes of safety, potential debugging, and to understand the functioning of the system's model to ensure its robustness. As discussed above, in examining the models of AI, we may be led to new insights about the body.

AI medical systems may lead to new insights in other ways. AI's high-powered pixel-by-pixel analysis allows it see certain things that cannot be seen by physicians, thus achieving access to whole new realms of data. Within diagnostic imaging, the field of "radiomics" is emerging, which focuses on mining images for such hidden data.[85] One study demonstrated that small changes in serum potassium (as small as 0.2 mEq/L, even within the normal reference range) manifested quantifiable changes on ECG that were detectable by AI interpretation but not by human review.[86] By applying deep learning, it has been discovered that retinal fundoscopy images contain information to robustly predict a person's age, gender, blood pressure, smoking status, diabetes control, and risk of adverse cardiovascular events.[87] MR images of low-grade gliomas contain information to predict deletion of chromosomal arms 1p/19q (an important prognosticator for treatment response). Using only MR images, deep learning system acquired this knowledge with 93.3% sensitivity, 82.22% specificity, and 87.7% accuracy.[88] Perhaps most interestingly, fluorine 18 fluorodeoxyglucose PET images of the brain contain information that can be used to predict diagnosis of Alzheimer's disease 75.8 months prior to the time of eventual diagnosis with 82% specificity at 100% sensitivity.[89] Interestingly, when this model analyzed via saliency mapping to determine which features it had extracted from the data to influence its predictions, it was found that rather than relying on a specific brain location or regions that could serve as anatomic biomarkers, the system appeared to utilize data from the whole brain to inform its predictions. (The system did consider certain areas to be more influential, with some influential regions corresponding to brain regions implicated in present understandings of Alzheimer's disease.) By virtue of AI's ability to see new things, including by pixel-by-pixel analysis, and by virtue of the power of machine learning algorithms to diverge from human understandings, medical models in AI systems may lead us to new explanations of intra-body phenomena, explanations that are divergent from an otherwise evolutionary, ad hoc mode of advancement of medical knowledge.[90]

A further distinct and intriguing possibility is that AI mathematical model parameters may possibly correspond to actual biological parameters within the body. "Theory-driven" efforts in the emerging field of computational psychiatry seek to generate computation models with parameters corresponding to brain neural circuitry parameters.[91] To this end, "biophysically-realistic neural-network models"[92] have captured specific, exquisite neurotransmitter disruption caused by ketamine use;[93] detailed models of particular neuroanatomical structures such as cortico-striato-thalamic loops[94,95] have demonstrated explanatory power for various neurological and psychiatric diseases.[92,96,97] Whereas computational psychiatry approaches address the brain as an algorithm to model, this framework may map onto other organs as well. Can the pituitary gland be modelled as an algorithm for transforming serum concentrations of certain hormones, with detailed mathematical model parameters corresponding to release stimuli for the various pituitary hormones? Can a kidney be modelled as a multi-layered algorithm for filtering blood, with model parameters corresponding actions of individual nephrons, or even to arrays of particular ion pumps along individual nephrons? Indeed, a detailed computational model of nephron transportation of water and solutes was published in February, 2019.[98] Perhaps computational endocrinology and computation nephrology await us as future endpoints. For now, progress is likely to move in the direction of gradually-increasing extent of accurate modelling.

However, on the opposite end of the spectrum of model-body correspondence, it is conceivable that certain AI predictive models may have nothing to do with bodily phenomena. AI systems could hypothetically base their predictions on emergent "data" and patterns that exist only inside the model, uncorrelated to any process in or affecting the original outside system (the patient). Such predictions could even hypothetically still be robust, however, they would run the risk of being "fooled" by confounding data.[99] However, as AI predictive models achieve better and better competence, its feature maps and pattern extractions will have to be more and more consonant with the actual body itself (assuming an efficiency incentive conferred by constraints in power supply and computational storage). Thus, most likely, the parameters within the predictive models will correspond more and more closely to *some* abstract informational state about the body. Perhaps, in the extreme, something like a unified computational biology can be approached. As this field progresses, investigating model parameters to understand the salient bodily features being mapped will be of increasing importance for purposes of safety, debugging, and advancement of knowledge.

5. Limits and obstacles to physician augmentation by AI

We have explored various ways in which AI systems and physician competence will intersect. Healthcare should be keen to capture the value of AI, which will include integration of physician-AI collaborations, and, in time, perhaps attaining some reliance on autonomous AI that is uncoupled from physician oversight. However, in incorporating AI into healthcare, certain difficulties must be faced.

First, physician-AI collaboration will be limited by the rate and extent of technological advancement in medically-purposed AI systems. While some promising systems already exist, and increasing resources are being devoted to AI and specifically AI in healthcare,[10,14] much work still remains. As part of this work, we must ascertain how best to harness and implement the information provided by medical AI. (Some have noted that medicine may in general benefit from greater emphasis on its "effector arm"– i.e., knowing when and how to act on information that is available.[100]) Second, AI systems appearing competent in retrospective validation trials may require further and more extensive prospective validation on sets of real, contemporaneous patients incoming to hospital facilities. This will likely be a necessary step to achieve sufficient trust in these systems, and to foster certainty in their real-world competence. Third, and also relating to the matter of sufficient trust, is the "black box" posed by some AI systems. What happens in the deep interior layers of a neural network? What patterns are being recognized and mapped? Ability of an AI system to account for the informational, pattern-recognized basis of its output will allow greater trust in the system (if in fact the basis appears reasonable), and will help to guard against oversights via human verification at the level of pattern extraction, data mapping, etc. Ironically, it is conceivable that AI systems may be applied to help us understand other AI systems — essentially, the behaviour of a deep learning system could serve as the input information to another deep learning system. Fourth, machine learning techniques in general may fail to imbue human-level ability to reason effectively in novel circumstances, given that they will tend to be trained on the data of the past.[101] With each new patient encounter presenting a potentially novel circumstance, this limitation alone may ensure a role for human physicians in clinical medicine for the foreseeable future. Fifth, due to physician discomfort with risk and uncertainty, imperfect "assistant" AI systems could come to be inappropriately relied upon for clinical decision making. Physician dependence on AI systems must scale with competence of the given system, and AI systems validated for assistive function must not be spuriously promoted to leadership function over and above physician judgement.

Some have also suggested that current machine learning algorithms may be overhyped.[102] Relatedly, certain leading AI researchers are pursuing more advanced modes of machine learning. Neural network pioneer Geoffrey Hinton (who has been called the Einstein of AI)[102] has begun working on a new type of network called "capsule network" which may prove allow machine learning techniques of even greater power than current neural network technology.[103]

Additional concerns surrounding AI in healthcare include those of patient privacy. Machine learning algorithms generally require a vast amount of training data to refine interpretations and achieve competency. For machine learning in healthcare, the requisite data will tend to be confidential patient data, raising the question of how to expose machine learning algorithms to sufficient volumes of training data without violating patient privacy. Fortunately, sophisticated computational techniques are being devised to overcome this challenge, anonymizing patient data and providing "formal, mathematical guarantees around privacy preservation."[104] Concern has been raised that certain modern anonymization techniques, such as those used in 2018 for deidentifying information obtained from wearable devices, may be inadequate to ensure privacy.[105] Moving forward, it will be crucial to ensure privacy of any patient with medical information passing through an AI algorithm.

Lastly, there is the concern that, to whatever extent AI is relied upon in healthcare — especially without physician oversight — a computer "crash" affecting the AI would be catastrophic. Existing EMRs do occasionally crash.[106] Redundant safety back-up measures for healthcare technology must scale to be increasingly robust alongside increasing reliance on AI.

6. Limitations of this paper

This paper has focused on how AI will affect the future of medicine by intersecting with physician competence. We have not discussed the arrival of AI competence in surgical medicine, nor in pre-clinical biomedicine; unsurprisingly, the possible capabilities of AI in these fields are also evident. Robotic surgical assistants are already in widespread use worldwide.[107] Despite gains in precision and accuracy, their use generally does not significantly alter outcomes;[108] however, emerging data demonstrates potential for outcome improvement.[109] It is believed that implementing touch sensors also will help advance their effectiveness, and such developments are now forthcoming.[110] Overall, it has been proposed that "clinically feasible" autonomous surgical robots will exist before the end of this century.[111] Regarding pre-clinical biomedicine, for recent excellent detailed reviews, see Angermeuller et al. 2016[112] and Ching et al. 2018.[90]

7. Conclusion

The continued advancement of medical AI will have a tremendous and complex impact on the future of medicine and the future of human life generally. If competence of medical AI systems continues to progress, the best-performing clinical executive systems will, at some future point, almost certainly be physician-AI collaborations. Moving forward, healthcare will be increasingly confronted by the question of what to do with AI medical systems that rival physician competence. The "meeting of minds" between physicians and AI has already begun, with AI systems deployed into healthcare in numerous countries worldwide. Given the potential of AI systems to enhance accuracy and improve outcomes in manifold aspects of medicine, and to enhance the standard of care in physician-underserved regions, we may be wise from perspectives of beneficence, non-maleficence, and justice to concentrate resources on their development. Navigating the evolving, dynamic intersection of physician and AI competence will be crucial to capture benefits, mitigate risks, and achieve optimal outcomes for patients. Time will tell what will be the ultimate role of human physicians in the future of medicine.

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