*Achievements, Milestones and Challenges in Biomedical and Health Informatics*
*J. Mantas et al. (Eds.)*

*doi:10.3233/SHTI220950*

# Health, Digital Health and Decision Support: Sisyphus and Pandora

Christian LOVIS[a,b,1]
[a] *University hospitals of Geneva, Diagnostic Department, Division of Medical Information Sciences, Geneva, Switzerland*
[b] *University of Geneva, Department of Radiology and Medical Informatics, Geneva, Switzerland*

**Abstract.** The history of medicine is punctuated by conquests, discoveries and revolutions. It is also marked by questioning. It is made of doubts and certainties. In this thousand years old history, certain recent battles bear witness to these questionings, such as quality, refocusing on the patient, medical errors, antibiotic resistance and the importance of gender, which has been neglected for so long in medicine. Digitalization is one of these many revolutions, and it is not immune to questioning. Building evidence and trust, equity of access for neglected populations, and training are among these issues. More specifically, in the field of decision support, the first enthusiastic hours of computing were followed by unexpected observations, such as the identification of human factors, such as alert fatigue. Today, immense hopes rest on the development of deep learning, and it is up to us to accelerate its development by investing energy, time and resources to build on evidence, trust, and a strong integration of health professionals and patients.

**Keywords.** Decision support, artificial intelligence, medicine, medical informatics

## 1. It all started because there are humans and there are Ancient Gods

Asclepius is supposed to be son of God Apollo and Coronis, a mortal woman from Trikala, Thessaly. There has been numerous children of Greek Gods and mortals, and there was more that made the birth of Asclepius so extraordinary. Coronis fell in love with Ischys, a mortal man, during her pregnancy, which made Apollo furious, and the God sent his sister Artemis to kill Coronis. Artemis burned Coronis on a funeral pyre. Apollo rescued the unborn baby by cutting open the womb of the burning mother. This is thought to have been the first Cesarean section in human history. Apollo entrusted the baby to wise centaur Chiron, famous for his skills in medicine, who became his mentor, making Asclepius becoming a famous and highly-regarded healer [1].

The history of mankind and the history of medicine are paved with complex relationships between beliefs and science, between human aspirations that draw their essence from the world of the Gods, and the reality of life that plunges its challenges into our human condition.

The Iliad of Homer describes the great plague which decimates the Greek army as a consequence of a human's unjust actions offended the gods [2]. The disease kills and

[1] Corresponding Author, Christian Lovis, Hôpitaux universitaires de Genève, 4, rue Gabrielle-Perret-Gentil, 1205 Genève, Switzerland; E-mail christian.lovis@hcuge.ch.

mutilates. On the other hand, for some like Fritz Zorn, in Mars, disease mutilates, strikes, irreparable and inescapable, and it is also, paradoxically, liberating: " wherever it hurts, it is me " [3], illustrating how disease can be perceived as redemption.

The concept of normality is an important driver in medical science, and medicine driven at understanding what causes deviations, how to detect them, to prevent them, and to correct them.

As a result, there is a scientific translation of this dichotomic, Manichean vision of the world, diseases are measured as deviations from the “normal”. Cure consists in reducing, or cancelling, this deviation.

The disease and its therapies, as well as the bearers of this knowledge, have always been confronted with a double component, science and pragmatism on the one hand, but also, on the other hand, beliefs and divinatory practices. The diagnosis and actions belonged to the diviners, the shamans, and the priests; the decisions and prognosis belonged to the Gods. With Hippocrates, the conception of medicine entered a more structured and rational approach. It took a long journey through time in the West to arrive at Harvey's demonstration of the circulation of blood, thus introducing mechanics into medicine; or Morgagni and the anatomical method, to name only two of a long and prestigious list of scientists (Vesalius, Sydenham, Auenbrugger, Corvisart, Laennec, Louis, Mueller, Osler, …) who have allowed the development of today’s medical science. Medical science isn’t just about scientific knowledge. It is also a lot about a singular relationship. Already with the school of Hippocrates, the importance of questioning the patient, his medical history, the specific history of a specific disease, the physical examination, where it was considered as cardinal aspects of medicine. Building an *understanding* of the case, which than was improved with increased knowledge on disease nosology (Sydenham), and the use of various tools such as percussion (Auenbrugger), stethoscope (Laennec), ophthalmoscope (Helmoltz), which started a long list still growing today. All of it leads to careful, meticulous, and precise description of the knowledge about a context, embedded in a larger knowledge, the images, the anatomy, bio pathways, physiology, and of course patients, differential diagnosis, therapies, evolutions. The science of medicine is now in the era of personalized medicine, and is increasingly seen as a deterministic cascade of events, starting with the DNA and ending in a complex network of causal elements up to environment and lifestyle building arrays of risk factors, evolution, prognosis [4,5].

## 2. And computers joined humans and Ancient Gods

In 1982, Peter Szolovits edited an AAAS symposium on “Artificial Intelligence in Medicine” held at the 1979 AAAS National Annual Meeting in Houston (TX), which he generously reconstructed in HTML and made available in Internet [6]. This collection illustrates the “Greek Oracle” vision of electronic decision support in medicine, combining sophisticated approaches and computing techniques to properly represent expert physicians, so that it becomes possible to produce tools for improving health care. Several pioneer systems are presented by their authors, such as *INTERNIST*, a diagnostic aid using on a large database of disease/conditions and manifestation associations building partionning functions; *EXPERT* and the Glaucoma Program based on physiological models for diseases; *MYCIN*, a rule-based program for infectious diseases; the *Digitalis Therapy Advisor*, an interpretable order entry support for prescription of digitalis; and *ABEL*, using pathophysiologic models for decision support of acido-basic and electrolyte abnormalities. These early pioneering systems triggered a wave of developments and new approaches. For example, QMR, successor of INTERNIST-1, used a homology function, a numeric score assessing how "alike" any two diseases are [7]. So much so that in 1992, 10 clinical experts created a test set of 105 diagnoses and compared the 4 best decision support systems available at the time (Iliad, Meditel based on Bayesian logic; Dxplain, QMR using semi-quantitative probabilistic associations of findings). The results found that the proportion of correct diagnoses was 0.52-0.71 and the mean proportion of relevant diagnoses was 0.19-0.37, so that less than half of the diagnosis suggested by experts was proposed by any of the 4 systems [8].

In 2011, it was estimated that the doubling time of medical knowledge in 1950 was 50 years; in 1980, 7 years; in 2010, 3.5 years and in 2020 projected to be 0.2 years—just 73 days [9,10]. The explosive growth of knowledge in medicine and life sciences is way beyond human's brain capacities.

The second part of the 20th century was fed by an extraordinarily enthusiastic wave of hopes that computers would support a new revolution in medicine, that of the computerization of medical records, of the simplification of medical data acquisition and processing, and of course of the support of medical decision making and patient care.

## 3. Errare humanum est, perseverare diabolicum

Patient safety concerns in the healthcare system has been a key element to boost digitalization and electronic decision support systems. Between 1990 and 2000, several alarming reports raised the awareness on care safety in healthcare systems [11–13]. At the turn of the Millennium, reports of the Institute of Medicine estimate that preventable fatal medical errors of all types cause between 44'000 and 98'000 deaths per year in the USA, among them about 7'000 due to medication-related errors [14]. In the same report, it is estimated that patients in hospitals could face more than one drug related error per day. In 1995, the pioneer work of Bates et al. and the associated editorial of Kahn in JAMA demonstrate and underline the preventable nature of drug prescription errors [15,16]. Of all adverse events, 1% were fatal and not preventable in this work, 12% life-threatening, 30% serious, and among them, 42% were preventable. This work demonstrated that adverse drug events were common and often preventable [15] and, in 2003, Bates et al. published a list of recommendations to achieve best decision support systems in clinical environments [17].

The following ten years have been remarkable at developing and deploying digital solutions in hospitals, and especially computerized providers order entry (CPOE) with all sorts of computerized decision support systems, alert modalities, user interfaces, and numerous studies evaluating and assessing the impact of these systems, reported in numerous peer-reviewed publications. For example, a positive effects on patient outcomes such as fewer duplicates, dosage errors, drug-drug interactions [18–21], improving cost-efficiency of care, either directly, as enumerated above, or indirectly, for example in reducing lengths of stay or rehospitalizations [22–24].

As these systems were increasingly and massively deployed, however, some concerns started to raise about their effectiveness or unintended effects [25]. In 2013, Jung et all. published a large international study analyzing the attitude of physicians towards alerting in CPOE systems which concluded that while most physicians found alerting system useful, half of them found alert overload as a major problem [26], and started constructive discussions on how to address these concerns extremely well summarized in a comment to this work by Bates et al. [27]. The critical importance of predictive values and false positive rate have been well summarized in a systematic review published by Carli et all. in 2018 which reports PPVs ranging from 8% to 83% with most results between 20% and 40% [28].

Altogether, the learnings of that period can be summarized in few key points:

- User interface, human-machine interactions and processes are key.
- Positive (PPV) and negative predictive values (NPV) are major determinants.
- Which requires accurate and timely knowledge and clinical data.
- Which requires a highly connected and interoperable clinical information system.

One of the key challenges is missing interoperability. To quote the literature review of Ahmadian : "*Lack of semantic interoperability is the most important obstacle in clinical decision support system implementation*" [29].

## 4. The Pandora dilemma

Decisions are influenced by numerous determinants, such as deep knowledge about the patient (clinical data, genomics, …) and his living context, knowledge (the global science of medicine and biology), and local information such as a-priori probabilities for Bayesian evaluations. They are also influenced by the effect of decisions, such as their impacts, but also the resources required, the time, the cost, etc.

Digitalization provides increasingly access to more data which opens the hope to improve massively decision support. Among the numerous sources more and more available, the clinical data originating in health electronic records (EHR) have massively increased. There are many reasons behind this, one of them being the need to improve efficiency of care processes, resource management and billing processes. These forces have led to unintended effects, mostly at increasing burden on health care providers, leading to a high workload interacting with EHR at the cost of patients time [30–35]. This effects is more important for US physicians than non US-physicians [36]. Additionally, digitalization has facilitated the development of tools to improve, increase and fasten data acquisition by care providers. For example, the work of Holmgren at al. has observed that up to 77.5 US physicians composed automatic notes, leading to information duplication. CPOE has been shown to decrease errors and is widely adopted, however has also been shown to potentially produce errors, such as wrong routing, wrong dose, and duplicates [37–39].

More data of better quality is made available thanks to digitalization, which itself increases data acquisition burden for care providers and potentially leads to data quality challenges, such as duplicates. EHR's have become the source of data for many different usages. Patient care is the primary reason, but there are countless other needs, such as planning resources, regulatory documentation, quality measurements, certification and accreditation, billing, clinical research, public health, etc. All of these have contributed to increase and diversify the data acquisition processes.

In 2018, Stanford Medicine mandate Harris Poll to do a national survey of over 500 primary-care physicians (PCPs) on EHRs and reported the following key points [40]:

- *PCP see value in EHRs but want substantial improvements.*
    - o 63% of PCPs think EHRs have generally led to improved care (63%)

  - 40% believe there are more challenges with EHRs than benefits
  - 62% of time devoted to each patient is being spent in the EHR
  - 49% of office-based PCPs think using an EHR detracts from their clinical effectiveness
  - 71% physicians (71%) agree that EHRs greatly contribute to physician burnout
  - 59% think EHRs need a complete overhaul
- *EHRs are not seen as powerful clinical tools but rather storage systems*
  - 44% of PCP think EHR is essential for storage.
  - 8% say the primary value of their EHR is clinically related
- *Physicians agree on what needs to be fixed and when*
  - 72% think that improving EHRs' user interfaces could best address EHR challenges in the immediate future
  - 67%) consider interoperability deficiencies should be the top priority for EHRs in the next decade
  - 43% want improved predictive analytics to support disease diagnosis, prevention, and population health management

Altogether, it seems that decision support in EHRs has brought a lot, but at a high cost and without achieving yet its full potentials. The wave of *massive data* is now moving to the era of *actionable data*, which is the rise of semantics.

Science has been driven by understandability and the hypothetico-deductive approach proposed by Karl Popper in his cornerstone work on building a rational approach of science [41,42]. This work has considerably influenced science based on experimentation, reproducibility, and refutability. It thus comforted the development of decision support systems based on formal and verifiable knowledge. In medicine, it had several consequences. One of them was the idea that any complex system can be decomposed in small verifiable and simple components. In this movement, decision support systems have built increasingly large set of rules, originating from experts, from knowledge database, observations, understanding of physiology, metabolism. It has soon become impossible to keep the pace of such systems with the parallel massive increase of knowledge in all fields of medicine. In addition, the compositionality of decisions-based processes, that is that complex decisions can be made from numerous simple and verifiable smaller elements, has been increasingly questioned. All of it has open the door to the Pandora "black box" reasoning, which is one of the challenges of deep learning. Building post hoc interpretability and explainability [43–45].

## 5. Sysiphus and the new Eldorado

Interoperability has been shown to be at cornerstone of decision support. Interoperability means being able to put together many different data sources, modalities, and types considered a complex temporal framework. However, addressing interoperability is a complex question, as it requires to take into account the meanings of things being handled, their definitions and interpretations in various contexts. Decision taking processes are usually based on meaningful determinants interpreted with various instruments.

At the beginning of the second book of his "Posterior Analytics", Aristotle claims that there are four questions for investigating the nature of things and their properties, whose answers lead to demonstrable knowledge, or knowledge of a "scientific" nature.

- That it is (*to hoti*): Is it a fact that a thing has a property?
- Why it is (*to dioti*): Why does a thing have a property?
- Whether it is (*ei esti*): Does a thing or property exist?
- What it is (*ti esti*): What is the nature and meaning of a thing or property?

Building decision support systems is thus also facing the question of the nature of decision processes. For example, which decision processes do require intelligence, and which type of intelligence. One of the learning of the evolution of decision support systems in CPOE is that despite the fact that every rule is excellent with a low false positive rate, with the typical complex cases taken care off and the huge size of knowledge base, systems will fire thousands of rules for each case, thus with a high probability of having a few false positive. And, consequently, the system has a low predictive positive value. A comparison of two commercial products recently published by Shah et al. has reported that the one system triggering 94% fewer alerts for inpatients and 93% fewer for outpatient setting also had much higher sensitivity and specificity, with PPV of 83.81% versus 3.55% (p< 0.0001%) for inpatients and PPV 82.54% versus 4.84% (< 0.0001) [46]. Or the unexpected application of the *Less is More Medicine* [47].

Artificial intelligence, as a field of computer science, was born in the aftermath of the Second World War. History says that the term Artificial Intelligence was coined by McCarthy, during the Dartmouth Summer Research Project on Artificial Intelligence, a scientific workshop organized in the summer of 1956 by Marvin Misky and John McCarthy, in which about twenty researchers from many disciplines participated, and who have left their mark on history (Claude Shannon, Ray Solomonoff, Olive Selfridge, Herbert Simon, Alan Newell, etc.) [48].

In truth, the very definition of intelligence is subject to debate, and the same is true for artificial intelligence. These questions were already raised more than 50 years ago, leading Alain Turing to propose his famous Turing Test, which consists in having a blind observer examine a conversation between a human and a machine. If the observer is not able to identify the human and the machine in the conversation, then the test is passed[49]. In recent years, with the development of huge linguistic models such as GPT-3 from Google's subsidiary OpenAI [50,51], the performance of neural networks has required much more refined tests to evaluate whether these models are "intelligent" or simply gigantically probabilistic [52].

Data driven science and its corollaries in machine learning and the wider field of artificial intelligence (AI) have the potential to drive important changes in medicine. By nature, AI is a large field of research and development that requires multi-disciplinary approaches to address many aspects of it, from tools and methods used up to application fields. Since a few years, AI is mostly seen as the field focusing on autonomous learning, especially using methods regrouped under “Deep learning”. However, the landscape of AI research is much richer, and traditionally include knowledge representation and engineering; rule-based and symbolic reasoning; temporal reasoning and planning; sensing and perception; learning; evolutionary, emerging, social behaviors; and the ability to move and manipulate objects, to name the most important [53]. In one form or another, AI is already broadly used today in medicine. Decision support based on knowledge engineering and rule-based systems are implemented widely in CPOE worldwide. Advanced signal processing is implemented in pacemakers, implemented defibrillators to take decisions, in imaging to improve images, decrease irradiation, support diagnosis, in oncology to find the best matches between patients and existing literature, to quote a few examples. Consequently, the field draws at large through philosophy, mathematics, information sciences, computer science, psychology, anthropology, social sciences, linguistics, and many other.

This richness is also building silos between fields and generations of researchers, building waves of research and discoveries that repeat themselves across domains, and time. It is certainly an important hope of AI that it will help avoiding researchers to research and find what has already been researched and found.

## 6. Conclusions

The future of decision support in medicine is built around the evolution from complication to complexity. There is no one-fits-all solution to the wide area of decision support in medicine. Each problem will have to get the best answer, a sort of *problem-centric personalized decision support*. For this aspect, a rule-based approach will work best. For another, it will be about Bayesian networks.

Most of all, it is critical to enforce health technologies assessment towards digital health and artificial intelligence [54–56]. As written in a 2018 editorial of the Lancet :"*Continuing to argue for digital exceptionalism and failing to robustly evaluate digital health interventions presents the greatest risk for patients and health systems*" [57]. And also, make sure that no one is left behind [58], patients and care professionals.

## Abbreviations

| | |
|---|---|
| AAAS | American Association for the Advancement of Science |
| AI | Artificial intelligence |
| CPOE | computerized providers order entry |
| DL | Deep learning |
| EHR | Electronic health record |
| HTML | HyperText Markup Language |
| JAMA | Journal of the American Medical Association |
| NPV | Negative predictive value |
| PCP | Primary care physician |
| PPV | Positive predictive value |
| QMR | Quick Medical Reference |

## References

[1] Asclepius, Wikipedia. (2022). https://en.wikipedia.org/w/index.php?title=Asclepius&oldid=1102557957 (accessed August 20, 2022).
[2] Michelakis P. Naming the Plague in Homer, Sophocles, and Thucydides, Am. J. Philol. 140 (2019) 381–414. doi:10.1353/ajp.2019.0025.
[3] Zorn F, Muschg A, Lambrichs G. Mars, FOLIO, Paris, 1982.
[4] Thompson RP. 2 Causality, theories and medicine, (2011). doi:10.1093/acprof:oso/9780199574131.003.0002.

[5] Erikainen S, Chan S. Contested futures: envisioning “Personalized,”“Stratified,” and “Precision” medicine. New Genetics and Society. 2019 Jul 3;38(3):308-30.
[6] Szolovits P. Artificial Intelligence in Medicine, Westview Press, Inc., 1982. http://groups.csail.mit.edu/medg/people/psz/ftp/AIM82/ch0.html (accessed August 21, 2022).
[7] Berman L, Miller RA. Problem area formation as an element of computer aided diagnosis: a comparison of two strategies within quick medical reference (QMR). Methods of information in medicine. 1991;30(02):90-5.
[8] Berner ES, Webster GD, Shugerman AA, Jackson JR, Algina J, Baker AL, Ball EV, Cobbs CG, Dennis VW, Frenkel EP, Hudson LD. Performance of four computer-based diagnostic systems. New England Journal of Medicine. 1994 Jun 23;330(25):1792-6.
[9] Elsevier, Medical knowledge doubles every few months; how can clinicians keep up?, Elsevier Connect. (n.d.). https://www.elsevier.com/connect/medical-knowledge-doubles-every-few-months-how-can-clinicians-keep-up (accessed August 20, 2022).
[10] Densen P. Challenges and opportunities facing medical education. Transactions of the American Clinical and Climatological Association. 2011;122:48.
[11] Phillips DP, Christenfeld N, Glynn LM. Increase in US medication-error deaths between 1983 and 1993. The Lancet. 1998 Feb 28;351(9103):643-4.
[12] Leape LL, Brennan TA, Laird N, Lawthers AG, Localio AR, Barnes BA, Hebert L, Newhouse JP, Weiler PC, Hiatt H. The nature of adverse events in hospitalized patients: results of the Harvard Medical Practice Study II. New England journal of medicine. 1991 Feb 7;324(6):377-84.
[13] Brennan TA, Leape LL, Laird NM, Hebert L, Localio AR, Lawthers AG, Newhouse JP, Weiler PC, Hiatt HH. Incidence of adverse events and negligence in hospitalized patients: results of the Harvard Medical Practice Study I. New England journal of medicine. 1991 Feb 7;324(6):370-6.
[14] Institute of Medicine (US) Committee on Quality of Health Care in America, To Err is Human: Building a Safer Health System, National Academies Press (US), Washington (DC), 2000. http://www.ncbi.nlm.nih.gov/books/NBK225182/ (accessed September 26, 2015).
[15] Bates DW, Cullen DJ, Laird N, Petersen LA, Small SD, Servi D, Laffel G, Sweitzer BJ, Shea BF, Hallisey R, Vander Vliet M. Incidence of adverse drug events and potential adverse drug events: implications for prevention. Jama. 1995 Jul 5;274(1):29-34.
[16] Kahn KL. Above All'Do No Harm'How Shall We Avoid Errors in Medicine?. JAMA. 1995 Jul 5;274(1):75-6.
[17] Bates DW, Kuperman GJ, Wang S, Gandhi T, Kittler A, Volk L, Spurr C, Khorasani R, Tanasijevic M, Middleton B. Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality. Journal of the American Medical Informatics Association. 2003 Nov 1;10(6):523-30.
[18] van Rosse F, Maat B, Rademaker CM, van Vught AJ, Egberts AC, Bollen CW. The effect of computerized physician order entry on medication prescription errors and clinical outcome in pediatric and intensive care: a systematic review. Pediatrics. 2009 Apr;123(4):1184-90.
[19] Abramson EL, Kaushal R. Computerized provider order entry and patient safety. Pediatric Clinics. 2012 Dec 1;59(6):1247-55.
[20] Radley DC, Wasserman MR, Olsho LE, Shoemaker SJ, Spranca MD, Bradshaw B. Reduction in medication errors in hospitals due to adoption of computerized provider order entry systems. Journal of the American Medical Informatics Association. 2013 May 1;20(3):470-6.
[21] Bates DW, Gawande AA. Improving safety with information technology. New England journal of medicine. 2003 Jun 19;348(25):2526-34.
[22] Forrester SH, Hepp Z, Roth JA, Wirtz HS, Devine EB. Cost-effectiveness of a computerized provider order entry system in improving medication safety ambulatory care. Value in Health. 2014 Jun 1;17(4):340-9.
[23] Vermeulen KM, van Doormaal JE, Zaal RJ, Mol PG, Lenderink AW, Haaijer-Ruskamp FM, Kosterink JG, van den Bemt PM. Cost-effectiveness of an electronic medication ordering system (CPOE/CDSS) in hospitalized patients. International journal of medical informatics. 2014 Aug 1;83(8):572-80.
[24] Georgiou A, Prgomet M, Paoloni R, Creswick N, Hordern A, Walter S, Westbrook J. The effect of computerized provider order entry systems on clinical care and work processes in emergency departments: a systematic review of the quantitative literature. Annals of emergency medicine. 2013 Jun 1;61(6):644-53.
[25] Strom BL, Schinnar R, Aberra F, Bilker W, Hennessy S, Leonard CE, Pifer E. Unintended effects of a computerized physician order entry nearly hard-stop alert to prevent a drug interaction: a randomized controlled trial. Archives of internal medicine. 2010 Sep 27;170(17):1578-83.
[26] Jung M, Hoerbst A, Hackl WO, Kirrane F, Borbolla D, Jaspers MW, Oertle M, Koutkias V, Ferret L, Massari P, Lawton K. Attitude of physicians towards automatic alerting in computerized physician order entry systems. Methods of information in medicine. 2013;52(02):99-108.

[27] Bates DW, Baysari MT, Dugas M, Haefeli WE, Kushniruk AW, Lehmann CU, Liu J, Mantas J, Margolis A, Miyo K, Nohr C. Discussion of "Attitude of Physi-cians Towards Automatic Alerting in Computerized Physician Order Entry Systems". Methods of Information in Medicine. 2013;52(02):109-27.
[28] Carli D, Fahrni G, Bonnabry P, Lovis C. Quality of decision support in computerized provider order entry: systematic literature review. JMIR medical informatics. 2018 Jan 24;6(1):e7170.
[29] Ahmadian L, van Engen-Verheul M, Bakhshi-Raiez F, Peek N, Cornet R, de Keizer NF. The role of standardized data and terminological systems in computerized clinical decision support systems: literature review and survey. International journal of medical informatics. 2011 Feb 1;80(2):81-93.
[30] Muhiyaddin R, ElFadl AH, Mohamed E, Shah Z, Alam T, Abd-alrazaq AA, Househ MS. Electronic Health Records and Physician Burnout: A Scoping Review. ICIMTH. 2021:481-4.
[31] Johnson KB, Neuss MJ, Detmer DE. Electronic health records and clinician burnout: A story of three eras. Journal of the American Medical Informatics Association. 2021 May;28(5):967-73.
[32] McPeek-Hinz E, Boazak M, Sexton JB, Adair KC, West V, Goldstein BA, Alphin RS, Idris S, Hammond WE, Hwang SE, Bae J. Clinician burnout associated with sex, clinician type, work culture, and use of electronic health records. JAMA network open. 2021 Apr 1;4(4):e215686.
[33] Adler-Milstein J, Zhao W, Willard-Grace R, Knox M, Grumbach K. Electronic health records and burnout: time spent on the electronic health record after hours and message volume associated with exhaustion but not with cynicism among primary care clinicians. Journal of the American Medical Informatics Association. 2020 Apr;27(4):531-8.
[34] Gardner RL, Cooper E, Haskell J, Harris DA, Poplau S, Kroth PJ, Linzer M. Physician stress and burnout: the impact of health information technology. Journal of the American Medical Informatics Association. 2019 Feb;26(2):106-14.
[35] Moy AJ, Schwartz JM, Chen R, Sadri S, Lucas E, Cato KD, Rossetti SC. Measurement of clinical documentation burden among physicians and nurses using electronic health records: a scoping review. Journal of the American Medical Informatics Association. 2021 May;28(5):998-1008.
[36] Holmgren AJ, Downing NL, Bates DW, Shanafelt TD, Milstein A, Sharp CD, Cutler DM, Huckman RS, Schulman KA. Assessment of electronic health record use between US and non-US health systems. JAMA internal medicine. 2021 Feb 1;181(2):251-9.
[37] Amato MG, Salazar A, Hickman TT, Quist AJ, Volk LA, Wright A, McEvoy D, Galanter WL, Koppel R, Loudin B, Adelman J. Computerized prescriber order entry–related patient safety reports: analysis of 2522 medication errors. Journal of the American Medical Informatics Association. 2017 Mar 1;24(2):316-22.
[38] Schiff GD, Amato MG, Eguale T, Boehne JJ, Wright A, Koppel R, Rashidee AH, Elson RB, Whitney DL, Thach TT, Bates DW. Computerised physician order entry-related medication errors: analysis of reported errors and vulnerability testing of current systems. BMJ quality & safety. 2015 Apr 1;24(4):264-71.
[39] Koppel R, Metlay JP, Cohen A, Abaluck B, Localio AR, Kimmel SE, Strom BL. The impact of computerized physician medication order entry in hospitalized patients—a systematic review. JAMA. 2005;293:1197-203.
[40] Stanford Medicine, National Physician Poll by The Harris Poll, EHR Natl. Symp. (2018). http://med.stanford.edu/ehr (accessed August 21, 2022).
[41] Popper KR. Logik der forschung: zur erkenntnistheorie der modernen naturwissenschaft, J. Springer, 1935.
[42] Hermann G. Karl Popper: Logik der Forschung. Zur Erkenntnistheorie der modernen Naturwissenschaft, vi+ 248 pp. Springer: Berlin 1935. Journal for General Philosophy of Science. 2020 Dec;51(4):621-3.
[43] Erasmus A, Brunet TD, Fisher E. What is interpretability?. Philosophy & Technology. 2021 Dec;34(4):833-62.
[44] Holzinger A, Langs G, Denk H, Zatloukal K, Müller H. Causability and explainability of artificial intelligence in medicine, WIREs Data Mining Knowl Discov. 9: e1312, 2019.
[45] McDermid JA, Jia Y, Porter Z, Habli I. Artificial intelligence explainability: the technical and ethical dimensions. Philosophical Transactions of the Royal Society A. 2021 Oct 4;379(2207):20200363.
[46] Shah SN, Seger DL, Fiskio JM, Horn JR, Bates DW. Comparison of medication alerts from two commercial applications in the USA. Drug safety. 2021 Jun;44(6):661-8.
[47] Less is More, (n.d.). https://jamanetwork.com/collections/44045/less-is-more (accessed August 21, 2022).
[48] Solomonoff RJ. The time scale of artificial intelligence: Reflections on social effects. Human Systems Management. 1985 Jan 1;5(2):149-53.
[49] Turing AM. Computing machinery and intelligence. Mind59, 433–460 (1950)., (n.d.).
[50] GPT-3, Wikipédia. (2022). https://fr.wikipedia.org/w/index.php?title=GPT-3&oldid=194250140 (accessed June 14, 2022).

[51] GPT-3, A robot wrote this entire article. Are you scared yet, human? | Artificial intelligence (AI) | The Guardian, The Guardian. (2020). https://amp-theguardian-com.cdn.ampproject.org/c/s/amp.theguardian.com/commentisfree/2020/sep/08/robot-wrote-this-article-gpt-3 (accessed September 13, 2020).

[52] Lacker K. Giving GPT-3 a Turing Test, (n.d.). http://lacker.io/ai/2020/07/06/giving-gpt-3-a-turing-test.html (accessed June 14, 2022).

[53] Luger GF. Artificial intelligence: structures and strategies for complex problem solving, 6th ed, Pearson Addison-Wesley, Boston, 2009.

[54] Murray E, Hekler EB, Andersson G, Collins LM, Doherty A, Hollis C, Rivera DE, West R, Wyatt JC. Evaluating digital health interventions: key questions and approaches. American journal of preventive medicine. 2016 Nov 1;51(5):843-51.

[55] Labrique A, Vasudevan L, Mehl G, Rosskam E, Hyder AA. Digital Health and Health Systems of the Future. Glob Health Sci Pract. 2018 Oct 10; 6 (Suppl 1): S1–S4. doi: 10.9745. GHSP-D-18-00342. http://www. ghspjournal. org/cgi/pmidlookup;.

[56] Bélisle-Pipon JC, Couture V, Roy MC, Ganache I, Goetghebeur M, Cohen IG. What makes artificial intelligence exceptional in health technology assessment?. Frontiers in Artificial Intelligence. 2021:153.

[57] Lancet T. Is digital medicine different?. Lancet (London, England). 2018 Jul 14;392(10142):95.

[58] Eyrich NW, Andino JJ, Fessell DP. Bridging the digital divide to avoid leaving the most vulnerable behind. JAMA surgery. 2021 Aug 1;156(8):703-4.