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Methodological Review

Cognitive and learning sciences in biomedical and health instructional design: A review with lessons for biomedical informatics education

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ABSTRACT

Theoretical and methodological advances in the cognitive and learning sciences can greatly inform curriculum and instruction in biomedicine and also educational programs in biomedical informatics. It does so by addressing issues such as the processes related to comprehension of medical information, clinical problem-solving and decision-making, and the role of technology. This paper reviews these theories and methods from the cognitive and learning sciences and their role in addressing current and future needs in designing curricula, largely using illustrative examples drawn from medical education. The lessons of this past work are also applicable, however, to biomedical and health professional curricula in general, and to biomedical informatics training, in particular. We summarize empirical studies conducted over two decades on the role of memory, knowledge organization and reasoning as well as studies of problem-solving and decision-making in medical areas that inform curricular design. The results of this research contribute to the design of more informed curricula based on empirical findings about how people learn and think, and more specifically, how expertise is developed. Similarly, the study of practice can also help to shape theories of human performance, technology-based learning, and scientific and professional collaboration that extend beyond the domain of medicine. Just as biomedical science has revolutionized health care practice, research in the cognitive and learning sciences provides a scientific foundation for education in biomedicine, the health professions, and biomedical informatics.

1. Introduction

We approach the field of education and training in biomedicine and informatics as researchers in the area of cognitive and learning sciences. Biomedical informatics is becoming a part of biomedical curricula and, over time, it is likely to become a more integrated part of health professional and biomedical education. In this paper, we review the role of cognitive and learning sciences in addressing current and future needs in designing biomedical curricula, including biomedical informatics. In our view, the cognitive and learning sciences are an integral component of the basic science dimension of biomedical informatics education, and lessons from such work can inform practical issues in the design and implementation of training programs.

We begin this review by describing various theories of cognitive learning and their implications for instructional design and learning in general, and in biomedical curricula in particular. Essential to understanding how such theories provide a rationale for instructional design and learning is the nature and development of expertise and adaptive expertise [1], which is the subject of the next section of the paper. Investigators in this area, including authors of this review, have studied the acquisition of skilled performance and the organization of knowledge using a range of methods, including experimental, quasi-experimental, and naturalistic methods, which are described in Section 3.3. Subsequently, we provide a brief history of medical education and describe important types of medical curricula and current trends in this area (e.g., use of technology-based learning, incorporation of ethics and behavioral sciences into biomedical curricula), as well as an overview of empirical findings on research in this area. Although this section focuses on medical education, the lessons learned are equally applicable to other biomedical sciences such as training and education in biomedical curricula and informatics. The last section of this paper describes the role that technology plays in

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learning and instruction and the scientific basis that supports its use, as well as the impact of technology-based instruction on thinking and reasoning. This review concludes with a summary of how reform in biomedical curricula, including changes in instructional design and the education process, can find its scientific base in cognitive and learning sciences, emphasizing lessons for biomedical informatics. It should be noted that the review presented in this paper does not provide a comprehensive account of all learning theories and research on expertise and curricula in medicine; we have restricted our discussion to more current and influential cognitive learning theories, excluding behaviorist and other learning theories and instead emphasizing medical expertise and curricular research that is conducted using a cognitive framework, including our own contributions in this area. The reason for excluding behaviorist theories is that these have been devoted almost exclusively to simple learning, relating environmental conditions to overt behavior, eschewing the underlying brain or cognitive processes, and have therefore found little applicability to the kind of complex learning that goes on in knowledge-rich domains, such as biomedicine.

Medicine is a complex, multifaceted, knowledge-rich domain encompassing a range of performance skills and knowledge domains. Clearly, it is not likely that any one pedagogical or learning theory will adequately account for all skills and knowledge involved in biomedical instruction. However, research on medical expertise is beginning to inform the development of medical competence in real-world settings. Although this research may be used to suggest changes to the structure of medical and biomedical informatics education, we still need to understand more about the conditions of learning that lead to optimal levels of performance. In addition, much of the practice of medicine is collaborative in nature, and cognition in the workplace is shaped by the social context as well as the technological and other artifacts that are embedded in the physical setting. In medicine, the attainment of expert-level performance in the workplace is predicated on the subject's ability to function smoothly in an environment in which the coordination of tasks, decisions, and information is essential [2]. In complex dynamic decision-making environments, the situational and distributed aspects of expertise are emphasized—such as communication capabilities, the ability to convey plans and intentions, and the allocation of resources not only for one's self, but for others. Learning in such circumstances necessitates the development of pattern recognition capabilities that lead to rapid, heuristically-guided decisions under conditions of uncertainty and incomplete information. It also necessitates a complex socio-cognitive coordination process in which information-gathering, decision-making and patient management are highly interactive and distributed activities [3].

1.1. Cognitive science as key content in biomedical informatics education

We believe that the cognitive and learning sciences—the multidisciplinary field involving cognitive psychology, cognitive anthropology, linguistics, philosophy and artificial intelligence—have a foundational role in biomedical informatics education and training [4,5]. Cognitive science in particular has had a close relation to the biomedical field. Medicine has been a test-bed for cognitive science theories, and historically, was one of its first areas of application [6]. Research in cognitive science in medicine has also contributed to the conceptual and empirical development of the cognitive sciences (e.g., the study of diagnostic reasoning). Furthermore, a. number of areas central to biomedical informatics, such as the usability of information technologies; the processes of technology-supported decision-making and problem-solving; the comprehension of information to deliver Internet-based health care; and the design and implementation of collaborative tools in our increasingly interconnected health care environment, can benefit greatly from an understanding of the fundamental principles underlying human learning and performance [5]. Table 1 presents an illustration of how some biomedical informatics issues parallel those in the cognitive and learning sciences.

In addition, there are further motivations for including the cognitive and learning sciences as a foundation for biomedical informatics training. First, human and organizational issues in biomedical informatics are involved in many of the grand challenges that our discipline faces and that must successfully overcome [7,8]. Second, the cognitive and learning sciences are critical in providing a theoretically-based account of numerous issues underlying those challenges. Third, because the cognitive and learning sciences look at fundamental psychological and social processes, they allow us to have an in-depth understanding of the mechanisms of many practices essential to our discipline. In particular, understanding the issues involved in learning biomedical informatics concepts and skills seem essential for effective education and practice. It is accordingly important for biomedical informaticians to understand the concepts that have been developed in the major theories of learning.

2. Overview of learning theories

Although learning most often occurs informally through everyday experiences, and competence can be achieved without formal training, the rapid advances and the accumulation of knowledge in the sciences makes it unlikely that someone could attain proficiency and especially achieve full mastery of a domain without undergoing formal training.

Table 1
Examples of areas of mapping between cognitive and learning sciences and biomedical informatics.

Cognitive & learning sciences	Medical cognition	Biomedical informatics
Memory	Clinical case recall	Decision aids and reminders
Knowledge organization	Medical schemata & scripts	Knowledge and data representation
Problem-solving	Diagnostic and management clinical problem-solving	Medical information management
Heuristics and strategies	Reasoning strategies in diagnostic and patient management	Computer-based reasoning methods
Decision-making	Medical decision-making	Cognitive assessment of human-computer interaction in decision support system design, implementation, and use
Collaborative learning	Student and resident learning in medical teams	Targeted training in tele-medical applications
Anchored instruction	Learning in the ICU and other hospital environments	Usability of medical instrumentation to optimize learning
Apprenticeship	Cognitive learning of patient management at the bedside	Design and assessment of tutoring systems in medical informatics training
Discourse analysis	Medical discourse	Medical coding systems and ontologies

As our society progresses in the accumulation of knowledge and as the complexity of this knowledge increases, it becomes more important to determine how to structure education to provide individuals with the most comprehensive base of knowledge without sacrificing either depth and complexity or broadness of material. Human beings have an extraordinary capacity for storing large volumes of organized information in memory. How does one apply such detailed knowledge to practical, real-world problems and situations? What is the optimal mode of learning that will promote flexibility and transfer of general knowledge across domains during problem-solving?

In the past century, different theories of learning were developed in the field of psychology, including, among others, behaviorist theories of classical and operant conditioning (e.g., the work of Pavlov, Thorndike, Watson and Skinner, among others); developmental stage theories (e.g., [9,10]), information processing theories [11], and social learning theory [12]. Over the last three decades or so, perspectives on learning have moved from behavioral theories that emphasize simple repetition and practice to theories that focus on understanding and application of knowledge. In particular, cognitive theories have focused on how individuals organize information in memory, on how this affects learning, problem-solving, and decision-making, and on the roles that self-regulatory activities and the socio-cultural environment play in understanding and reasoning. In order to optimize learning, instruction and curricula need to be supported and informed by these theories, some of which are described in the next section.

2.1. Cognitive learning theories

Theories of cognition have increasingly permeated instructional research and shaped instructional practices. Cognitive researchers, having originally focused on characterizing the nature of cognitive processes (from attention to understanding and decision-making), have shifted their attention to implications of this research for learning and instruction. In fact, cognitive approaches to learning have become the dominant intellectual paradigm [5]. In particular, there has been considerable research on engineering classrooms and computer-based learning environments based on emerging cognitive principles of learning and instruction. The current state of affairs has resulted not in a cohesive unified learning theory but rather in a family of such theories or frameworks. Although the emphasis of theories has changed through time, some of the major aspects have remained the same, including an emphasis on transfer of knowledge and skill, and the importance given to contextual and situational factors in learning.

In this section, we offer a brief review of some cognitive theories of learning. Despite the existence of different theories with diverse origins and motivation, these do not offer competing conceptualizations as much as complementary ones, as they stress different aspects and forms of learning. We shall explain the distinction between those theories that stress learning of well-structured and relatively simple domains (e.g., basic arithmetic) and those theories that focus on complex, ill-structured domain knowledge (e.g., biomedicine).

2.1.1. Learning and transfer in complex domains

One of the goals of learning is the ability to transfer acquired knowledge to new and unfamiliar problems and situations. Behavioral research on learning transfer was based on the hypothesis that transfer was determined by the similarity between the *conditions of learning* and the *conditions of transfer* [13]. For example, in his theory of transfer, Edward Thorndike, the founder of educational psychology in the US, assumed that how much information transferred from initial to later learning was dependent on how well facts and skills matched across the two learning events [14,15]. This research on learning and transfer omitted the consideration of the cognitive components of the learners themselves. The emphasis, instead, was on drill and practice.

Practice and similarity of conditions, although important, are now seen as insufficient to ensure transfer in complex domains. Assessment of learning transfer can indicate the degree of adaptability, flexibility, and competence beyond the mere memorization of information. Transfer can include applying knowledge from one known concept to a new concept; applying knowledge and skills from one domain to another domain; or from a familiar situation to an unfamiliar new situation.

Current views on transfer in complex domains posit that the ability to transfer knowledge is dependent on several factors [13]. First, it is necessary to have a solid foundation of knowledge and learning to support the transfer. In this regard, time spent on practice does not automatically translate into effective learning. Practice has to be deliberate, i.e., it allows learners to self-monitor and reflect on their learning [16]. Second, transfer of learning requires possessing understanding of a topic, not just memorization of details and factual information. Third, to be most effective, learning should occur in multiple contexts, which promotes flexible transfer across domains and contexts. Fourth, learning should

Table 2
Cognitive theories of learning relevant to biomedical education and training showing basic concepts, conceptual differences, and diverse emphases.

Theory	Basic concepts	Most applicable	Example
Adaptive Character of Thought-Rational (ACT-R)	Declarative and procedural knowledge, production rules	Well-structured domains, formal knowledge acquisition	Learning of anatomy, basic biochemistry using cognitive tutors
Cognitive Load Theory (CLT)	Cognitive load, working memory, memory limitations	Well-structured domains and somewhat ill-structured domains; formal knowledge	Learning of basic clinical medicine in classroom situations; design of instructional materials
Situativity theory	Situation, context, activity system, social interaction, collaboration	Ill-structured domains, apprenticeship	Learning in residency training involving interactions with clinical teams; acquisition of tacit knowledge
Cognitive Flexibility Theory (CFT)	Advanced learning, conceptual understanding involving abstract concepts	Formal learning of complex concepts, conceptual structures	Learning of advanced physiology, genetics, and clinical medicine during specialization

involve underlying principles and concepts that can be applied to a variety of problems. Fifth, the learner's problem representations should be abstract and in multiple forms. Sixth, meta-cognition and self-monitoring have to be involved in the learning process for optimal transfer. Seventh, the learner's prior knowledge and experiences play a critical role in the current learning and how they may affect performance. Finally, because transfer of learning is an active process, assessment should occur over multiple sessions, seeing how the learning affects subsequent learning, such as an increase in speed of learning the new domain [13].

Current theories of learning underscore the importance of several of these factors (see Table 2). ACT-R theory, developed by John Anderson, emphasizes learning of highly-structured domains, such as mathematics [17,18]. Cognitive Load Theory [19–21], developed by Sweller and colleagues, emphasizes the amount of information that either facilitates or prevents optimal learning. Cognitive Flexibility Theory, as exposed by Spiro and colleagues, emphasizes an account of learning in complex domains [22,23]. Situativity theory, developed by James Greeno and colleagues, emphasizes the situational character of learning in real-world settings [24]. Several other notions are also stressed in the literature that have been shown to be critical for optimal learning, such as the use of elaborations, self-explanation, and scaffolding [13]. In any case, although differing in emphasis, most current theories support the notion of active learning [13], stressing the need for learners to be actively involved in their own learning through reflection and action.

2.1.2. Adaptive Character of Thought Theory (ACT-R)

Anderson [17,18] developed a cognitive theory of learning, known as Adaptive Character of Thought (ACT-R) which attempts to understand how knowledge is organized and used for problem-solving. This theory describes complex cognitive processes, such as problem-solving, as an interaction between procedural and declarative knowledge. Declarative knowledge consists of facts or the "what" units of knowledge, whereas procedural knowledge consists of how to perform various cognitive tasks, represented as *production rules*. These rules contain information for certain cognitive actions to be taken under specific conditions for the purpose of fulfilling certain goals and sub-goals [25].

According to the ACT-R theory, understanding involves having a sufficient amount of knowledge (declarative and procedural) about a concept that one can solve significant problems flexibly using the concept. This theory states that learning starts with the accumulation of declarative knowledge units in memory, which are combined to form *production rules* (procedural knowledge). This occurs with practice, resulting in the "automation" of the rules. Here, declarative knowledge can be learned by encoding information from the environment or from storing solutions from previous mental computations. Procedural knowledge is learned by analogy, when one is actively trying to solve a current problem by referring to past problem solutions. This acquisition of knowledge and generation of cognitive structures represents symbolic knowledge. Retrieval and use of this knowledge represents the activation process. According to the ACT-R theory, selecting a problem-solving strategy involves choosing a production rule based on two factors: the expected effort and the probability of expected success. Experience and practice allow one to give values to these two factors. Due to an emphasis on generation of *production rules*, the ACT-R theory conceives of learning at a finer level than some other theories of learning [26]. Complexity arises out of the large number of simple *production rules* involved in executing a cognitive task.

Ongoing research focuses on applying the ACT-R theory to the modeling of complex real-world tasks and the integration of brain imaging data into the theory, with the goal of informing training and education [27]. Anderson and Schunn [25] advocate extensive practice in order to develop a high level of competence, arguing that "time on task" is the most important factor for developing lifetime competencies. However, practice may not develop competence if the wrong knowledge is being emphasized and learned. Thus, ongoing feedback on students' learning is needed.

Based on the principles of the ACT-R theory, cognitive tutors have been developed that may have application to biomedical training. Cognitive tutors are computer-based instructional systems that simulate what the student does in real-time in an attempt to understand student behavior [28]. This information is then used by the system to aid student learning by monitoring performance and providing real-time feedback. Currently, cognitive tutors are used in schools around the United States, mostly for mathematics education. However, they can also be applied to other domains of learning, including biomedicine. For example, biomedical education involves learning many facts about human anatomy and physiology (declarative knowledge) as well as the processes and relationships between the biological systems and how to perform clinical tasks when there is disorder in these biological processes (procedural knowledge). Therefore, cognitive tutors that are theoretically grounded and developed based on how biomedical students learn and solve clinical or research problems can provide the necessary support for effective learning, at least in the simpler, more highly-structured, biomedical domains.

2.1.3. Cognitive Load Theory

Cognitive Load Theory (CLT) was proposed by Sweller and colleagues [29] as an attempt to characterize and account for the role of memory and the complexity of learning materials in the learning process. The theory makes use of a number of hypotheses about the structure of human memory. First, it assumes, as has been shown in memory research [30,31], that working memory (WM) is limited in terms of the amount of information it can hold. Second, and in contrast to working memory, it assumes no limits to long term memory (LTM). Third, it also assumes that LTM is organized in the form of schemata, which are mental structures that serve to organize information in typical ways; are easily retrievable from memory; are often automatic, requiring no effort to use; and are used to interpret new, unfamiliar information.

With these assumptions, CLT has been used to design instructional interventions that help to ease the learning process by preventing or limiting the learner's high memory load, which can result from either of two sources: The kind and amount of information presented to the learner as part of the instructional intervention (called 'extraneous' cognitive load) and the complexity of the information itself (called 'intrinsic' cognitive load), such as the number of idea units inherent in the information and the interaction among those units.

The specific focus of CLT on the limitations of working memory and on the ways to circumvent such limitations through the development of instructional interventions makes this theory readily applicable to education in complex biomedical areas, especially in instructional and text design (e.g., appropriate use of graphs to support learning). Complex learning may promote cognitive load by forcing attention resources to be split among different aspects of a task. For instance, complex learning may require the learner to split his or her attention, such as when the learner is asked to learn the content of a problem as well as the ways to solve it [25], as it is sometimes the case in problem-based learning. It has been suggested, based on CLT, that an attempt to learn clinical medicine at the same time as one is learning a method of clinical inquiry, such as the hypothetico-deductive method, can negatively affect the learning of both [26]. Thus, CLT may be used to guide instructional interventions in areas of medical knowledge that are prone to cause cognitive overload and help to facilitate the process of learning by paying attention to the effects that the complexity of the material has on knowledge and skill acquisition.

2.1.4. "Situative" learning theory

While ACT-R and CLT deal with the cognitive processes of individuals involved in formal structured learning, the "situative" approach focuses mainly on *activity systems* of complex social organizations, rather than on individuals [24]. The situative approach to learning is also called situated action, situated cognition, or situated learning (e.g., [32–34], respectively). Situative theory is also closely related to socio-cultural psychology, activity theory, distributed cognition, and ecological psychology. The situated approach involves a shift from viewing cognition as a property of the individual to viewing cognition as a property of individuals interacting with people and artifacts in the environment.

Thus, some of the basic principles of a situative approach are that learning is context-dependent (although not exclusively; see [35]) and that communication and understanding occur in the specific context as "meaning" is actively constructed within the specific environment, or *activity system*. In other words, all interaction is actively constructed and negotiated by the subjects using the available information and materials (termed *artifacts*) within the context of the activity. In addition, there is the opportunity for learning in any social organized activity, although this may not be formal and structured learning. According to this perspective, learning environments should be designed that would encourage learning of desired and valued knowledge pertaining to specific educational goals. From the situative perspective, the "goal is to understand cognition as the interaction among subjects and tools in the context of an activity" ([24] p. 84). In a situative study, data are regarded and analyzed as records of interactions rather than verbal reports of one's thought and reasoning processes.

Although the situative approach does not explicitly recommend specific educational practices, implications of this approach would suggest that learning environments should be designed as collaborative, active, and inquiry-oriented [36]. In the biomedical domain, situative theory appears to be most useful in the characterization of learning in practice settings and situations where apprenticeship constitute the main form of instruction (e.g., group projects, learning by doing), where the dynamic nature of learning and the use of environmental resources are more important, such as the experiential learning during clerkships or residency training. Given the emphasis on social components of learning, situative theory provides a useful framework for understanding how individuals construct their representation of medical practices through collaborative activities.

2.1.5. Cognitive Flexibility Theory

Cognitive Flexibility Theory (CFT) was proposed by Spiro, Feltovich and Coulson [22] to account for the nature of learning in complex and ill-structured domains. In an ill-structured domain, the application of knowledge to a problem requires the simultaneous interaction of multiple concepts (knowledge structures) that are individually complex (concept and case complexity), where there is irregular variance across cases [22]. A domain's ill-structured nature is not a problem for introductory learning if information is expected to be learned only superficially. However, it becomes a considerable problem for advanced knowledge acquisition, where the expectation is that students attain a deep understanding of the content material and acquire the ability to use it flexibly and productively for real-world problem-solving in response to different task demands and in diverse contexts [22]. Oversimplification of concepts and compartmentalization of knowledge are common in introductory learning in well-structured domains, but are not helpful for advanced knowledge acquisition in ill-structured domains. In ill-structured domains, multiple representations are required to cover multiple meanings of concepts fully.

Medicine can be construed as an ill-structured domain of advanced knowledge acquisition in the sense that medical tasks, such as clinical problem-solving, are typically complex and ill-structured; the initial states, the definite goal state, and the necessary constraints are often not well known [37]. For instance, for many clinical cases, signs and symptoms are non-discriminatory and the number of potential diagnoses is very large. The clinical problem space becomes defined through the imposition of a set of plausible constraints that facilitate the application of specific decision strategies [38].

CFT is a theory of learning with obvious implications for instruction and teaching. On a philosophical level, CFT is based on the notion of "constructivism", which refers to the position that learners' develop their understanding of the world by constructing models of reality in their minds. When given a text or a problem, the learner constructs its meaning by using the given information in conjunction with his or her prior knowledge to come to an adequate understanding, or representation, of the text or problem. CFT de-emphasizes the retrieval of already formed knowledge structures, and focuses on the need to use one's knowledge and various sources of information to create new understandings and new representations. Thus, CFT involves constructive processing, which requires the flexible use of prior knowledge along with the given information. One application of CFT has been in medicine, in the recognition and understanding of hypertension [39].

Feltovich and colleagues [37] have outlined some principles for instruction in advanced knowledge acquisition based on the following assumptions of CFT: (1) learning should be conceived as knowledge construction rather than the acquisition of information, (2) learning is best when the material to be learned can be approached from different perspectives and points of views, and (3) the learner is viewed as making interconnections among the ideas in the learned topic to develop his or her holistic understanding, rather than compartmentalizing knowledge.

In instructional settings, CFT [37] suggests (1) focusing on students' common beliefs and the possible misconceptions that are likely to result from such beliefs and directly challenging such misconceptions, by addressing clusters of related concepts, not just individual concepts; and (2) de-emphasizing the compartmentalization of knowledge, and focusing on connection of multiple concepts and their interaction and variation across contexts, with the use of multiple analogies and multiple representations for each complex concept. In this regard, according to CFT, one avoids what the authors call the reductive bias, the natural tendency to oversimplify complex concepts. This means that simple, sequential learning will work in domains where the task required for competence are simple. This does not hold for complex domains such as health care, where simple, sequential learning does not capture the complexity of the domain. Thus, de-emphasizing the compartmentalization of knowledge can be accomplished by pairing cases of application with learning the conceptual knowledge relevant to such cases, and indicating differences among similar concepts and similarities among disparate concepts. Furthermore, the cases used should cover a range of situations and problems that use different pieces of knowledge or the same knowledge in different ways. Also, emphasis should be put on the relations among problem cases and between cases and concepts, showing how knowledge can be reconstructed for novel cases, going through the same cases from multiple perspectives with different goals.

CFT is most useful in situations of non-linear learning, such as that involved in learning complex concepts that can be approached by students from various perspectives and where learning does not proceed from the simpler to the more complex and where there are no right or wrong answers (c.f., ACT-R, which emphasizes the gradual process of first acquiring simple relations while incrementally adding complexity as new, more elaborate material is taught). An area of application has been learning through hypermedia [22]. In these situations, the learner—instead of approaching the topic by first acquiring basic concepts and then proceeding to learn increasingly complex concepts—acquires a domain in a non-linear manner by navigating the topic in an exploratory manner (where there is no fixed sequence). The argument is that by approaching the topic to be learned from various points of view or perspectives, the learner can construct a more individualized and deeper representation of the domain. Furthermore, seeing relations among concepts fosters integration of knowledge from different but related areas. For example a medical student may learn to form a complex representation of a disease by making connections between its biochemical, physiological, and clinical aspects.

Models based on constructivist theories, such as Cognitive Flexibility Theory, develop an instructional format based on "successive approximations" that may best foster learning. One especially important notion of successive approximations is that of "scaffolding", a concept based on the notion of a zone of proximal development first developed by the Russian psychologist Lev Vygotsky [40]. The "zone of proximal development" refers to the student's problem-solving abilities, ranging from what he or she can do with guidance (according to the actual developmental level) to what he or she can do independently (according to the level of potential development). The range of this zone constantly changes with the student's increasingly independent competence. Similarly, scaffolding refers to an instructional format where learning occurs with the support of an expert or a teacher, where students, usually in their early years of training, who do not have adequate knowledge to solve problems by themselves, will be guided until they can perform adequately on their own. The amount of support given to the student decreases as the student becomes increasingly more able to perform the task by him or herself. This lessening of support should occur gradually and should adjust depending on the needs of the student. The use of scaffolding aids the ability to transfer knowledge to another context and to develop competent problem-solving skills, after the support is withdrawn.

2.1.6. Medical cognition and learning theory

It may appear that cognitive learning theories (ACT-R, CLT)—which focus on individual structured learning—and constructivist learning theories (Situative, CFT)—which focus on complex learning within interacting systems, are incompatible and conflicting. However, this is not actually the case. As Anderson et al. [41] argued, both perspectives are important, and one perspective should not be used to the exclusion of the other. Both views attempt to explain learning in individuals and groups, although they use different ways to accomplish this goal. Ultimately, both perspectives provide significant and valuable insights into how effective performance and learning occurs. Anderson and colleagues [41] also assert that the cognitive and situative perspectives do not conflict in their implications for the design of learning environments, but that learning systems that focus on only individuals or groups are incomplete because a more comprehensive approach would involve integration of individual and group and context-based aspects. Similarly, we have argued [42] for a re-conceptualization of information processing theories, taking into account the situative approach. Both the cognitive and situative programs of research have resulted in important knowledge about human learning that can, and should, inform the other when designing effective learning environments and instructional methods.

More fundamental than the difference in focus on individuals or systems is the difference between the cognitive and situated approaches as to the nature of mental representations, and specifically symbols, as used in cognitive activities [42]. In cognitive science, two perspectives have been developed. The first perspective, termed "symbolic", rests on the assumption that cognition involves the internalization of external situations and events in the form of symbols representing those situations and events. Cognitive activity consists of the mental manipulation of those symbols, involved in activities such as planning. The second perspective advocated by situative theorists, which is often called "sub-symbolic", proposes that cognition does not always involve the manipulation of symbols, but rather that agents in activity perform many cognitive processes by directly using aspects of the world around them without the mediation of symbols. The learning of surgery, for instance, can be seen as an example of situated learning in that the surgery apprentice learns to perform different tasks without having to represent symbolically the procedures involved in such tasks.

Much of clinical performance, especially in routine situations, involves non-deliberative aspects, where deliberation would result in considerable inefficiency. For instance, there are diagnostic tasks in perceptual domains, such as dermatology and radiology, in which a significant degree of skilled performance relies on pattern recognition rather than on deliberative reasoning [42]. Also, there are numerous medical problems that require quick responses, such as in emergency situations, where deliberative reasoning is not possible most of the time. In such cases, the situated approach can be used to characterize cognition as a process of directly using resources in the environment, rather than using reflective thinking to arrive at conclusions [33,43]. The notion of a direct connection with one's environment is prominent in cognitive engineering [44] and human-computer interaction research [45], where well-designed artifacts can be closely adapted to human needs and capabilities through the appropriate use of invariant features (e.g., panels on a screen display) [46]. Well-designed technologies provide "affordances" that are perceptually obvious to the user, making human interactions with objects virtually effortless [47]. Affordances refer to attributes of objects that enable individuals to know how to use them (e.g., a door handle affords turning or pushing downward to open a door) [47].

One particular situated approach emerged from the investigation and development of intelligent systems that support performance in complex "dynamic real world domains". Such systems are characterized by severe time constraints and continuously changing conditions, such as in emergency departments, surgical operating rooms, or intensive care units [2]. Learning in complex real-world environments also presents a challenge to symbolic theories because agents need to respond adaptively to continuously changing conditions and in concert with other agents under great time pressure. Individuals have to be able simultaneously to perceive information and coordinate action in a manner that would preclude the use of plans or intermediate representations. Such environments provide a challenge for cognitive theories and are of particular concern to investigators of medical cognition.

The claim made by the situative approach, that the individual and the environment dynamically interact, suggests that the combined products of a cognitively distributed system cannot be accounted for by only the operation of its individual components [48]. This claim has implications for instructional design where the use of information technologies in a cooperative and distributed way plays an important role. Specifically, integrating team-based learning in biomedical curricula becomes critical, especially in clinical situations where problem-solving requires cooperation and coordination among multiple team members.

The well-documented problems of implementing knowledge-based systems in medical practice mirror the gap between theories of learning and their application to medical education. The notion of learning in context is clearly one of the most important messages for education and instructional training. However, when training is situationally-bound, and no provisions are made to emphasize the conditions of transfer, generalizability from one situation to another may be compromised. For instance, proponents of problem-based learning (discussed in later sections) assert that learning in context facilitates retrieval, and that most learning should be context-bound, where biomedical knowledge is taught in relation to specific clinical problems to ensure their integration. However, although biomedical knowledge is indeed integrated into clinical problems in PBL situations, this integration is often so context-dependent that its transfer to other situations is difficult [49,50]. These problems speak of the need to understand how physicians can acquire basic competency in clinical practice through the apprenticeship process, but there is an equally pressing need to understand how expert physicians acquire robust abstract conceptual models that have generalizability across contexts. Thus, to the end of developing learning competencies, traditional cognitive theories as well as constructivist and situated theories should play a role in the design of biomedical curriculum and instruction.

2.2. Development of learning competencies

Any adequate theory of learning and instruction should have at least three component sub-theories [51–54]: (1) a theory of competent, skilled, and knowledgeable performance as exemplified by domain experts, (2) an acquisition theory concerning the process of learning and development, and (3) a theory of intervention describing methods for enhancing teaching and learning. Progress in these components has been made mostly in the first component, but some advances have been made in the area of skill acquisition and instruction. In addition, more recently, theories of performance have become more closely aligned with models of learning and instruction [55].

In the case of clinical performance, there are multiple competencies involved, some of which are informally acquired in the context of practice, whereas others are best acquired through a formal learning process. Conceptual competence develops through the deep understanding of general principles of a domain [56], which is characterized by generativity and robustness. Generativity refers to the ability to use knowledge in a variety of task and contexts, whereas robustness refers to the ability to adapt acquired concepts to unfamiliar task situations. The extent to which aspects of a domain are best learned in context is determined jointly by the nature of domain knowledge and the kinds of tasks that are performed by practitioners.

2.2.1. Assessment of competence in biomedicine

Assessment of performance includes establishing criteria and minimum standards for competence. Trainees may show competence in solving familiar problems because of a well-organized and easily accessible knowledge base, but may not show the same competence when dealing with unfamiliar or novel problems. This addresses the issue of viewing competence as an ability to be flexible and to transfer knowledge across problems and domains. Competence is a function of level of training, amount of "deliberate practice" [57], and reflection on one's experience. Therefore, seasoned physicians would have a higher level of competence than less experienced professionals, residents, or medical students. Assessment of these abilities can include the measurement of adaptiveness, flexibility and competence beyond memorization. These component factors can also be used to measure competency in clinicians' interaction with technology in the heath care system. Context may also have a strong influence on performance, so assessment of competence needs to take such external factors into account [58]. Discussion of competence and its assessment in this section could equally be applied to other health professions other than medicine, such as nursing, pharmacy, and dentistry.

The Association of American Medical Colleges (AAMC) [59] defines *professional competence* as the acquisition of a strong and broad knowledge base, a range of clinical and professional skills, and exemplary professional and humanistic behaviors. The challenge and need is to develop strategies for teaching such competence and methods of assessing progress in achieving competence. The Accreditation Council for Graduate Medical Education (ACGME) has developed a model that has become the basis for the assessment of competence in medical residents and students. The six domains that are assessed are (1) medical knowledge, (2) patient care, (3) professionalism, (4) communication and interpersonal skills, (5) practice-based learning and improvement and (6) systems-based practice [60]. Current assessment of competencies have been expanded to include learning by practice, reflection on experience, and self-direction in multiple areas, such as procedural, management, and critical thinking skills [59]. This report also suggests that medical education should address development of competency along a continuum, defining specific milestones for students. In sum, the AAMC advocates for a competency-based model for undergraduate, graduate and continuing medical education [59].

Assessment of competence in biomedicine has been typically based on the notions derived from the Bloom's taxonomy of educational objectives. Benjamin S. Bloom developed the original taxon-

Table 3a
The structure of the knowledge dimension of the revision of Bloom's taxonomy (reprinted from Krathwohl, 2002 [63], with permission).

Knowledge dimension of the revised taxonomy
A. Factual knowledge—The basic elements that students must know to be acquainted with a discipline or solve problems in it
Aa. Knowledge of terminology
Ab. Knowledge of specific details and elements
B. Conceptual knowledge—The interrelationships among the basic elements within a larger structure that enable them to function together
Ba. Knowledge of classifications and categories
Bb. Knowledge of principles and generalizations
Bc. Knowledge of theories, models, and structures
C. Procedural knowledge—How to do something; methods of inquiry, and criteria for using skills, algorithms, techniques, and methods
Ca. Knowledge of subject-specific skills and algorithms
Cb. Knowledge of subject-specific techniques and methods
Cc. Knowledge of criteria for determining when to use appropriate procedures
D. Metacognitive knowledge—Knowledge of cognition in general as well as awareness and knowledge of one's own cognition
Da. Strategic knowledge
Db. Knowledge about cognitive tasks, including appropriate contextual and conditional knowledge
Dc. Self-knowledge

omy in 1956 [61]. His original taxonomy included six overarching categories (containing subcategories) in the cognitive domain: *Knowledge*, *Comprehension*, *Application*, *Analysis*, *Synthesis*, and *Evaluation*. These categories were ordered based on level of complexity and abstraction, and the taxonomy was considered hierarchical, in that a simpler category would need to be mastered before mastery of a more complex one. The original taxonomy was often used to classify curricular objectives and test items. Such evaluations showed that objectives mostly fell into the *Knowledge* category, thus emphasizing mere recognition or recall of information. However, objectives related to understanding and use of knowledge (categories from *Comprehension* to *Synthesis*) are generally considered the most important educational goals.

This taxonomy has recently been revised [62,63], moving from a one-dimensional (*Knowledge*) to a two-dimensional (*Knowledge* and *Cognitive Processes*) framework. The revisions were made in recognition of cognitive research, which had uncovered aspects of learning that were not reflected in the original taxonomy, such as meta-cognitive processes. Corresponding to the general structure of learning objectives, which includes some type of content (in the form of a noun) and an action of what is to be done with or to the content (in the form of a verb), the taxonomy was divided into knowledge categories (in the form of nouns) and cognitive processes (in the form of verbs), which served to clarify the multiple combinations of noun-verb phrases possible. The original categories were rearranged and renamed, and the revised taxonomy still uses a hierarchical structure, although to a lesser degree. The knowledge dimension (see Table 3a) includes factual, conceptual, procedural, and meta-cognitive (new to the revised taxonomy) knowledge. The Cognitive Process dimension (see Table 3b) includes *Remember* (former Knowledge category), *Understand* (former Comprehension category), *Apply* (former Application category), *Analyze* (former Analysis category), *Evaluate* (former Evaluation category), and *Create* (former Synthesis category). Whereas the original taxonomy put more emphasis on the six major categories, the revised Taxonomy places more emphasis on the subcategories (cognitive processes) for the Cognitive Process dimension. These cognitive processes characterize the breadth and depth of each main category. Although the revised categories are hierarchical, similarly to the original Taxonomy, there is some overlap in complexity. In the revised taxonomy's two-dimensional framework, all educational objectives can be classified according to both the *Knowledge* and *Cognitive Process* dimensions, thus forming a taxonomy table, with Knowledge on the vertical axis and Cognitive Process on the horizontal axis. One advantage to this table is the ability to see which categories are lacking based on the educational objectives that are outlined. This affords the opportunity to evaluate the instruction and teaching to identify those areas that need to be strengthened. In addition, the taxonomy table can be used to classify the instructional and learning activities used to achieve the objectives and the assessments used to evaluate students' progress in achieving the objectives. Thus, the revised taxonomy has added the additional ability of classifying standards, in addition to educational goals and objectives.

Although the revised taxonomy takes into account cognitive learning, as presented in the cognitive processes dimension, cognitive theories of complex learning go farther by including the notion of *conceptual competence*, defined as the potential to employ concepts flexibly in a range of contexts. A *theory of competence* would imply that there is a specific reference or expert standard indicating the content and form of knowledge in a given domain. Thus, competence, defined as the potential to perform to a standard, is not necessarily reflected in one's performance. Deviations from the standard may result from a lack of knowledge, as it is often assumed in traditional assessment, or may be the result of biases in reasoning or misconceptions [37]. A key issue in this regard is that learning in complex domains may develop non-monotonically, where conceptual confusion may be necessary for deep learning, as it has been shown in the "intermediate effect" [64,65], which shows a temporary decline in performance as knowledge is acquired and organized. Thus, although a revised taxonomy is certainly an advancement over the original taxonomy in the sense that it brings to bear recent research findings in the cognitive domains, it may not reflect all there is to complex learning.

Table 3b
The structure of the cognitive dimension of the revision of Bloom's taxonomy (reprinted from Krathwohl, 2002 [63], with permission).

Cognitive dimension of the revised taxonomy
1.0 Remember—Retrieving relevant knowledge from long-term memory
1.1 Recognizing
1.2 Recalling
2.0 Understand—Determining the meaning of instructional messages, including oral, written, and graphic communication
2.1 Interpreting
2.2 Exemplifying
2.3 Classifying
2.4 Summarizing
2.5 Inferring
2.6 Comparing
2.7 Explaining
3.0 Apply—Breaking material into its constituent parts and detecting how the parts relate to one another and to an overall structure or purpose
3.1 Executing
3.2 Implementing
4.0 Analyze—Knowledge of cognition in general as well as awareness and knowledge of one's own cognition
4.1 Differentiating
4.2 Organizing
4.3 Attributing
5.0 Evaluate—Making judgments based on criteria and standards
5.1 Checking
5.2 Critiquing
6.0 Create—Putting elements together to form a novel, coherent whole or make an original product
6.1 Generating
6.2 Planning
6.3 Producing

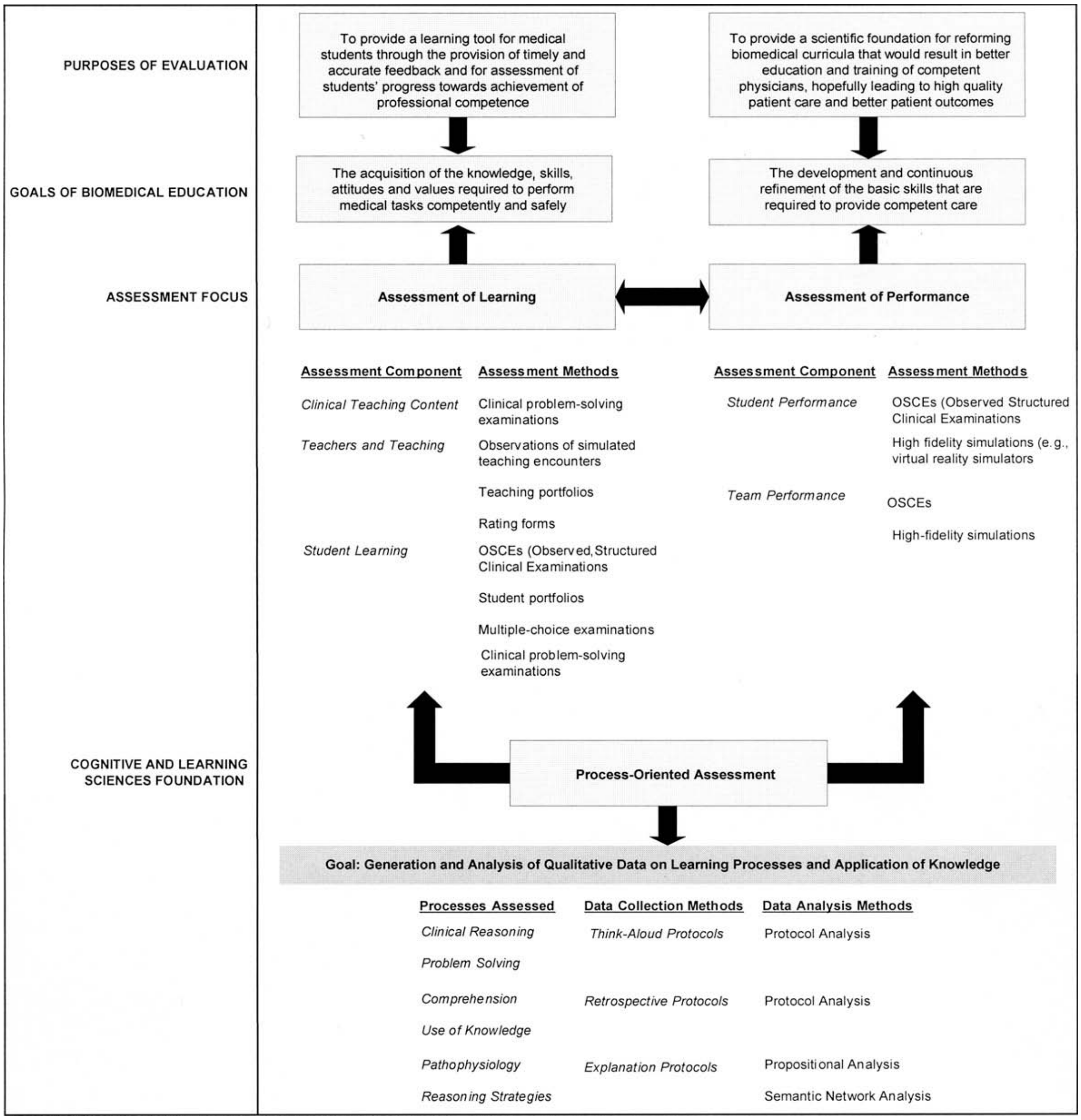

Fig. 1. Relationships between the purposes of evaluation, the goals of biomedical education and the types and specific methods of assessments that can be conducted, namely assessment of learning and assessment of performance. The third type of assessment is process-oriented assessment, which has its foundations in the cognitive and learning sciences.

2.2.2. Assessment of conceptual competence

If there is a change in the method of learning, then a change in the assessment process is also needed. Fig. 1 depicts how the purposes of evaluation and the types of assessment are related to the goals of (bio)medical education. In this paper, we argue for the addition of process-oriented assessment, which has its foundations in the cognitive and learning sciences.

Cognitive theories of complex learning shed light on how to assess for competence by suggesting methods of testing that emphasize the flexibility inherent in conceptual understanding. Part of the evidence and the arguments that are needed for fostering more effective instruction relate to a characterization of conceptual competence that entails "acquiring and retaining a network of concepts and principles about some domain that accurately represent key phenomena and their interrelationships and that can be engaged flexibly, when pertinent, to accomplish diverse, sometimes novel objectives" [37]. Traditional methods of assessing achievement and competence are not sufficient for testing for flexible understanding with more difficult and complex material. Instruction and assessment needs to be reformed to effectively test flexible understanding and problem-solving. Feltovich and colleagues [37] have proposed some guidelines for such a goal (see Section 2.1.5 for details). Given the importance of having a flexible understanding of the domain, and knowing that students often hold incorrect beliefs and misconceptions, medical instruction should include a diagnostic component, where student's preconceptions are identified and clarified; and a prescriptive component, where direct challenges to areas of knowledge that may present barriers to understanding are provided. The presence of preconceptions and misconceptions in students' understanding is not typically a focus of attention in traditional forms of assessment, and the goal of conceptual flexibility is inconsistent with the current view of hierarchical learning emphasized by behavioral perspectives on instruction and assessment, e.g., Bloom's taxonomy and cognitive theories of simple learning. In short, a conceptual competence view of assessment emphasizes relations among cases and between cases and concepts, and shows how knowledge can be reconstructed for novel cases looking for generality in learning by providing views of the same concepts and cases from multiple perspectives with different goals.

Fostering conceptual competence requires, however, that some goals be met, such as developing a coherent understanding of related concepts that make up a particular domain, learning to instantiate these concepts in specific examples, and transferring them to different situations. Conceptual understanding (for instance as reflected in the ability to generate an explanation) does not guarantee accurate application of such knowledge. Typically, research has shown that students who learn a concept, with a focus on one specific problem, have difficulty in applying the concept to other similar problems (when the related problems have some differences in critical areas, such as Bacterial Endocarditis with Aortic insufficiency acquired from intravenous drug use, and Bacterial Endocarditis with mitral valve stenosis acquired from lack of antibiotics after a dental treatment) [66]. In addition to understanding conceptual competence, as described by the theory of complex learning, the needed flexibility to adapt to changing situations required for learning and skill transfer can be informed by research on the nature and development of expertise. In particular, the development of expertise involves the acquisition of complex theoretical knowledge as well as the contextualized knowledge of practice. By looking into the nature of expertise and its development, we may be in a better position to provide a theoretically and empirically-based input to a theory of effective instructional intervention to support curricular transformation.

In the next section, we provide an overview of what is known about the nature and development of expertise, beginning with a brief history of expertise research and methodology, followed by some key research findings and an explanation of more recent notion of adaptive expertise and implications for educational strategies. In particular, the study of expertise has influenced the domain of health education several ways: (1) it has formed the basis of expert technology-based systems to aid clinical practice, and (2) it has provided a more comprehensive and detailed picture of clinical reasoning in medicine than the evaluation techniques commonly used in medical education [67], and (3) it has helped us to develop cognitive-based criteria for setting competency levels for professional training.

3. The nature and development of expertise

3.1. History of expertise research

Cognitive research on the nature of expert-novice differences began with the classic work of deGroot (1965) [68] on the game of chess, where clear differences were found in memory organization between experts and novices. This work was replicated later by Chase and Simon (1973) [69] and subsequently in other domains, such as physics [70,71], biology, social science, and medicine [66,72]. The study of expertise was conduced mostly in tasks involving reasoning and problem-solving. At the same time, research on expertise and problem-solving in the field of medicine was conducted by Ledley and Lusted (1959) [73] and Rimoldi (1961) [74], who found that expert physicians were better able to selectively attend to relevant information and to narrow the set of diagnostic possibilities (i.e., consider fewer hypotheses). Subsequent research on medical reasoning involved the examination of the *thinking* and *reasoning* processes (i.e., use of inferences and hypotheses and understanding underlying disease processes) used in solving clinical problems and making clinical decisions. Much of this research compared performance of experts to novices.

Expertise research was conducted using two approaches [75,76]: (1) one, called absolute expertise, which studies "exceptional" experts in their respective domain of expertise (e.g., outstanding "memorizers"; or top athletes), and how their performance separates them from most individuals; and (2) a second approach, called relative expertise, which compares the performance of novices to experts, along the continuum of expertise, where experts are assumed to have qualitatively different competence and performance than the novices, based on certain measures, such as number of years of schooling, training, or experience in the domain [66,77,78].

This research has served to identify why experts excel in their domain, or fail in certain situations (see [75] for a thorough review of this area). Experts are more accurate, faster, and efficient in their problem-solving, can detect subtleties that novices cannot, spend a lot of time constructing representations of the problem, are better able to self-monitor for errors and understanding, are more successful at choosing the appropriate strategies, use more sources of information, and can retrieve relevant knowledge and strategies with minimal cognitive effort. Experts also have limitations: their expertise is limited to the domain of practice, they may be overly confident, they do not attend to less relevant details of the problem or may not recall such details, their ability to make an accurate diagnosis is context-dependent, they may be inflexible in their strategy use, they may have inaccurate predictions of novice's abilities, they are subject to biases (e.g., overconfidence bias), and they may be limited in their ability to generate creative solutions (functional fixedness). Some of these limitations highlight the need for flexibility and adaptiveness in problem-solving.

The study of expertise in the health science domain became established with the influence of cognitive science, through the theory of problem-solving developed by Newell and Simon [79,80]. This resulted in the seminal work of Elstein, Shulman, and Sprafka (1978), who were the first to use experimental methods and cognition to investigate clinical competency [6]. Their extensive empirical research led to the development of an elaborated model of hypothetico-deductive reasoning, which proposed that physicians reasoned by first generating and then testing a collection of hypotheses to account for clinical data (i.e., reasoning from hypothesis to data). This model of problem-solving had a substantial influence on studies of both medical cognition and medical education.

Parallel to the advances into the nature of human expertise in the 1970s and 1980s, developments were also seen in medical artificial intelligence (AI), particularly, expert systems technology. AI in medicine and medical cognition mutually influenced each other in a number of ways, which included (1) providing a basis for developing formal models of competence in problem-solving tasks; (2) elucidating the structure of medical knowledge and providing important epistemological distinctions; and (3) characterizing productive and less-productive lines of reasoning in diagnostic and therapeutic tasks. A highlight of this period was work by Anthony Gorry (1970) [81] comparing a computational model of medical problem-solving with physicians' actual problem-solving, which provided a basis for characterizing a sequential process of medical decision-making that differed from other diagnostic computational systems based on Bayes' theorem. Pauker and colleagues (1976) [82] built on his work and developed the Present Illness Program (PIP), designed to take the history of a patient with edema.

Medical expert consultation systems such as Internist [83] and MYCIN [84] introduced ideas about knowledge-based reasoning strategies across a range of cognitive tasks. MYCIN, in particular, had a substantial influence on cognitive science, through several advances (e.g., representing reasoning under uncertainty) in the use of production systems as a representation scheme in a complex knowledge-based domain, as well as the emphasis on differences between medical problem-solving and the cognitive dimensions of medical explanation. Clancey's follow up work [85,86] in GUIDON and NEOMYCIN was also influential in the evolution of models of medical cognition, given that the focus was on explanation-based reasoning used for teaching novices.

Subsequent empirical studies by Feltovich and colleagues [87], and Patel and Groen [88] characterized differences in knowledge organization and the use of knowledge-based solution strategies between physicians of different levels of expertise. These findings challenged Elstein and colleagues' [6] hypothetico-deductive model of reasoning, which did not differentiate expert from non-expert reasoning strategies.

Much of the early research in the study of reasoning in domains such as medicine was carried out in laboratory or experimental settings. There has been a shift in more recent years toward examining cognitive issues in naturalistic medical settings, such as medical teams in intensive care units [2], anesthesiologists working in surgery [89], nurses providing emergency telephone triage [90], and reasoning with technology by patients [91] in the health care system. This research was informed by work in the area of dynamic decision-making [92], complex problem-solving [93], human factors [94,95], and cognitive engineering [44]. Naturalistic studies reshaped researchers' views of human thinking, as expressed in "situativity" theory's terms (as described in Section 2.1.4) [23–26], by shifting the onus of cognition from being the unique province of the individual to being distributed across social and technological contexts.

3.2. Defining levels of expertise

Most research on expertise focuses on the characteristics of the expert (e.g., how their knowledge is organized, performance on tasks), using the novice or sub-expert for comparison. Some researchers have extended their empirical approach to include the study of novices, of different ability levels and at different levels of training (for review, see [75]). However, expertise should be viewed as a developmental path addressing the conditions that lead from novice to expert. This is particularly important to advance learning theories and to design effective instruction.

There are four general levels of expertise usually considered that reflect a continuum from a beginner to highly-experienced professional. These include (1) *novice*, an individual who has only everyday knowledge of a domain or one who has the prerequisite knowledge assumed by the domain, e.g., first year medical student; (2) *intermediate*, an individual who is above the beginner level but below the sub-expert level, e.g., second year medical student; (3) *sub-expert*, an individual with generic knowledge but inadequate specialized knowledge of the domain, e.g., senior medical resident; and (4) *expert*, an individual with a specialized knowledge of the domain, e.g., attending physician [78].

Although many studies contrast an expert group with a novice group, expertise is best viewed as a continuum with a number of levels that result in unique performance characteristics. The development of expertise is marked by specific transitions corresponding to reorganizations of knowledge and non-monotonic (not linear) increases in mastery of domain-specific tasks [96]. This refers to observed periods of transition in the developmental process in which subjects exhibit a drop in performance, when a linear increase in performance with length of training or time on task would be expected. In the development of expertise, there exists a distinctive developmental phenomenon known as the *intermediate effect*. The developmental pattern is non-linear, and is shaped like either a U or an inverted U (depending on the measures used). The *intermediate effect* has been observed to occur with many tasks and at different levels of expertise, showing this to be a fairly robust phenomenon.

The intermediate phenomenon may occur because while students in the middle of their training and education may have acquired an extensive body of knowledge, they have not yet reorganized this knowledge in a functional manner to perform various tasks. In contrast, although novices have not yet acquired a sufficient base of knowledge from which to solve many clinical problems effectively, they may be able to understand routine problems without getting "confused" about the cases. It seems that at several points in a person's training where large bodies of new knowledge or complex skills are acquired, there is likely to be a subsequent decrease in performance while the knowledge is being consolidated and organized. The existence of the intermediate effect has been supported by research studies showing that learning new material after basic knowledge has been acquired can result in periods of knowledge reorganization where relations acquired earlier become disrupted by the new learning [97]. This means that a decline in performance soon after the introduction of new, and of a different nature, information or technology should not be interpreted as a failure.

3.3. Methods for studying expertise

The methods used to investigate expertise have varied from experimental tasks in carefully controlled conditions to studies of individual experts while working in their natural environment, to the investigation of collaborative expertise in team interactions. Furthermore, studies of expertise have also varied in terms of the identification of what an expert is, ranging from recognized experts in the real-world (e.g., Nobel laureates, Grand Master chess players) to experts defined in terms of greater experience and training relative to others (e.g., advanced students of a domain).

3.3.1. Methods of data collection and analysis

Methods of data collection include the use of a range of experimental and quasi-experimental tasks aimed at exploring cognitive processes in reasoning, problem-solving, and decision-making. There are comprehensive published reviews of laboratory methods used in the study of expertise, in general [76], and in biomedical domains. We briefly describe the following commonly used tasks: (1) think-aloud tasks, (2) recall and summarization tasks, (3) explanation tasks, and (4) knowledge elicitation tasks. In think-aloud tasks, subjects are asked to verbalize what they think as they solve a problem, without making comments or interpretations about their own processes [99]. This is assumed to provide a window into the subjects' cognitive processes during problem-solving.

The use of recall tasks is standard in many psychological studies investigating the differences in knowledge representation between novices and experts. Generally, the task consists of free recall, where the subject is asked to remember (verbally or written) as much as possible from a text (e.g., clinical case) after reading it over for a couple of minutes. Findings from recall tasks have shown that experts are more accurate and faster than novices in recalling the information (in their domain of expertise) (e.g., [69,100,101]). The importance of the recall task is that the better recall by experts is usually reflective of a more highly organized structure of knowledge of the domain. A related task, the summarization task, requires the subject to focus on remembering and organizing the relevant information to the case. As such, experts have been found to recall more relevant information to the clinical problem and filter out the irrelevant information, whereas novices are not able to readily distinguish between relevant and irrelevant information (e.g., [102,103]). Thus, performance on the recall and summarization tasks could be used as markers for an individual's acquired level of expertise.

Explanation tasks generate data that provide post-hoc explanations of an event. This method is a reflective process. When used in a clinical environment, a subject is asked to "explain the underlying pathophysiology" of a patient's condition. Typically, physicians respond to this question by explicating the patient's symptoms in terms of a diagnosis by indicating its relationship to the clinical symptoms (the fit between diagnostic hypotheses and the patient data). This is a useful strategy for looking for coherence in one's thought processes, although one's judgment is influenced by bias because there is room for reconstructing events during reflective thought. This is unlike prospective data collection, where the influence of bias is less likely.

Knowledge elicitation tasks are structured forms of eliciting knowledge [104]. Although obtaining verbal protocol data is the preferred method, this method is frequently time consuming. However, there are modern technological advances in data collection tools, which aim to facilitate efficient data collection. For example, there are several knowledge elicitation techniques that do not require obtaining direct protocols. One such task is the concept grouping (e.g., [91]). This requires simply that the subjects indicate those concepts that go together; out of an unorganized list of concepts. Subjects are given a series of concepts (either verbally or in pictures) and are asked to cluster them in a way that makes sense to them. The result is a hierarchical structure that represents the way the concepts are held together in memory. The conceptual hierarchies are then compared to one another to assess the extent to which the knowledge structures are shared among the subjects. One form of the task involves presenting a series of cards, where each card contains a word representing a particular concept relevant to the issue being investigated. Each subject is asked to sort the concepts into groups of related concepts. The concept grouping task is one of the easiest methods of knowledge elicitation and can be applied in a relatively shorter time than other methods.

Based on data collected through one of the above-described methods, there are several types of analysis that are used depending on the granularity of information needs. These include propositional analysis (analysis of basic idea units) and semantic network analysis. There are several propositional analysis systems, such as van Dijk and Kintsch's [105] and Frederiksen's [106], based on the assumptions that a propositional representation is one way to represent verbal information in working memory. Usually built from the results of propositional analysis, semantic network analysis consists of a representation of the structure of the discourse, showing its completeness and coherence [78]. These results could be interpreted as the extent to which the subjects represented the concepts, related one concept to another, and applied these concepts in real practice situations. For more detail on this analytical method, the readers are referred to specific literature on the subject [107].

3.4. Directionality of reasoning

Cognitive literature (mostly psychological research) describes two major patterns of reasoning about problems: data-driven reasoning and hypothesis-driven reasoning. Data-driven reasoning involves reasoning "forward" from the available data to the unknown and requires a great deal of organized background knowledge. It is also known as "heuristic" reasoning. This type of reasoning is quick as it does not require multiple pathways from hypotheses to the data, but is also error-prone because it does not have a built-in check for the legitimacy of inferences. In contrast, hypothesis-driven reasoning, which involves working from a hypothesis about the unknown back to the given information, is slower, makes heavier demands on working memory, and is more likely to be used when domain knowledge is inadequate [66,78]. The key finding from research by Simon and Simon [70] in the domain of physics was that experts used data-driven reasoning (forward-directed) and novices used hypothesis-driven (backward-directed) reasoning This is also true for the health science domain, where data-driven reasoning is often used for clinical problems in which the physician or a nurse (i.e., an expert) has ample experience and knowledge, but will resort to hypothesis-driven reasoning when the problem is unfamiliar or complex (e.g., [108]). In some circumstances, the use of data-driven reasoning may lead to a heavy cognitive load. For instance, when students are given problems to solve while they are being trained in the use of problem-solving strategies, the situation produces a heavy load on cognitive resources which may diminish students' ability to focus on the task [19]. The reason is that students have to share cognitive resources (e.g., attention, memory) between learning the problem-solving method and learning the content of the material.

It can be argued that the way medical knowledge is organized can be a determining factor for the type of reasoning used by experts and novices when solving clinical problems, and thus the accuracy and effectiveness of the physician's clinical decisions [78]. The next section defines the nature and organization of medical knowledge and of research, particularly cognitive research, on the use of this knowledge for problem-solving. Importantly, the type of knowledge used in clinical problem-solving is indicative of the type of instructional method that was used in medical education. Retrospectively, one can look at the effectiveness of a particular instructional method by assessing clinical performance, specifically how different types of knowledge are used. There is a close tie between instruction and cognition, and the nature of competence.

3.5. Biomedical and clinical knowledge and clinical performance

There are two major types of knowledge in the field of medicine: biomedical (or basic science) and clinical. Clinical knowledge includes knowledge of diseases and associated findings. Basic science knowledge incorporates subject matter such as biochemistry, anatomy, and physiology, and provides a scientific foundation for clinical reasoning. As expertise develops, the individual relies more on clinical knowledge and less on biomedical knowledge when solving clinical problems. Does this shift in use of knowledge lead to better clinical performance? This is an important issue to understand as we begin to introduce more technological support in medical training and practice.

Considerable research has been conducted that addresses the role of basic medical science knowledge in clinical medicine. Some research in this area has focused on perceptual expertise in medicine (e.g., [109–112]). Findings indicate that (1) experts have richer mental representations of underlying pathophysiology that is needed to solve clinical problems, and (2) expert knowledge is organized around domain principles, which facilitate the rapid recognition of significant problem features [113,114]. This supports the idea that experts employ a qualitatively different kind of knowledge to solve problems based on a deeper understanding of domain principles. Thus, the quality of knowledge represented could be used as a marker for the level of expertise acquired by the individual.

Other research has investigated the ability of clinicians to apply basic science concepts in diagnosing (and managing) clinical problems [88,108,115,116]. In a series of experiments to determine the precise role of basic science in clinical reasoning, Patel and colleagues [118,121] found that junior medical students made little use of basic science when solving clinical problems and use whatever clinical knowledge they have acquired. In contrast, senior students rely on their clinical knowledge to enhance their knowledge of basic science when solving clinical problems.

Research has also shown that basic science information is not used directly as expertise develops. This does not mean that it is not useful, but rather basic science knowledge gets integrated into clinical practice and may result in oversimplification of basic science concepts. Specifically, studies have shown medical students' and physicians' significant misconceptions in understanding biomedical concepts when these concepts are being used to solve clinical problems (e.g., [37,117–120]). In other words, given the nature of the domain complexity, simplification of complex concepts taught to students did not support the development of relevant clinical reasoning strategies. What is taught should reflect domain complexity. For example, students can be taught multiple representations of the same concept (teaching with closely related classes of problem sets), an idea supported by Cognitive Flexibility Theory (see Section 2.1.5 for further detail).

Given the medical expertise research findings that we have described, there are particular implications for the development of curricula and methods of instruction. Medical students, at all levels of training, will generate some errors and misconceptions in providing clinical explanations of the problem. The negative consequences of such errors depend on the direction of reasoning. If heuristic-driven reasoning is used in the explanation, then the student is likely to view his or her knowledge base as adequate and will have a high level of confidence, and will continue to hold the same misconceptions that are resistant to change. However, if hypothesis-driven reasoning is used, the student may modify his or her hypothesis to move toward a more adequate explanation of the problem. Thus, the student will learn how to reflect on the adequacy of one's explanation rather than on the accuracy of the solution. The key to effective instruction is predicated on finding the right balance between explanation and problem-solving. These processes can be elicited by different pedagogical activities.

3.6. Adaptive expertise and its development

The following section gives an overview of more recent research on expertise that focuses on self-regulation and adaptability of the professional in one's domain. This is termed "adaptive expertise" [121]. Through their extensive experience, experts develop a critical set of self-regulatory or "metacognitive" skills that controls their performance and allows them to adapt to changing situations. For example, experts monitor their problem-solving by predicting the difficulty of problems, allocating time appropriately, noting their errors or failure to comprehend, and checking questionable solutions. Novices are less understanding of task demands or how these match their capabilities, and this prevents them from tackling problems strategically.

Hatano and Inagaki [122] have differentiated between two types of experts: routine experts and adaptive experts. Adaptive expertise can be conceptualized as the balance of efficiency and innovation, over time and in specific situations/tasks [123]. In the development of biomedical informatics expertise, we need people to be innovative as well as to be able to do routine tasks competently. Efficiency requires the use of routine strategies to solve problems, whereas innovation requires transfer of knowledge across domains and problems, and an ability to invent new strategies depending on the situation. A routine expert may be highly efficient, but low in innovation, whereas an adaptive expert is high and balanced in both efficiency and innovation. A novice is usually not efficient, but some studies have shown that novices may have high levels of innovation as they are more flexible in their problem-solving because they have not yet laid down routine strategies and schemas for solving problems and their knowledge is less organized (e.g., [124]). In contrast, other research has found novices to be less innovative [125,126]. Adaptive experts are continually learning and updating their knowledge structures and schemata based on their experiences with novel problems and situational demands. For example, one study found that variability in experience supported subsequent transfer of knowledge and the use of more theoretical reasoning, where business consultants performed better than restaurant owners on a novel "restaurant" problem [127]. These are important strategies to remember for designing instruction in any educational program, including training in biomedical informatics. In addition, the concept of adaptive expertise is important in education and training through its role in continuous learning through practice and in developing cognitive flexibility in the application and transfer of knowledge learned in a formal educational context to practice, such as a clinical context involving patients.

The next section provides a context for understanding the importance of approaching curricular reform in medical education from a cognitive and learning sciences framework. In summary, we describe the main curricular approaches in medical education and research on the effectiveness of such approaches.

4. Learning and instruction in (bio)medical curricula

For many years after the Flexner report [128], there was a medical curriculum standard. However, disillusionment with the conventional curriculum (because of the problem of large group teaching, motivation, and a lack of integration of biomedical and clinical components of the curricula) led to the development of problem-based learning. In the past few years, there has been an update in the current objectives for reform in undergraduate, graduate and continuing medical education, which have been outlined by recent AAMC reports [59,129] and also addressed at other international organizations such as the Association for Medical Education in Europe (AMEE; http://www.amee.org), which is a worldwide organization with members in 90 countries on five continents. These objectives promote a focus on patient-centered care and the need for a more rigorous approach for ensuring that students and residents are acquiring the knowledge, skills, attitudes and values that are required to provide high-quality patient care. To this end, the reports focus on the development of clinical skills and competencies, and an earlier introduction of clinical experiences into the undergraduate medical curriculum. These issues echo those that took prominence nearly a century ago around the time of the Flexner report [128], and highlight the continuing need to integrate clinical and basic science components effectively into the medical curriculum under the constraints of accommodating the ever-growing medical and scientific knowledge base and the effective development of clinical skills. In this section, we describe the main curricular approaches in medical education and research on the effectiveness of such approaches.

4.1. Types of medical curricula

Since the Flexner report (1910) [130], medical schools have made a strong commitment to the epistemological framework outlined in Feinstein [131] that biomedical and clinical knowledge could be seamlessly integrated into a coherent knowledge structure that supported all cognitive aspects of medical practice, such as diagnostic and therapeutic reasoning. Although Flexner's report recommended dividing the medical curriculum into a basic science component and an applied clinical component, there has been considerable controversy as to how to structure the medical curriculum to integrate both components [88,115,132].

There are four common types of medical curricula that are currently used in medical schools: (1) the conventional approach (CC), (2) the problem-based learning (PBL) approach, (3) the organ- or systems-based approach, and (4) a hybrid approach that integrates components of two or more of the other approaches. The organ- or systems-based approach attempts to build medical competence by focusing on learning one organ system at a time, and integrates biochemistry, physiology and anatomy. In the section that follows, we illustrate the role of cognition and learning sciences insights in curricular issues, based on research findings regarding the two most common curriculum formats: the conventional curriculum (CC) and problem-based learning curriculum (PBL). The other two approaches, while increasingly popular, have not been studied as extensively.

4.1.1. Conventional (CC) and problem-based learning (PBL) curricula

The following statements underlie the approach of conventional curricula (CC) and problem-based curricula (PBL), respectively: (1) Basic science provides a foundation for clinical reasoning, and (2) Physicians rarely use basic science knowledge in thinking about clinical problems [133]. In other words, in CC, basic science is taught as an independent discipline (science-oriented approach), whereas in PBL, basic science instruction is taught in clinical contexts (clinically-oriented approach). In CC, courses are divided into preclinical courses (mostly consisting of the basic sciences), which are taken during the first and second years of medical school, and clinical courses and practica (e.g., clerkships), which are taken during the remaining two years of medical school and during postgraduate training. This model has predominated medical education for most of the 20th century and it remains currently in use. However, due to the growth of biomedical and clinical knowledge placing increasing pressures on medical schools to accommodate more classes, basic science training became increasingly detached from clinical training. This has led, in part, to the growing popularity of PBL. In PBL programs, instruction involving clinically meaningful problems is introduced at the beginning of the curriculum. This is guided by the assumption that scientific knowledge taught abstractly does not help students to integrate this knowledge with clinical practice [134]. PBL also stresses self-directed learning, problem-solving skills and effective collaboration skills [134]. Most research has found negligible differences in clinical skill performance when comparing students from PBL and CC programs [135–138]. Thus, there is an ongoing debate as to the effectiveness of problem-based learning over conventional methods, and the focus of research has shifted from "Does PBL work?" to "Why and how does it work?" [136,137,139,140]. Recent empirical studies suggest that the mechanism underlying the positive effects of PBL is the integration of a new concept with existing knowledge, providing for greater understanding of the concept, including possible knowledge reorganization and enhanced conceptual coherence [141]. PBL emphasizes the importance of bridging learning theory and actual implementation of the learning and teaching method. In addition, there is incredible variation in how PBL is implemented, suggesting that how it is practiced has deviated significantly from the core assumptions underlying the method. This may be a reason for the inconclusive findings regarding student outcomes, as reported in the literature [142].

The CC and PBL approaches are based upon different assumptions: PBL focuses on connecting scientific concepts to the clinical context of application, whereas CC emphasizes fostering a broadly applicable foundation of general scientific knowledge. Thus, CC has the disadvantage of merely imparting to students inert knowledge, much of which is not retained beyond medical school (e.g., models of cardiovascular physiology that are not readily applicable to clinical contexts). On the other hand, PBL may impede transfer and application of knowledge across clinical situations if the knowledge learned is too tightly coupled to the specific context in which it was learned (e.g., a featured clinical case of hypothyroidism). Recently, CC schools have embraced the idea of emphasizing a more clinically-relevant basic science curriculum [143]. Following PBL, they have also incorporated small group teaching and have focused more on fostering clinical skills. The renewed emphasis on skills and competency has been partly in response to reports from the Institute of Medicine indicating that the quality of patient care is sub-optimal [144–146].

4.2. Knowledge integration and reasoning in different (bio)medical curricula

Several studies have compared performance of graduates of problem-based learning (PBL) and conventional curricula (CC) medical schools, finding that there were no fundamental differences between the graduates on many variables, including knowledge, clinical and communication skills, learning ability, and critical thinking (e.g., [147–149]). However, other studies have shown significant differences between trainees of both types of curricula. Early studies examining the effects of conventional curricula (CC) on the use and integration of basic science knowledge and clinical knowledge in diagnostic explanation indicated that very little biomedical information was used in routine problem-solving and that biomedical and clinical knowledge were not integrated [117,150,151]. In light of these findings, Patel and colleagues studied the process of knowledge integration by students who had been trained in different medical curricula. Based on the assumptions underlying PBL, one would expect to find that PBL students show better integration of basic science and clinical knowledge. Analyses revealed a more complex picture. When given a clinical problem without any basic science information, students from CC schools used more clinical information than basic science information in explaining patient problems, whereas students from the PBL school provided detailed basic science information. In contrast, when basic science information was provided before the clinical problem, there were few differences between the two groups, where both groups could not integrate basic science information into the clinical problems. All students, no matter where they are trained have difficulty remembering basic science information abstractly and then attempting to search their memory for the pieces of information they just read that apply to the clinical problem. One of the major reason for this lack of memory is that the problem provides the structure (with discrete features, such as one seen in patient problem), within which relevant science knowledge is easily selected and integrated, and thus remembered. This is not true for the structure of scientific knowledge, which cannot incorporate the clinical problem within it [133].

Basic science taught in the specific context of the clinical problem (as in PBL) was very closely tied to the clinical problem such that both were integrated and remembered simultaneously. So, although the integration was successful, it had a problem of a lack of transfer of knowledge because the clinical knowledge and biomedical science knowledge were so tightly coupled that the basic science could not be "pulled out" and applied effectively in a different context. It also took a long time for students to solve the problem because the heuristic did not develop easily, indicating an interference of detailed basic science in clinical problem-solving utility.

Cognitive studies have also been carried out on the long-term effects of PBL and CC programs on the use of basic biomedical knowledge and the patterns of reasoning when solving clinical problems [152]. Studies with residents who had their medical training in either CC or PBL schools showed that CC-trained residents made more use of clinical concepts, whereas PBL-trained residents used more biomedical concepts. Furthermore, the pattern of the use of strategies persisted, where CC-trained residents displayed a greater use of heuristically-driven reasoning than PBL-trained residents, who showed more hypothesis-driven reasoning and elaborations. CC appears to encourage the organization of clinical information in such a way that data-driven reasoning is easily acquired, whereas the PBL curriculum seems to promote the generation of detailed biomedical explanations that impedes such heuristically-driven reasoning [152].

Although PBL students did not appear to acquire adequate data-driven reasoning, which has been shown to be a hallmark of expertise, they do retain the hypothesis-driven reasoning pattern characteristic of medical students. On the other hand, residents with their medical training in the CC school developed hypothesis-driven reasoning, which was not evident in the previous study of undergraduate CC medical students [153]. This distinction between graduates of PBL and CC schools is important, and suggests that some aspect of the PBL approach may hinder the acquisition of data-driven reasoning, which is highly automated and promotes efficiency and accuracy when used under the condition that one's knowledge base is adequate and the problem is routine. Therefore, is it a necessity to have an early integration of biomedical and clinical knowledge as in the PBL approach? If it is a necessity, how should the form of instruction be modified to promote, rather than hinder, the development and acquisition of a data-driven reasoning pattern? A possible explanation for the observed differences is that in the PBL schools, the early integration of biomedical and clinical knowledge impedes the development of expert clinical knowledge by encouraging the development of a causal reasoning pattern, to the detriment of the development of a clinically-driven knowledge base. Students in a CC school learn basic science in an abstract, de-contextualized form and learn clinical medicine after the theoretical basis has been mastered. Learning clinical knowledge separate from basic science knowledge may foster the development of efficient data-driven reasoning, while learning abstract basic science principles seems to be beneficial for, or at least does not seem to interfere with, the acquisition of clinical knowledge. Supporting such an explanation, Anderson et al. [35] have argued that optimal learning occurs when a combination of abstract and situation-specific training is provided. In fact, learning through abstraction seems to play an important role in effective and efficient instruction, and may aid in the transfer of knowledge from one situation to another [35]. Thus, the PBL approach may be restricting the ability of students to transfer knowledge to other clinical problems and contexts. Similarly, the PBL approach may also be restricting acquisition of clinical schemata (i.e., models of types of patients including typical signs and symptoms) that are needed for efficient problem-solving [35,154].

However, there may be a negative effect of conventional curricula-based instruction in that the use of data-driven reasoning is associated with confidence in making a diagnosis, perhaps to excess, and when errors or misconceptions are generated, they become more difficult to remove or change. In contrast, students from problem-based learning curricula have more opportunity to reconsider their reasoning process and diagnoses, given their use of hypothesis-driven reasoning. Therefore, these students are better able to learn from their experiences. The possible negative effects of both PBL and CC-based approaches need to be considered when designing and implementing curricular changes in medical schools or assessing implications for instructional approaches more broadly in biomedicine or the health professions.

In this section, we have provided some illustrations with empirical evidence for the impact of different curricular approaches on clinical reasoning and problem-solving in the domain of medicine. Contemporary theories of cognition and learning have been used to support the different curricular approaches to medical education. For example, cognitive apprenticeship, situated learning, and case-based reasoning have been used to support a problem-based learning (PBL) approach [155], whereas, theories of expert performance, conceptual change, and Cognitive Load Theory have been used to argue for a type of curriculum that maintains a certain division between the basic and clinical sciences [156].

It is important to use such research to form the basis for curricular reform. Currently, most rationale for educational reforms are guided only partly by theoretical considerations, and tend to be sets of practical ideas based on expert opinions. The design and reform of educational curricula in complex advanced knowledge domains, such as biomedicine, rely on the identification of those concepts and knowledge that are deemed necessary to become an effective and skilled scientist-practitioner. As exemplified in the debate between conventional and problem-based curricula, such concepts and their role in clinical practice have not been clearly defined. Discussion of such issues in greater detail can be found in various reviews [143,152].

5. Technology in learning & instruction

Technology can be used to support the creation of effective learning environments through (1) use of media to bring real-world problems into the classroom or other learning environments, (2) "scaffolding" support with computer-based models and scientific visualizations, (3) software tutors that give feedback and monitoring of performance (4) representational tools, and (5) learning through simulations using virtual reality environments.

Advanced learning environments would particularly benefit from appropriate technology-based training and education. However, although in domains such as biomedicine, supportive technology for clinical support is being developed, it is often not based on empirical research of how people learn [13].Thus, there is a need for basic research on how such technology-based training methods can improve human learning. Although there is some research being conducted in this area (e.g., [157–162]), it is not yet sufficiently comprehensive to inform the development of training technologies. Instead, the design of technology-based training is largely based on opinions and intuition rather than on a research-based theory of learning. This process runs counter to the emphasis on conducting evidence-based practice in medicine and other similar domains.

5.1. Multimedia learning

The rationale for using technology for learning is based on an earlier focus on learning using different media. *Multimedia learning* has been defined as learning or building mental representations, from both words and pictures and *multimedia instruction* as "presenting words and pictures that are intended to foster learning" [163]. In addition, they define *meaningful learning* as "deep understanding of the material", which is assessed by the ability to transfer material flexibly from one problem-solving situation to another. The multimedia learning hypothesis states that "people can learn more deeply from words and pictures than from words alone" [157]. Studies have consistently shown that students perform significantly better on problem-solving transfer tests with the use of both words and pictures than words alone, which is referred to as the multimedia principle and is the rationale for studying the use of multimedia as a basis for learning [157]. Other research on lay individuals' comprehension of instructions for administering medication reinforce the idea that the addition of written text to visual information enhances understanding [164], as long as there is a close relationship between what is written in the text and what is being represented in pictorial form.

One important challenge when designing methods of multimedia instruction is limiting the amount of cognitive load that is required to complete the task to develop meaningful learning, as there is always the possibility of cognitive overload because an individual's capacity for cognitive processing is limited. Mayer and Moreno [163] describe three basic assumptions about how the mind works in multimedia learning, based on cognitive theory: (1) the dual channel assumption that individuals have two distinct processing channels for verbal and visual information; (2) the limited capacity assumption, that there is only a limited amount of processing capacity in either of the channels; and (3) the active processing assumption that learning requires significant cognitive processing in both channels [165]. Based on the theory of multimedia learning, in order to minimize unnecessary cognitive load when designing learning and instructional environments, the way in which individuals think and perform tasks in an environment needs to be taken into account.

Similar to multimedia learning, e-learning is a type of learning where the medium of instruction is computer technology. In some instances, no in-person interaction takes place. The purpose is to aid learning in a particular domain [166]. E-learning includes both distance learning and computer-assisted instruction, and focuses mainly on the use of the Internet. Some advantages of e-learning may include (1) an increased accessibility to information, (2) easily updated electronic content, (3) individualized instruction, (4) an ability to standardize content, (5) wide distribution to students, and (6) inclusion of assessment measures and immediate feedback [166]. E-learning has been evaluated with regard to process (i.e., peer review of a program's strengths and weaknesses, including content quality and usability) and outcomes (i.e., a program's effectiveness measured by changes in learners' knowledge, skills or attitudes), and learner satisfaction [167,168].

5.2. Designing technology-based learning environments

One challenge when designing new technology-based learning environments is how to balance meeting learning objectives while also creating environments that are engaging and fun [169]. Kirkley and Kirkley [169] discuss a set of areas that should be considered in the design of new technology-based learning environments. Several factors need to be taken into consideration, including learning needs and goals, space (physical and/or virtual), tasks, assessment methods, learner characteristics, domain area, technological capabilities and possibilities, among others. One possibility for technology-based training is to use computer-based simulations or games that allow students to practice in realistically-simulated decision situations. There is currently a movement in the serious games domain that is trying to incorporate entertainment video technology into the design of learning environments. The "next generation technologies" that are being developed and refined include mixed and virtual reality and pervasive computing, which allow the possibility of bringing learning and training into the real-world. Mixed reality refers to a blended virtual (digital objects) and real-world environment, which is also referred to as *augmented reality*, where digital objects are overlaid onto the real-world environment so that the user perceives the digital information as part of the familiar world. For example, *augmented reality* has been used in medicine in highly controlled environments, where medical information, such as ultrasound images, is overlaid onto the body to aid the surgeon in conducting a biopsy [170]. Games and simulations can utilize such mixed reality technologies, and there is evidence of both positive (e.g., environment that is safe and able to be manipulated and controlled by the learner, opportunity for immediate feedback and assessment tailored to the individual) and negative (e.g., challenges for novice learners) aspects of using such technology for educational applications.

Research has shown that biomedical trainees need to be provided with practical hands-on experience in realistic environments for successful learning. These factors have encouraged researchers to develop novel and innovative approaches for medical and biomedical informatics education. Simulation-based gaming has emerged as a leading technology that can aid in offering engaging and effective biomedical and professional education [171], especially in the area of emergency medicine [172]. While in the past simulation-based gaming has been mainly targeted towards psychomotor skill acquisition and orientation purposes, it is now increasingly being employed for fine tuning cognitive functions such as attention, decision-making and memory, providing environments for embodied learning [173]. Gaming-based simulations have an advantage of being immersive and engaging. They provide an interactive reward-based mechanism for learning and objective evaluation. Furthermore, games are a safe alternative to practice on patients and offer a rich compendium of experiences including rarely seen medical condition. With the advent of massively multiplayer virtual environments, such as SecondLife® (http://www.secondlife.com) and OLIVE (http://www.forterrainc.com) that allow several members to participate, virtual games can also be employed for team training and procedural training.

Medical gaming has been employed in several domains, prominent among which is surgical education. With the advent of new gaming consoles such as Nintendo Wii®, it is possible to include natural human motion into gaming environments for more immersion. Such games include a novel combination of both psychomotor and cognitive skill, which has led to its widespread popularity. Modern day surgery involves both cognitive and psychomotor resources. It is possible to exploit the inherent skill base required to master Nintendo Wii games to train and hone certain surgical skills. Kahol and Smith [171] have developed a generic methodology to develop simulation exercises or employ off the shelf simulation exercises for training surgeons. Kahol and his colleagues used Nintendo Wii® games that closely mimicked surgical movements and the games were employed as practice games for surgical residents before and after laparoscopic exercises. This study showed the positive effect of gaming on skills, but an increased amount of training time was required with the games as residents found the games more engaging than conventional educational paradigms.

Instead of taking a technology-centered approach to the design of training programs, there is a need take a learner-centered approach, in which technology is one of the cognitive tools used to aid and support learning. In order to take this approach, research needs to form a theory of learning that incorporates interaction with technology and its impact on learning. Although mixed reality technologies have been developing for the past three decades, there has been little research on the impact of the technology on learning. What are the best methods and strategies of instruction that can be implemented in technology-based training to improve learning? In addition, training programs need to specify the knowledge to be learned and continuous assessments of learning that will approximate real-world performance. Assessment also needs to employ real-time feedback, and multiple methods of assessment will provide the most comprehensive picture of learning and performance. Recent discussion has centered on individual differences regarding learners' physiological states, affective processing, and use of nonverbal behavior, which will all affect how the individual learns and thus how the training system should be designed to optimize learning.

5.3. Impact of technology-based instruction on thinking and reasoning

Reviews in the literature have suggested that computer-based instruction may increase efficiency and decrease training time compared to conventional instruction [174–177]. For example, in the medical education domain, the use of an interactive web-based curriculum to teach medical students about evidence-based medicine was found to be superior to a traditional classroom-based curriculum in teaching students to effectively search MEDLINE effectively for evidence-based practice related articles to identify higher quality articles as well as to have greater confidence and satisfaction in their information retrieval and analysis skills [178].

Fletcher's review [175] suggests that technology-based instruction may increase instructional effectiveness, reduce time and costs for learning, and can make individualization of learning affordable and available to all students. However, this does not necessarily mean that computer-based instruction will be more effective in all areas. The primary determinant of effectiveness is not the medium used but the strategies and assessments implemented during instruction [177,179,180]. Sitzmann et al.'s meta-analysis [177] of the comparative effectiveness of web-based and classroom instruction provides some important findings. Results support Clark's [181,182] theory that the instructional method, not the type of media used, is more important for determining effective learning. When including all studies in the analysis, there were slight differences between web-based and classroom instruction, but these effects disappeared when the analysis focused solely on studies randomizing subjects to the two conditions. This suggests that web-based learning's effectiveness is predominant for those who self-selected this condition, thus emphasizing the importance of individual learner characteristics and preferences (e.g., motivation to learn, cognitive ability, level of technical skill, personality preferences;[183–185]) when designing learning environments. Therefore, the design of appropriate and effective technologies must take into account individual differences in learning, through systems that adapt based on assessments of individual progress in learning and performance or through explicit choices made by the learner.

Researchers have also investigated the mediating role of technology in clinical practice. For example, we studied the use of the electronic medical record (EMR) in real clinical settings [186]. Specifically, we observed the effects of physicians changing from using paper-based patient medical records to computer-based medical records (EMRs), and subsequently going back to the paper-based records six months later. Results indicate that use of the EMR was associated with changes in physicians' strategies for reasoning and gathering information. The content and structure of the information in the medical record differed based on the medium used for gathering data; paper-based records were written in narrative form, whereas computer-based records were organized as discrete pieces of information. These differences in knowledge organization affected how the physicians collected information during their patient encounters. Subsequent use of the paper-based records, after exposure to the EMR, showed that the structure and content of the paper records closely resembled the organization of the EMR. The new organization of information

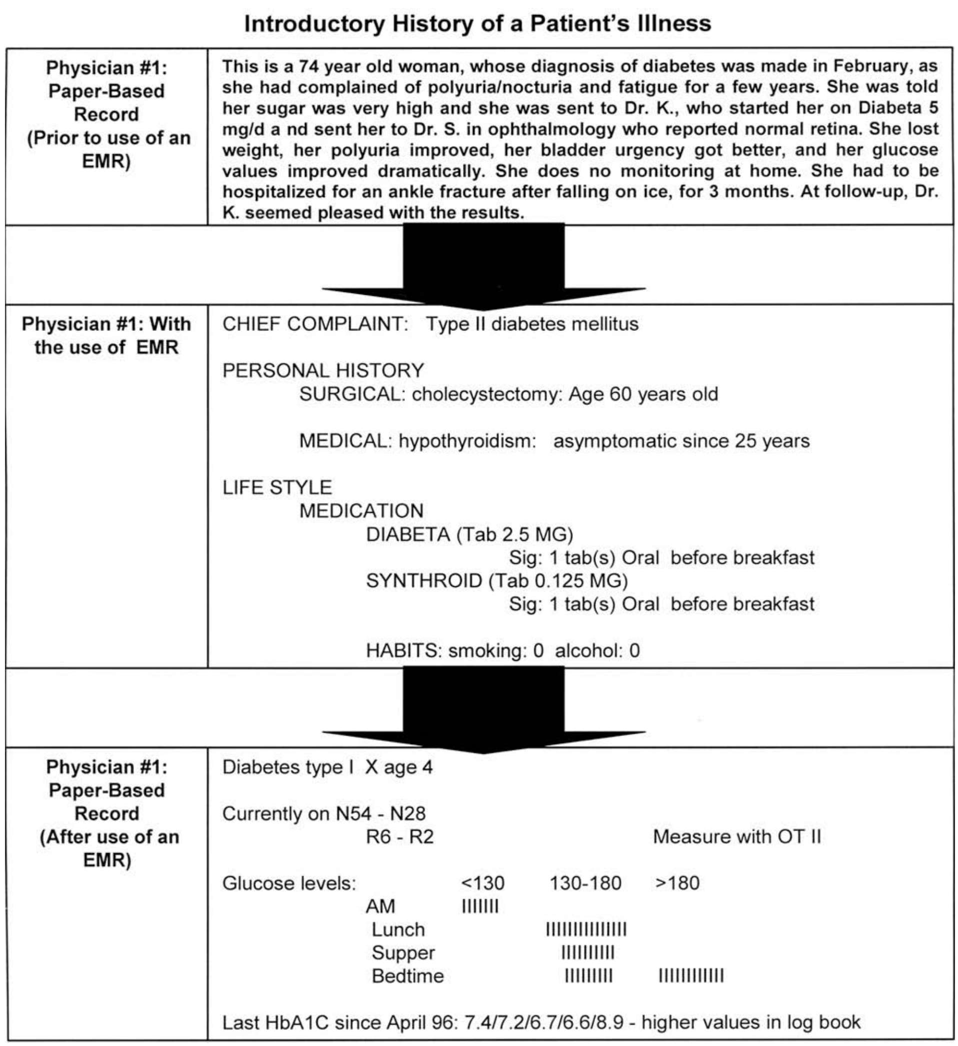

Fig. 2. A representative physician's introductory history of a patient's illness, prior to using an EMR, using the EMR, and after the EMR, indicating the influence of the EMR on the structure of the physician's narrative

in the EMR also influenced the reasoning strategies used by the physicians to solve patient problems. This shows the enduring effects of technology on behavior and reasoning. Fig. 2 gives an example of one physician's narratives in three situations (before the use of EMR, with EMR, and after the EMR was removed), indicating the influence of use of the EMR on the physician's organization of medical information and subsequent reasoning.

In summary, this section provided an overview of the importance of technology for learning and assessment in biomedical education, as well as the significant impact technology has on thinking, reasoning, and performance. Thus, work on human-computer interaction in the health education domain needs to take into account a cognitive perspective. It is essential to understand the foundation of how technology impacts performance and the precise role technology can have as it is incorporated into the continuum of biomedical education.

6. Summary and conclusions

Although there are various frameworks related to expertise and learning from a cognitive science perspective, we are still attempting to integrate and translate them into a coherent theoretical framework that may serve to guide effective educational programs, including in the biomedical sciences and informatics. Research conducted within the framework of cognitive and learning theories discussed in this paper has generated important knowledge about human learning and performance that can, and should, inform the design of effective learning environments and instructional methods. Other learning theories focus on different aspects of the learning process, and they complement each other in providing a strong foundation and rationale for effective teaching and learning strategies. Whereas situative theory centers on context-based learning and information processing theory (such as Cognitive Load Theory) focuses on individual learning under a set of processing constraints (e.g., working memory capacity). Both of these perspectives need to be integrated into a theory that could form a basis for the design of effective learning environments. The goal is that such environments foster learning in context, given individual information-processing constraints, without promoting learning that is so contextually bound that it impedes transfer to other contexts; or learning that narrowly focuses on the individual. In the latter case, we find that students' learning or performance can be limited when they attempt to generalize the lessons to other situations.

The primary goal of biomedical education is the acquisition of competencies that are integral to the functioning of either a professional or a scientist. Medical trainees must develop competence in a number of clinical skills (performance-oriented) as well as competence in the understanding of domain concepts that are necessary for supporting clinical problem-solving. In addition, competence needs to be demonstrated in the application and transfer of knowledge and skills to different situations and into the "real-world" clinical environment. The development of conceptual and skill-based competence can be understood in terms of the development of expertise in any domain, in general, and specifically, in biomedicine.

Based on key findings in this review, we suggest the following as implications for learning and instruction in biomedical curricula, including informatics:

(1) Training largely focuses on the development of skills that are generally sufficient for competent performance in routine tasks. However, when one encounters a complex or a novel task, education that fosters conceptual understanding is needed to support performance, as the individual cannot fall back on their skills training. For a biomedical informatics program, this argues for providing foundations of biomedical informatics that support hands-on learning of technological skills. Many biomedical informatics training programs have introduced such "foundations" or "methods" courses that attempt to define the underlying conceptual basis of informatics, only secondarily demonstrating their broad applicability to biomedical fields ranging from molecular biology, genomics, and biomedical imaging to clinical care and public health. Such courses attempt to tease out the recurring concepts that define the scientific basis of informatics while also contributing to a wide variety of applications across all of biomedicine. Foe example, such foundational courses are being used for students at Stanford, Columbia and Arizona State Universities' graduate biomedical informatics training programs.

(2) In the revised Bloom's taxonomies (Tables 3a,3b), all educational objectives can be classified according to the *Knowledge* and *Cognitive Process* dimensions. The taxonomy table can be used to classify the instructional and learning activities used to achieve the objectives and the assessments needed to evaluate students' progress in achieving the objectives. The revised taxonomy provides this added ability of classifying standards, in addition to educational goals and objectives. This taxonomy can provide a good guide to learning and evaluation in a biomedical informatics program. Furthermore, more linear learning objectives can be supplemented with non-linear learning to reflect how people learn, as suggested by the revised taxonomy.

(3) Cognitive theories of complex learning go farther than the revised Bloom's taxonomy by including the notion of *conceptual competence*, defined as the potential to employ concepts flexibly in a range of contexts. A *theory of competence* would imply that there is a specific reference or expert standard indicating the content and form of knowledge in a given domain. This means that competence, defined as the potential to perform to a standard, is not necessarily reflected in one's performance. Deviations from the standard may result from a lack of knowledge, as it is often assumed in traditional assessment, but may also be the result of biases in reasoning or misconceptions [37]. These notions may be used to argue that a solely summative evaluation, focusing on performance outcome, will not provide an accurate reflection of competency. A key issue in this regard is that learning in complex domains may develop non-monotonically. In this case, conceptual confusion may be a necessary step for deep learning, as has been shown in the "intermediate effect" [64,65], where a temporary decline in performance is observed, as knowledge is acquired and organized. This rationale argues for the inclusion of formative evaluation, as well as summative evaluation within this taxonomy, if we are truly to contribute to student learning. Formative evaluation captures the intermediate stages of development, rather than just the pre-post events. In addition, the process of development of expertise needs to be captured through a cognitively based evaluation such that both the performance outcome and the process are captured.

(4) Fostering the acquisition of expertise in a domain is dependent on helping students to gain a deeper understanding of biomedical phenomena, which can be linked and applied to various clinical problems. For a biomedical informatics program, this argues for teaching general problem-solving skills more flexibly, with multiple classes of problems (a set of problems that are somewhat similar, but that also differ enough to generate different diagnostic and therapeutic management plans) that facilitate transfer of learning to other situations. In a "methods" or "foundations" course,

the emphasis should be not only on conveying the fundamental techniques but also demonstrating (and engaging the student in exploring) their applicability to different domains across the biomedical spectrum. Training on prototypical problems in addition to the application of problem-solving strategies in non-prototypical (e.g., complex, non-routine) situations is desirable for optimal education in biomedical informatics. This will encourage flexibility in developing expertise.

(5) In order to foster adaptiveness for students in our training programs, we need to take into account the nature of the environment or workplace where the knowledge and skills acquired are more formally applied. This application needs to be reinforced early enough in the curriculum with the use of timely and individualized feedback. This way, formally learned knowledge is contextualized earlier with a better chance of contributing it to the set of general heuristics that is acquired and used as expertise develops. This argues for early introduction of biomedical informatics training into any health care professional curricular such that use of informatics in their daily practices becomes "a habit" and used as a default heuristic.

(6) Different instructional methods, such as lectures, small group interactions and hands-on problem-solving skills, are related to learning different kinds of knowledge and skills. In order to assess adequately which method combinations are best for a particular educational program, a task analysis (including cognitive task analysis) of the domain and its relationship to required competencies is desirable. In the biomedical informatics curriculum, identification of a set of competencies requires an informed analysis of what biomedical informaticians do currently in their jobs and what they are likely to do five to ten years from now. The next step will be to match these tasks to the knowledge, skills and attitudes necessarily to accomplish these tasks (short term and long-term). Instructional methods can be varied and ones that best match a specific task can then be developed. The evaluation of the curriculum should also be based on the same rationale, such that performance is assessed in each of the tasks (or selective, representative tasks by experimental design). An assessment of competencies is then developed based on a set of criteria for accepted levels of performance for competency (e.g., minimum accepted level). Constant feedback into curricular design is essential, given that sub-optimal performance could be due to instructional methods, instructors, complexity of materials taught and, most importantly, to curricular design itself. It should be noted that it is just as important (if not more) to consider *how* (process) the material will be taught than *what* (*content*) will be taught.

This review has identified several ways in which cognitive and learning sciences can contribute to objectives that concern researchers and instructional designers in the health care professions, specifically in biomedical curricula, including instruction in biomedical informatics. These contributions are illustrated with respect to the development and assessment of conceptual understanding and competence, as well as in the review of research on the nature and development of expertise that have informed the development of various instructional methods (problem-based, classical learning, and hybrid curricula). In addition, research on medical expertise is beginning to inform the development of biomedical education, by addressing the ways to measure the cognitive competence of novices and experts in real-work environments.

Although research findings on expertise can aid in making informed changes to this process, we still need to understand more about the learning conditions that result in more optimal levels of performance and competence. The methodologies and theories discussed in this paper are oriented toward understanding and characterizing the cognitive, and to some extent the social impact of technology, on learning and instruction. We have expanded on empirical studies conducted over a period of more than two decades on the role of memory, knowledge organization, and reasoning as well as studies of problem-solving and decision-making in health areas that inform curricular design. The study of practice or workplace can help shape theories of human performance, technology-based learning, and of scientific and professional collaboration that extend beyond the domain of biomedicine. Just as biomedical science has revolutionized health care practice, research in the cognitive and learning sciences can provide a scientific foundation for the development of education and training of health care professionals, as well as look towards development of new competencies which will be needed for such professionals. Currently, as discussed earlier, a number of these programs are being designed as more intuitive and based on expert opinions. In this review, we have attempted to illustrate how we can formalize the design of such programs in biomedicine, including training of biomedical informatics for health professionals. Formal methods and theories from cognitive and learning sciences would prove useful in development of assessment criteria and tools that match the competencies to be acquired by the trainees.

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