

Development and significance of automated history-taking software for clinical medicine, clinical research and basic medical science

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The best we can do is to divide all processes into those things which can be better done by machines and those which can be better done by humans.

John von Neumann, 1955

Introduction

The meaning of von Neumann's statement is that rule-based tasks are undertaken more faithfully by computers than by humans and that the potential benefit of computing can be assessed by evaluating whether there is less than acceptable adherence to applicable rules when a task is carried out by humans. von Neumann's prescient idea has been applied to essentially all theoretical, experimental and applied sciences and engineering. Today, computing is indispensable to these disciplines and fuels their progress. However, there has been little application of computing to the fundamental, rule-based processes underlying effective practice of medicine, specifically to collecting and interpreting clinical data from patients. The nature of information collected from examining patients is different, of course, from data in physical experiments. However, the processes for collecting these data, and their interpretation, are no less rule based. The absence of significant computing power in daily clinical practice cannot be attributed to lack of need as, whenever scrutinized, the processes by which physicians collect data from patients and make clinical decisions are noncompliant with applicable rules [1–10]. These failures contribute to less than acceptable outcomes for patients [11–14] and to as many as 98 000 deaths/year in the USA from medical errors [11]. Poor data collection in clinical practice also impedes progress in clinical [15–18] and basic science research [19, 20].

The purpose of this review is to summarize the development of automated history-taking software, considering the evidence for the validity and superiority of this method for collecting clinical data, and the continued need for history taking as the basis for quality care. Clinicians unfamiliar with programs for automated history taking need to begin to understand the power of the technology and its potential for improving clinical outcomes. Physicians are familiar with electronic health record (EHR) technology; however, EHRs do not incorporate formalized rules for history taking, cannot improve adherence to these rules and hence lack the benefits that come from automating rule-based tasks. True automation of history taking may be considered 'the second generation of EHRs' and, in our opinion, will be an inevitable development. This is the only mechanism for removing the incompatibility between unaided, finite human cognition and limited physician time and maximizing the value of healthcare at affordable cost.

Early innovations: 1950–2000

Automation of history taking and medical diagnosis

The knowledge base for medical practice is enormous, and is expanding continuously [21] and growing in complexity. Furthermore, established facts are subject to change. Apparently simple complaints can have extensive differential diagnoses. These cognitive loads are exacerbated by less time to see more patients. The profession's organized response to the cognitive challenges has been specialization so that each specialist manages repetitively a relatively narrow set of clinical issues. Specialization, however, has not improved clinical outcomes for patients, which are superior in geographical areas with higher proportions of primary

care physicians [22–25]. An alternative to specialization is the use of computing to reduce the cognitive load of practice. Efforts in this direction began in the late 1940s.

Brodman *et al.* [26] developed the Cornell Medical Index as a questionnaire to standardize data collection, orientated towards systems review to provide ‘... a quick and reliable method of obtaining important facts about a patient’s medical history without expenditure of the physician’s time’. It may seem trivial, but the Index demonstrated that history taking did not require a physician. In fact, the Index collected significantly more relevant information than physicians examining the same patients. Subsequently it was shown that a computer, when fed standardized, self-reported history data, was as accurate as physicians in diagnosing a wide array of common disorders [27]. This work thus dispelled the then prevalent notion that diagnosis was ‘... indefinable and intuitive...’ rather than ‘... logical and completely defined...’ [27]. The value of self-reported medical histories collected by questionnaire and processed by computer was replicated at Kaiser Permanente clinics using a questionnaire of 600 questions [28]. Results were reported only for the diagnosis of asthma. Sensitivity and specificity of the analytical method were good.

Slack and colleagues expanded the reach of self-reported history taking by programming a computer to collect the history directly from patients [29]. The rules for history taking were programmed by branching question trees so that the path from one question to another was determined by a prior answer and could be related to different, specific medical issues in different patients. This simple logic function made it possible to expand the number of questions posed by computer as compared with a paper questionnaire. This first computerized history-taking program was limited to allergy-related issues but was extended to separate programs for the review of systems and several problem-specific interviews [30]. The success of these programs was measured by the completeness of data collection as compared with physician-acquired histories, with which they compared favourably.

Mayne and colleagues at the Mayo Clinic were also early developers of computerized history-taking programs. Their program asked patients to select a chief complaint from a menu of complaints [31].

The program contained no follow-up to resolve the differential diagnosis of the chief complaint but encompassed a review of systems plus elements of the past medical history [31]. A program with clinical coverage similar to that developed at the Mayo Clinic was tested in a small number of inpatients by Grossman *et al.* [32] with similar results, i.e. far more clinical information was recorded by computers than by physicians.

Lawrence Weed was another pioneer in the field. Weed’s starting premise was different from that of his predecessors. He explicitly acknowledged that the knowledge for practice exceeded what anyone could learn and use for collecting relevant clinical data from patients and for interpreting the data to make accurate, timely diagnoses and that computing was a method for bridging this gap [33, 34]. His purpose was to improve decision-making through better data collection coupled to automated decision support. Weed’s history taking was committed to diagnosis by the closeness of fit between the set of clinical attributes displayed by a given patient with a specific chief complaint and the sets of attributes displayed by patients covering all the entities in the differential diagnosis of that chief complaint. For example, for a patient with vertigo/dizziness as the chief complaint, Weed’s scheme queried every patient for the presence of all attributes that could be displayed by any patient with any of the 78 diagnostic entities in his differential diagnosis for vertigo/dizziness [35]. The key output from the Weed program was not the facts of the history but the closeness of fit between the attributes of an interviewed patient and the attributes of a patient with each of the entities in the differential diagnosis of the patient’s chief complaint. Weed termed the history-taking routines ‘Problem Knowledge Couplers’. The ‘problem’ was the patient’s chief complaint, and the ‘knowledge’ was the database of attributes of well-characterized patients with known diagnoses. Published work with couplers does not cite a source for the ‘Knowledge’ databases. Furthermore, the overall scheme was not tested rigorously for utility and validity. A single clinical trial of the coupler program failed to establish diagnostic value as compared with routine care [36]. The patient population tested was relatively young, however, so this negative result does not mean that coupler programs are without value. Couplers have been reportedly used since 2005 only in a single small practice, but without data to assess how they are used and how they contribute to management [37].

The coupler programs are now owned by AskMD [38]. It seems unlikely that the couplers are being used as originally intended.

Many other investigators developed computerized history-taking programs during this period until 2000. A summary of these programs is provided in table 3 of the review by Bachman [39]. However, none of the programs cited expanded the technology beyond the range of issues addressed by Slack *et al.*, Mayne *et al.* and Weed.

Validity of self-reported clinical data in computerized histories

Self-reported history entries in the Cornell Medical Index questionnaire were documented by re-interview of patients and found to be highly accurate [26]. Discrepancies between self-reported entries for computer interview and physician records reflected equally low error rates by computer and physician [40]. Notably, however, computerized histories included more useful clinical data as compared with physician histories [40]. Analysis of data collected by self-reported, computerized history taking for pre-operative clearance showed that 97% of retest responses from 239 patients were identical to test answers [41]. A similar study of 48 patients interviewed using a general medical history program, showed a test-retest replication rate of 93% [42]. A quarter of the small number of discrepancies were patient errors in selecting the intended answers; another quarter occurred because patients were uncertain which of the available answers applied to them. Because self-reported clinical data acquired by computerized history taking are accurate, there is more clinically significant information in these histories as compared with medical charts. Indeed, comparisons of the accuracy of self-reported data and medical records [1, 2, 5, 7–9] show that the former are superior. This is not unexpected because computers do not interpret self-reported answers. There is no control over this aspect of history taking by physicians. Moreover, use of surrogates and scribes [43] in the era of EHRs makes entry of accurate clinical data into the record increasingly complex in ways avoided by automating the process.

Patient experience of self-reported computerized history taking

Even at a time when few had experience with or knowledge of computers, patients had a high level of acceptance of the technology for history taking

[29, 31, 44, 45]. This remains true now that computing is ubiquitous [42, 46]. Patient acceptance of computerized history taking extends beyond willingness to use these programs to belief that use will improve the quality of their healthcare [32]. Patients are also quick to humanize the computer [47, 48]. In addition, patients are willing to invest amounts of time inputting data that are not available to physicians, e.g. self-reported history-taking sessions exceeding 1 h [31, 42]. Another advantage of computerized history taking is that patients may reveal information about risky lifestyles to the computer that they will not share with physicians [49, 50]. It has not been tested for users of computerized history-taking programs; but studies of the impact of paper questionnaires on physicians show that patients using questionnaires are more satisfied with their care than those not providing the physician with self-reported clinical information [51].

Physician perception of clinical value from self-reported computerized histories

There has been no significant physician 'buy-in' to the use of computerized history-taking programs [31, 41]. Physicians who were questioned about the value of these programs believed that differences between their and computer findings were false-positive computer outputs or nonrelevant information [31, 41]. Quaak *et al.* [52] reported a similar view. Physicians who were not responsible for primary data collection were asked to compare the diagnostic value of information acquired by a computerized, general medicine history-taking program with information from physician-acquired histories [52, 53]. Although the computerized histories were acknowledged to contain more clinical information, physician histories were deemed more valuable for making diagnoses.

Given the test-retest reliability of automated histories, physician opinions of high rates of false-positive findings in self-reported histories are not correct. It seems instead that physicians consistently discount the value of collecting more clinical information than they typically acquire. This is likely to reflect the negative impact of limited human cognition on clinical decision-making. Thus, the information a physician can collect, analyse, record in a chart as an integrated note, and use to make a management decision is limited at all stages by a finite cognitive capacity. Physicians' opinions about the relevance of data to a

clinical decision depend on their cognitive capacity, with an upper limit susceptible to downregulation by distractions and time pressures. A computer has a limitless capacity for memory, recall and simultaneous factoring of very large numbers of variables not subject to downregulation by distraction and limited time. Hence, computerized history taking collects more clinically relevant information than a physician can process. The physician will regard some of this 'excess' as superfluous to decision-making especially when the information is unrelated to the acute problem or encompasses unfamiliar aspects of medicine. This mismatch between what computers can output and what physicians can make sense of is already a common problem. EHR alerts [54], for example, are '... rendered meaningless by their sheer number' [55]. The value of automated history taking cannot be determined, therefore, by physician opinions about the data collected by computer but must depend on the impact of the information on outcomes for patients.

Computerized history taking might collect and output information that a careful physician will detect as trivial and incorrect. But well-designed software follows positive findings to determine their relevance to a specific differential diagnosis and in this way finds inconsistencies as they occur during an interview. For example, when an entry violates a programmed rule, the program can pose a question to clarify inconsistencies for both false-positive and false-negative entries. Another method for improving automated history taking is to reduce the cognitive load of reporting to physicians by organizing findings as pathophysiological narratives. This method facilitates comprehension of complex information compared with a list of facts. Inadequate attention to the problem of conveying complex information probably underlies, in part, the negative results cited by Quak *et al.* [52]. It is difficult to grasp the meaning of data in the output from their program [56].

Development in the 21st century

Specialized history-taking programs

Some of the programs cited by Bachman [39] may be in use at institutions in which they were developed, but none seems to be in use elsewhere except for Instant Medical History [57, 58]. History-taking programs developed more recently by the academic community [59–62] interact with patients on single issues and seem to have had

limited use outside their sites of development. An exception is web-based, self-reported assessment of disease activity by patients with rheumatoid arthritis in Sweden [63]. In addition, The Science of Your Cycle [64] is a clinically directed automated history-taking application to track a woman's menstrual cycle, '... the next period, fertile window and PMS' and '... physiological processes ... throughout the cycle'. The Science of Your Cycle appears to deliver personalized advice to affect clinical outcomes by using data-driven analytical algorithms to personalize prediction and to leverage the power of standardized data to improve its analytics. There is no comparable program within the academic medical community. This history-taking program indicates how the future of practice may be impacted by nonmedical communities using computer technology to meet limited goals.

Complete history-taking programs

Slack *et al.* [42] have expanded on earlier work to create a general medicine, history-taking program. However, no details about its operation have been reported; nor is it clear that the program is in use. Instant Medical History is advertised as a method by which the patient's answers populate data fields in the physician's EHR [58]. Details of coverage and operation are not available. The program CLEOS® (Clinical Expert Operating System) may be the only automated history-taking program under continuous development for acquiring complete medical histories [65]. CLEOS® differs from other history-taking software described in the literature in that it emulates clinical thinking continuously as data are collected. The key to this is automated interpretation of all prior answers as the interview proceeds so that the next questions are determined by pathophysiology that relates all prior answers to the working differential diagnosis. This mechanism also enables continuous checking for entry errors and inconsistent answers. Fig. 1 is an example of the decision graphs that determine the pathway of questioning in a CLEOS® interview. How the logic functions operate to determine a pathway through the graph is described in the legend. Fig. 2 is a graphic representation of the more than 450 component decision graphs of the complete program at present. Every patient enters Fig. 2 by selecting a chief complaint at the point marked by the arrow and traverses the complete pathway of the graph of about 17 000 decision nodes. The logic functions (Fig. 1) determine which questions are relevant to

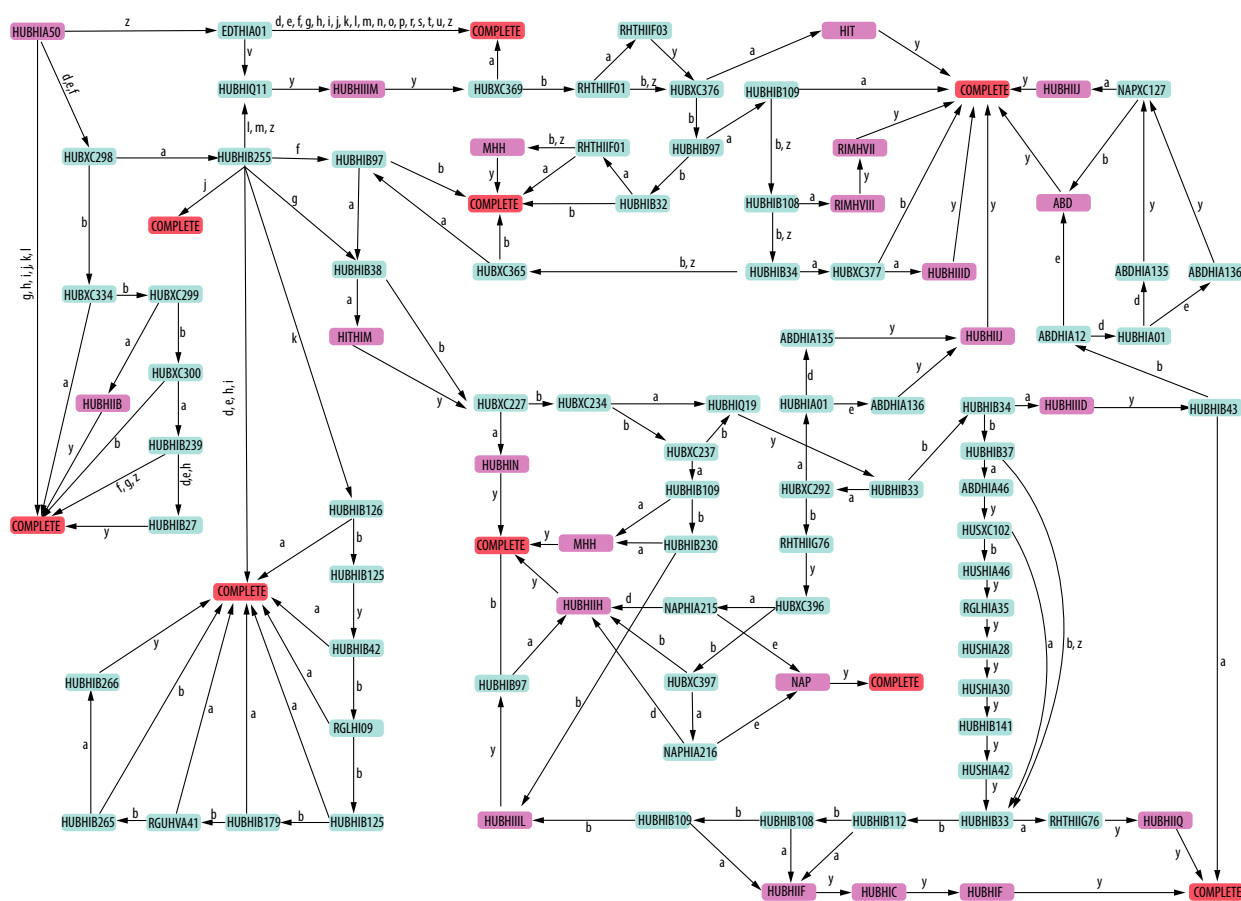


Fig. 1 Representative decision graph for collecting a medical history. The graph illustrated collects data from a patient with a chief complaint of chest pain. The nodes are points at which decisions occur. Each node has a unique code. Traversing a node that is a question (without XC in the code), opens that question to the patient. Letter codes, representing answers, are appended to the question code and direct the path to the next question. For example, answer 'Yes' to question NAPHIA205 is coded as NAPHIA205a. Labels d through x are codes for answers to multiple choice questions. Arrows labelled 'y' mean the path is traversed by any answer to the question from which the arrow emanates. The path can be directed along multiple directions. Arrows labelled 'a' and 'y' emanate from HUBHIB01. The path from HUBHIB01 will follow label 'a' until a complete node is reached and then follow the 'y' label from HUBHIB01. Arrows labelled 'z' encode the instruction not to pose that question in the case that it has not been asked previously. The root node ACSHIA01 has labels 'z' and 'y'. These instructions mean the graph shown will not be entered if ACSHIA01 has not already been asked. If ACSHIA01 has been answered prior to its appearance in this graph, any answer opens the graph. A question can appear any number of times but will be asked only once. Second appearances of answered questions are a mechanism for using stored answers to direct the patient to a 'next' question. Another mechanism for using the clinical meaning of prior answers is the use of nodes coded XC. These are inferences that are true or false. The path from ACSHIA01 to other nodes will be blocked for example when NAPXC179 is false (value b). Note also that the true/false value of an inference node can direct the question path along separate routes, as for the value of NAPXC1162. 'Gating' of content by clinical relevancy can occur at entry to a specific decision graph and anywhere downstream from a root node. In addition to questions and inferences, a graph contains nodes representing single (code RPUHIIIR) or complete sets of graphs (code PPU) that open when traversed. Insertion of graphs within graphs enables feedback and feedforward loops when the program interprets answers as indicating the working differential should be modified. Red nodes (complete) are at the end of a line of questioning.

problems identified and thus posed to a specific patient, and standardize data collection across all issues and for all interviews by ensuring that

questions not asked are nonrelevant to the patient's medical issues. There is no limit to the number of graphs that can be accommodated in

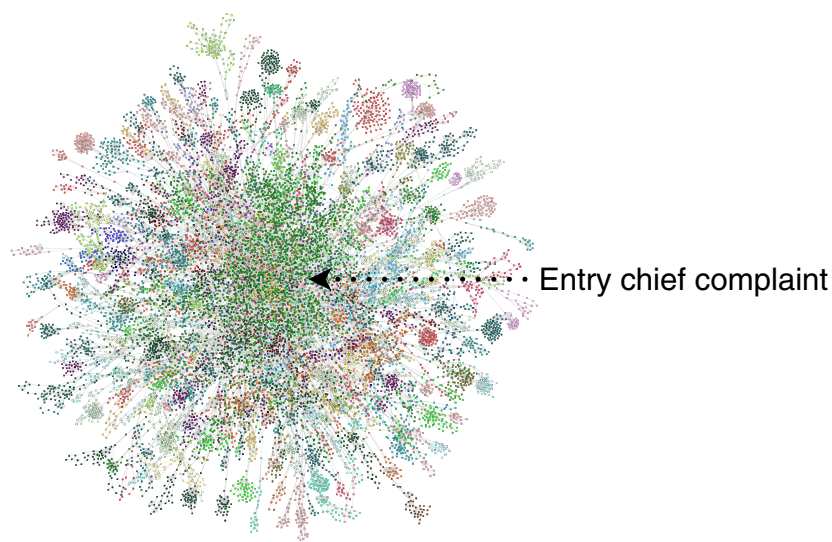


Fig. 2 Graphic representation of the complete CLEOS® program. The complete program comprises approximately 450 different decision graphs as in Fig. 1. The arrowhead indicates the entry point for a first history-taking session with entry of a chief complaint. Each dot is a decision node with codes and significance for guiding the interview pathway as in Fig. 1.

Fig. 2 and the range of clinical and lifestyle issues the program can address. With regard to the output, CLEOS® uses analytics to report findings as pathophysiological narratives, differential diagnoses, management recommendations and orders for diagnostic and confirmatory laboratory testing and suggested treatment plans [46, 65]. This is another important difference between CLEOS® and other automated programs, which report only factual findings. CLEOS® out-performs physicians using the metric of significant clinical problems identified [52], which is a direct measure of differences between computer and physician in finding clinically significant information. CLEOS® also out-performs physicians in adherence to guidelines, which was measured for the management of LDL cholesterol [66].

CLEOS® stores data elements as codes. This facilitates rule-writing (Fig. 3) and mathematical analyses of standardized data sets [67]. Rules that are true for the data in a given interview are also stored as codes. These can be managed by computer to improve methods for conveying complex clinical information. Furthermore, because clinical management is seldom a one-off event, automated history-taking programs have to function across time to provide automated data collection relevant to follow-up. This capability depends on internal intelligence to identify problems in the course of disease and clinical attributes expected to change in the process towards resolution or guideline-compliant achievement of targets. CLEOS® supports automated follow-up in the context of

identified problems and can incorporate physical examination and laboratory results for this purpose. CLEOS® is owned by a Swedish nonprofit foundation for which the governing board is appointed by the President, Karolinska Institutet, Stockholm, Sweden. Knowledge content and access to databases generated from the use of this knowledge are controlled by the academic medical community.

Incorporating computerized, self-reported history taking into routine practice

Computerized history taking transfers the time and cognitive demand for collecting clinical phenotype data from the physician to the patient and a computer. The technology can populate whichever data fields may be needed for automated decision support across a wide range of clinical issues. Only a single copy of the software needs to incorporate new knowledge to enable rapid translation of validated clinical advances to everyday practice. Additionally, by using a machine, the collection of clinical data can be standardized across all patients in contact with the healthcare system and included in a database to fuel clinical and basic medical research. With regard to development, it is possible to formalize the entirety of medical knowledge on a hard drive that can be purchased for a few hundred dollars. There are tools with which anyone who can use a Word program can formalize medical knowledge as software. Computing devices with readable screens are ubiquitous. Problems in delivering affordable care

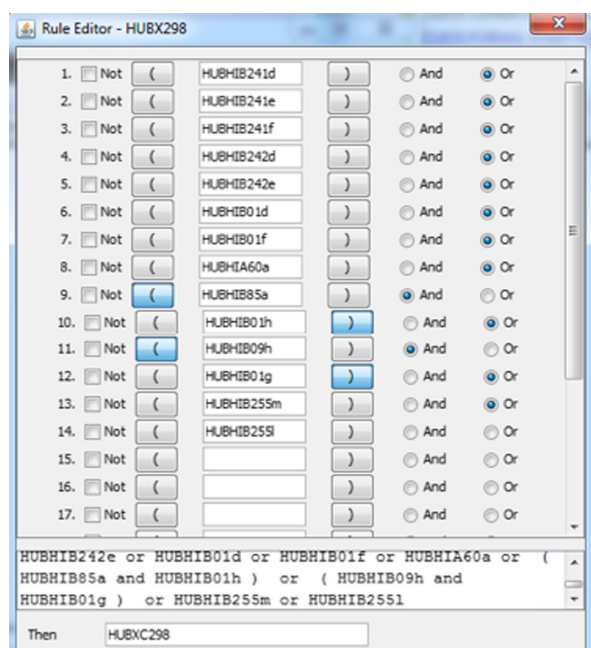


Fig. 3 Interface for writing rules in which arguments are answer codes, as shown here, or codes for another rule. The code for the rule shown is HUBXC298. Codes for rules have no appended lower case letters. The statement 'If HUBXC298...' has the implicit meaning that HUBXC298 is true. Arguments in a single rule can include answer codes, physical examination, laboratory result codes and codes for another rule. Arguments are connected by Boolean operators 'AND', 'OR' and 'NOT'. Parentheses are allowed but only as illustrated in this example

remain. Yet, after 50 years of development and validation, automated history taking is essentially not used in medical practice. Available evidence suggests that physicians who developed these programs focused more on demonstrating what was possible rather than on building sustainable programs that would be adopted widely by the clinical community [68]. Achieving widespread use depends on attracting young physicians to the programme for developing automated history taking, and maintaining continuous expansion and refinement of the medical knowledge incorporated into the software, continuous thinking to maximize the value of computing power and a rigorous schedule of clinical testing. The clinical community and patient advocacy groups must be engaged in these processes. In addition, testing for clinical efficacy must establish that automated history taking can impact the only goal that matters: clinical outcomes for patients. To our knowledge,

only one trial has been conducted to date that measured an effect on outcome. In this trial, selected established patients in primary care interacted with Instant Medical History from home [69]. Physicians determined from these data, available electronically, that 40% of 2500 patients did not need care. Their medical issues and how they differed from patients deemed to need office care were not provided. However, this is the only clinical outcome reported so far to be affected by the use of automated history taking.

Bringing automated history taking to everyday clinical use remains a sizable undertaking requiring an interdisciplinary team of specialist and primary care physicians, patient advocates, computer science, big-data analytics and experience design. A significant start has been made in recruiting this expertise by the development of CLEOS[®] within the Karolinska Institutet. We foresee further development and maintenance of CLEOS[®] as a cooperative, worldwide effort within the medical community, and are unaware of similar developments at any other institution.

Is the medical history still relevant?

Most physicians will subscribe to Osler's advice: 'Listen to the patient. He is telling you the diagnosis' [70]. Medical educators affirm this guidance, and text book discussions of the pathophysiology of a disease and its management begin with the instruction to take a history. In contrast to these 'official' positions, 'bedside' skills are considered less important than in the past [71–73] and performed poorly when residents are observed directly [74, 75]. Substantial numbers of young internists feel poorly prepared for interviewing patients [76]. Physicians are substituting laboratory data for history taking [77–82]. In addition, it is believed that medical practice is about to be revolutionized by genomics and related fields that will provide all the information needed to predict risks, make diagnoses and personalize treatment decisions. Given the difficulty in taking a history of sufficient detail to maximize the value of medical knowledge for patient outcomes, there would be enormous benefit from laboratory tests providing information at least equal in value to the detailed examination of patients. When tested in specific settings, however, the superiority of standard laboratory tests and/or imaging as compared with examining the patient cannot be substantiated [83–85]. More generally, there is an inverse

correlation between the use of laboratory testing and quality of outcomes for patients [22, 23, 82, 85]. In addition, although genetic markers appear to be useful for managing selected tumours [86–88], and this application is likely to expand, there is no experimental support for a soon-to-occur, genomics-driven, revolution in medical practice. Genomic and proteomic measurements provide information on the parts of cells. Normal function and disease result from interactions and disarray of interactions, respectively, between these parts, between complex systems in cells, and between cells, tissues and organs [89]. Of course, interacting molecules can be studied *in vitro*; however, it is extremely difficult *in vitro* to elucidate and account for the complexity of molecular interactions in cells of interest [90, 91]. A structural change in a specific 'part' can have variable functional consequences for different interacting systems of which it is a component. The effect on function from a structural change in any given part can depend on the structures of all other parts of the interacting system, i.e. epistasis is pervasive. Also, studies of two or a few interacting molecules *in vitro* cannot model interactions between systems, organization of cells into organs, interconnectedness of organ functions and the influence of the external environment on these complexities. In other words, functions of intact cells, organs and animals are too difficult to model meaningfully from molecular data [89, 92–96]: '... there is no way to gather all the relevant data about each interaction included in the model' [90, 97, 98]. In contrast with molecular level information, information from clinical examination reports on the overall status of complex interactions, i.e. whether normal or dysfunctional as well as the array of normal and dysfunctional interactions in an individual and how these interactions change with time. The best evidence, therefore, is history taking still provides the key data set for decision-making to maximize the quality of care for patients and that this will not change for the foreseeable future. Indeed, the most significant change in practice since Osler's time is the enormous expansion of the knowledge that informs practice, which, for effective use, requires more information about the patient than in the past.

Integration of clinical research into clinical practice

History taking is the only aspect of clinical data collection not studied from the perspective of how to maximize value. Automation of history taking in

everyday practice makes it possible to study this critical component by determining what information needs to be collected in which patients. Consider the example of prescribing statins to prevent ischaemic events. Applying the current guideline will prevent 1–2 events per 100 persons treated [99, 100]. This result means that outcomes in statin trials [101] are affected by uncontrolled variables [102] or that risk of ischaemic events cannot be determined for individuals with odds better than about 50 : 1. We can test whether this is a true upper limit on knowledge for predicting ischaemic events as a routine feature of everyday practice by employing automated history taking. Tables 1 and 2 show variables likely to influence ischaemic risk that are not controlled in statin trials and that are not included in statin guidelines [103]. The variables are labels for complex processes. For example, 'Past medications, Stopped for nonefficacy' (Table 2) provides information, medication by medication, on a linked set of complex processes that cannot be modelled *in vitro* [104]. In addition, basic biology indicates that the complex systems on which the labels report are unlikely to function independently of each other. There are millions of persons at risk of ischaemic attacks, many taking statins prescribed haphazardly [65, 105]. Automated history taking can acquire data shown in Tables 1 and 2 without expending physician time and store the data for analysis without burdening physicians with clinical facts seemingly irrelevant to decision-making at the present time. Data mining '... to find unsuspected relationships and to summarize the data in novel ways ...' [101] can be applied to the very large, complex data sets that will be collected. Outcomes, for example ischaemic events, can be mapped to subgroups determined by data mining techniques. Should these analyses improve prediction on an individual basis, minimal data sets to achieve this goal can be defined, and new guidelines, together with the data elements supporting a clinical decision to treat, can be delivered automatically to physicians on a patient-by-patient basis. This general scheme is applicable to any problem for which there are no or inadequate guidelines. Thus clinical research can become an integral component of routine care [106–109]. Automated history taking can connect every practice and everyone receiving healthcare to the framework of clinical research. Automated history-taking also will have a positive effect on the progress of basic medical research [19, 20]. The key to the quality of clinical data for correlation

Table 1 Factors that can affect risk of ischaemic events but are not considered for calculating risk scores

Data set	Data elements
Demographic	Ethnic origin, place of birth; education; economic status; current occupation; occupational history
Habitus	BMI; waist/hip ratio; lifetime weight changes
Environment	Physical activity, current and lifetime; diet, current and history; current residence by postcode; potential toxin exposure Use of tobacco: type, quantity, duration; exposure to secondary smoke Use of alcohol, current and history Use of cocaine, current and history All current medications All past medications with ADEs
Epigenetic	Birth weight (or gestational age at birth), birth order, maternal diabetes during pregnancy
Comorbidities with duration, severity, response to treatment	Presence/absence of chronic inflammatory diseases; renal disease; pulmonary disease; or noncoronary heart disease Cancer history and treatment with cardiotoxic agents

Except for smoking, data elements listed are not considered in evaluating risk of ischaemic events. Smoking history in risk calculations does not consider individual differences in amounts and types of tobacco consumed. Nonsmoking status in risk calculations does not discriminate between never smoked and stopped smoking nor the duration of smoking in past smokers and interval since last smoked. Exposure to second-hand smoke in nonsmokers is not factored into risk scores. ADE, adverse drug events.

with findings at the molecular level is the scope of the data and its standardization across very large numbers of individuals.

There is a current view that EHRs will have an impact on clinical and basic science research similar to that envisioned for automated history taking [110, 111]. However EHR data cannot support a robust programme of clinical research. Because of the greater time demand of EHR use compared with hand-written or dictated notes [112], data entered into EHRs may be collected by physicians, by personnel with nonmedical training [113] or by scribes [43]. Physicians using EHRs do not collect data by a standard protocol or even with a standardized EHR programme. Furthermore, the integrity of data in EHRs is suspect for many other reasons [114–117].

Effect of automated history taking on physicians and physician–patient interactions

The physician reading the output from an automated history-taking program is in the position of a consultant providing a second opinion. This will enhance interactions with patients by removing the burden of data collection and thereby providing time to discuss in more detail the patient's issues

and options. In addition, automated history taking will avoid the use of current EHRs, which can interfere with patient interaction [118]. Physicians have embraced computer-based technologies across medicine, including imaging technology, Lasik eye surgery, robotic surgery in general and auto-analysers for laboratory medicine. However in these uses, computer technology does not provide patients with insight into the processes of practice. History-taking computers provide patients with a view of a key process by which medicine is practised that they might even understand. Physician resistance to use of automated history-taking in prior work may be rooted partly in this issue [22, 41, 52]. Since the power of automated history-taking is necessary for achieving better outcomes at affordable cost [11, 12], this question needs to be studied by involving clinicians in discussions and development of the technology as it emerges. It will also be important to start acknowledging that physicians, like everyone else, have finite cognitive abilities and that medical practice is an extraordinarily difficult cognitive task. Additionally, it may be important to note the analogies between robotic surgery and computerized history taking. Surgical robots provide a better view of the anatomy and surgical problem confronted than the unaided eye. The history-taking robot provides a more precise

Table 2 Factors related to the presence of diabetes and/or hypertension that affect incidence of complications but that are not considered in estimating risk of coronary disease

Comorbidity	Characterization of comorbidity
Diabetes	Age at onset
	Method of discovery
	Regulation of blood sugar:
	HbA1c, daily variation of blood glucose
	Hypoglycaemic events
	Severity, frequency, manifestations
	Current hypoglycaemic agents
	Adherence
	Past hypoglycaemic agents
	Stopped due to ADE
	Stopped due to nonefficacy
	Reversible vision changes
	Nonvascular complications (e.g. neuropathy, gastropathy)
	Vascular complications other than coronary
Hypertension	Age at onset
	BP at diagnosis
	BP current
	Self-monitored BP
	Current medications
	Adherence
	Past medications
	Stopped due to ADE
	Stopped due to nonefficacy
	Vascular complications other than coronary

Diabetes and hypertension are variables included in vascular risk scores. But the variable clinical characteristics of these states in different patients are not factored into risk scores. Treatment details for both diseases specify adverse drug events (ADEs) and agents with no efficacy because this information reports on complex interactions that are otherwise not available in any other data set (see [106]). HbA1c, haemoglobin A1c; BP, blood pressure.

view of the anatomy of problem(s) than is otherwise available to the unaided clinician. Problem(s) revealed are understandable only to a trained physician. What is missing in the analogy is evidence for better clinical outcomes from the use of history-taking robots. This is crucial for successful employment of automated history-taking programs.

Conclusion

Data from direct history taking and examination of patients remains essential for delivering quality outcomes. Contrary with expectation, advances in genomics and related fields will not revolutionize data collection in everyday practice. Indeed, the range of information available from interview of patients that should be factored into clinical decisions is expanding. Furthermore, in addition to the cognitive demand of history taking, there is less time for data collection. These critical problems in routine practice can be addressed with computer technology because history taking is a rule-based task. It is established that computers can acquire medical histories by direct interview of patients, that automated history taking collects more clinically significant information than physicians examining the same patients and that the data are valid. Lay persons have a positive response to interview by computer. At present, software is sufficiently powerful to extend automated data collection to any domain of interest, to emulate detailed clinical thinking and to enable computers to be critical observers of and interactors with the patient. Automated, self-reported history taking is a key technology for maximizing outcomes for patients, and will improve the physician–patient dialogue. It is also increasingly clear that clinical practice and clinical research must be integrated to improve the validated knowledge base for practice, which can only be achieved through automated history taking.

Conflict of interest statement

DZ declares no conflicts of interest. DZ is the inventor on US patents for technology related to the CLEOS® program that are assigned without any royalty rights to Stiftelsen CLEOS® Foundation in Stockholm.

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