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Types and Qualities of Knowledge

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Research in learning and instruction claims a central role for the concept of *knowledge*. The knowledge base of a person, it is now generally assumed, is made up of different types of knowledge. The most well-known examples are declarative and procedural knowledge, but more elaborate distinctions exist. Furthermore, the knowledge base is characterized by different qualities, such as level (deep or surface) of knowledge, generality of knowledge, level of automization of knowledge, modality of knowledge, and structure of knowledge. The present article examines the concept of knowledge by presenting a matrix that takes *types* and *qualities* of knowledge as its dimensions. This matrix can be used to classify research on knowledge by linking aspects such as knowledge assessment techniques, expert–beginner differences, instructional measures, and learning goals to the cells of the matrix.

In literature on learning and instruction, *knowledge* plays a pivotal role and is attributed a wide variety of properties and qualities. Among the examples encountered are generic (or general) and domain specific knowledge, concrete and abstract knowledge, formal and informal knowledge, declarative and proceduralized knowledge, conceptual and procedural knowledge, elaborated and compiled knowledge, unstructured and (highly) structured knowledge, tacit or inert knowledge, strategic knowledge, knowledge acquisition knowledge, situated knowledge, and metaknowledge. For example, in an article by Reif and Allen (1992), at least eight different knowledge terms are used: main interpretation knowledge, general knowledge, definitional knowledge, ancillary knowledge, supplementary knowledge, case-specific knowledge, entailed knowledge, and concept knowledge. In an earlier article on the same topic (interpreting scientific concepts), Reif (1987) also used the terms declarative knowledge, procedural knowledge, formal knowledge, compiled knowledge, special knowledge, general knowledge, procedural interpretation knowledge, and coherent knowledge. Apparently, researchers need many and fine-tuned terms for describing the knowledge state of individuals.

A number of studies have signaled this explosion of constructs and terms and have undertaken to structure the field, approaching the various aspects of knowledge from a general cognitive perspective (Alexander & Judy, 1988; Alexander, Schallert, & Hare, 1991; Snow, 1989). In this article, we also attempt to give a systematic description of the various aspects of knowledge, but we approach this goal from the perspective of *knowledge-in-use*. This means that task performance forms the basis for the identification of relevant aspects of knowledge. In this approach, we have found it efficient to introduce two dimensions that describe knowledge: type of knowledge and quality of knowledge.

We consider these dimensions to be independent, and we make a systematic distinction between characteristics specifying the *type* of knowledge (e.g., conceptual knowledge) and characteristics specifying the *properties or qualities* of knowledge, which can in principle be relevant for several types of knowledge (e.g., modality). We think this distinction is necessary to avoid the introduction of still more types of knowledge that do nothing more than describe properties of generally accepted types of knowledge. An example of such an introduction can be found in Jonassen, Beissner, and Yacci (1993), who introduced "structural knowledge ... the knowledge of how concepts within a domain are interrelated" (p. 4). The idea of structural knowledge could be described more parsimoniously as a combination of knowledge type or types (e.g., conceptual knowledge) and quality (structure).

In this article we demonstrate the general importance of the concepts of type and quality of knowledge for theory, research, and practice in the field of learning and instruction. By using the two concepts type and quality of knowledge as dimensions, a matrix can be created that can structure general

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topics such as learning goals and expert–novice differences. The studies we review here are restricted in the sense that we focus mainly on one type of criterion task, *problem solving*, and on domains from the sciences, particularly *physics*.

TYPES OF KNOWLEDGE

Frequent attempts have been made to give a systematic description of knowledge. Some attempts have been based on cognitive theories, whereas others have been formulated to serve as a basis for instructional design theories. Still another approach is to characterize knowledge from an epistemological point of view. This implies that elements of the knowledge base are characterized by the *function* they fulfill in the performance of a target task. Epistemological approaches are *task dependent*. This means that different classifications (ontologies) of knowledge types are contrived for different types of tasks (Gott, 1989) and that within one domain, the same elements of subject matter may be characterized by different ontological typologies, depending on the task in which they function (de Jong, de Hoog, & Schreiber, 1988; Messick, 1984).

Numerous authors introduce distinctions between types of knowledge, often without taking into account these characteristics of epistemology. From the perspective of cognitive theories, intrinsic in the description of knowledge is a classification that has absolute qualities. Alexander and Judy (1988), for instance, in their review article on the interaction of domain specific and strategic knowledge, distinguish three types of domain specific knowledge: declarative (factual information), procedural (compilation of declarative knowledge into functional units that incorporate domain specific strategies), and conditional (understanding when and where to access certain facts or employ particular procedures). In a later review article by Alexander et al. (1991), this same distinction is used, and reference to the task is only made in the term *task knowledge,* understanding of the cognitive demands of a task. The same type of absolute classification is found in instructional design theories, of which Gagné (1985), Merrill (1983, 1987), Reigeluth (1983), and Romiszowski (1981) are renowned authors. Central elements of this type of theory are objectives and criterion tasks, which are typical for a domain. However, a variety of types of knowledge is introduced, including concepts, principles, and procedures, without reference to their function in complex task performance. Although absolute classifications may serve a general goal, we think a more pragmatic typology of knowledge takes into account the context in which the knowledge has to function.

Our own work (e.g., de Jong & Ferguson-Hessler, 1984, 1986, 1988, 1991; Ferguson-Hessler & de Jong, 1987, 1990, 1993) has been in the field of physics, where task performance in the form of problem solving and experimental work plays a central role. Knowledge of physics is characterized by strong links between elements, a high degree of abstraction, and a hierarchical nature. In other words, expert knowledge of physics is strongly and hierarchically structured, and at the lower levels of the hierarchy local chunks are tailored to applications.

The explicit focus of our work has been on problem solving. On the basis of a detailed task analysis we distinguished four types of knowledge: situational knowledge, conceptual knowledge, procedural knowledge, and strategic knowledge. In defining these types of knowledge, we make use of an example from mechanics (see Figure 1) to clarify the differences between knowledge types. This problem is a typical example of exercises usually found in first-year university textbooks on physics. It is the same type of problem used by Chi and Bassok (1989); Chi, Feltovich, and Glaser (1981); Hammer (1994); and Zajchowski and Martin (1993).

Situational knowledge is knowledge about situations as they typically appear in a particular domain. Knowledge of problem situations enables the solver to sift relevant features out of the problem statement (selective perception) and, if necessary, to supplement information in the statement (Braune & Foshay, 1983). It may serve to create a representation of the problem from which, if the organization of knowledge is adequate, additional knowledge (conceptual, procedural) can be invoked. In Figure 1, examples of situational knowledge could be knowing that a rough surface means a frictional force, which acts against motion, or knowing that there are other forces working on the blocks than the ones explicitly mentioned—for instance, a normal force from the plane.

A wooden block of mass m is sliding up a rough, inclined plane, which makes an angle α with the horizontal. The block is pulled up the plane by means of a string, connected to it, and running parallel to the plane. The string runs over a pulley at the top of the plane, and at its other end, it supports a second block of mass M, which is hanging freely from the string. The coefficient of dynamic friction between plane and block m is μ. Find the direction and size of the acceleration of each of the blocks.

FIGURE 1 Example problem from mechanics.

Conceptual knowledge is static knowledge about facts, concepts, and principles that apply within a certain domain. Conceptual knowledge functions as additional information that problem solvers add to the problem and that they use to perform the solution. In our earlier work we used the term *declarative knowledge.* Now we prefer to use the term *conceptual knowledge* (see also Greeno, 1978), and, following van Berkum and de Jong (1991), we use the term *declarative* as a quality characteristic, being the opposite of compiled knowledge. An example of conceptual knowledge in Figure 1 could be knowing that the size of the friction force is the coefficient of friction times the normal force, or knowing that the total force vector acting on a body equals its mass times its acceleration.

Procedural knowledge contains actions or manipulations that are valid within a domain. Procedural knowledge helps the problem solver make transitions from one problem state to another. It can have a specific, domain-bound (strong) character, or it can be more general (weak). In the example presented in Figure 1, procedural knowledge concerns knowing how to identify and delimit each of the two interacting mechanical systems, how to choose a coordinate system, and how to resolve the forces acting on the blocks in the chosen system.

Strategic knowledge helps students organize their problem-solving process by directing which stages they should go through to reach a solution. A strategy can be seen as a general plan of action in which the sequence of solution activities is laid down (Posner & McLeod, 1982). Elements of knowledge belonging to the first three types are specific, applicable to certain types of problems in a domain, whereas the last type, strategic knowledge, is applicable to a wider variety of types of problems within a domain (Bransford, Sherwood, Vye, & Rieser, 1986; Polya, 1957). In Figure 1, strategic knowledge concerns knowing how to organize and interpret the information given, structure it in a diagram, define the mechanical system(s) to be used in the analysis, distinguish internal and external forces, list all external forces acting on each of the system(s), and translate the resulting force diagrams into equations that can be solved for the acceleration.

The previous analysis illustrates the importance of epistemological domain analysis for instruction. A proper classification of relevant types of knowledge may be used to organize and present subject matter and to direct the process of learning. For a full description of the knowledge base, however, we need to be able to distinguish not only various types of knowledge, but also the quality of the components of the knowledge base.

QUALITIES OF KNOWLEDGE

A large number of concepts are used to describe qualities of knowledge: Generic, abstract, informal, elaborated, and structured are but a few examples. Some qualities refer to relations between knowledge types, whereas others refer to types as such. Some qualities are more suited for specific types of knowledge (e.g., compiled for knowledge of procedures), whereas others are used in a general way (e.g., depth). Although we discuss a number of qualities separately, it should be noted that in many cases there seems to be some overlap. Again, we illustrate various qualities of knowledge with elements from the mechanics problem in Figure 1.

Level of Knowledge: Deep Versus Surface

Level of knowledge is a term that is used loosely in literature and in educational practice. Mostly, a rough distinction is made between *surface* or *superficial* knowledge and *deep* knowledge, with the connotation that deep is good and surface is poor. Knowledge is called deep when it is firmly anchored in a person's knowledge base and when external information has been translated to basic concepts, principles, or procedures from the domain in question. Such knowledge is different from the concrete appearance of the external information from which it stems.

Deep-level knowledge is associated with comprehension and abstraction, with critical judgment and evaluation, and the like (see, e.g., Marton & Säljö, 1976). This knowledge has been thoroughly processed, structured, and stored in memory in a way that makes it useful for application and task performance (Glaser, 1991). Even so, the general structure may well have idiosyncratic features. Snow (1989) described the desired end states of learning in terms of "articulated, deep understanding of a domain, including the ability to reason and explain in causal terms, and to adopt multiple viewpoints about a problem or phenomenon" (p. 9). Surface-level knowledge is associated with reproduction and rote learning, trial and error, and a lack of critical judgment (Glaser, 1991). This knowledge is stored in memory more or less as a copy of external information.

Larkin (1983), when discussing experts' knowledge representations, made a distinction between a basic representation (made up of concrete objects from a problem statement), a technical representation (that includes concepts from the domain), and a computational representation (made up of equations). In a later study, based on the well-known study by Chi et al. (1981), Chi and Bassok (1989) described the problem representations of students of mechanics in the following terms: The poor problem solver has a basic representation consisting of explicit entities from the problem description (the surface model), whereas the successful problem solver has a physics representation that includes, in addition, generated physics entities not explicitly described (the deep model). The physics representation, as mentioned by Chi and Bassok, is similar to Larkin's technical representation and reflects the application of a deep level of knowledge.

Looking at the solution of our mechanics problem from Figure 1, we identify surface elements such as the rough inclined plane, wooden block, string (elements of situational knowledge), or searching for a formula containing acceleration (as part of strategical knowledge). The corresponding deep elements would be something like an object sliding up an inclined surface pulled by a string and slowed by a friction force (situational knowledge), or knowing how to draw a force diagram for one of the blocks and translate this diagram into an equation (elements of a strategy). Strategic knowledge offers well-known examples of differences between superficial and deep elements of knowledge. Superficial strategies are, for instance, an algebraic search for a formula containing the unknown entity, or filling in given quantities in a formula. Deep elements of strategic knowledge are, for instance, analyzing and interpreting the information given, structuring this information by means of a diagram, and explicitly defining the physical system that is being analyzed.

Structure of Knowledge

One of the first researchers to stress the role of the structure of knowledge in memory was Larkin (Larkin, McDermott, Simon, & Simon, 1980). She concluded from her studies on problem solving in experts and novices that the large amount of knowledge stored in the memory of an expert is made possible not by a general superiority of memory, but by the chunking of information into large, meaningful units—a type of organization that most novices lack. These results are consistent with the early results found by Chase and Simon (1973) on the perception and memory of chess masters, in which groups of stimuli were perceived and remembered as units.

The importance of structuring knowledge has been stressed by Reif (1984; Reif & Heller, 1982) and others (Camacho & Good, 1989; Elio & Scharf, 1990; Prawat, 1989). Reif stated that a hierarchic knowledge structure is the type most suited for retention of knowledge, for quick and efficient search processes, and for fitting in new elements of knowledge without restructuring knowledge already present. This type of structure, which contains abstract and general concepts at the higher levels, is typical of expert knowledge (see also Boshuizen & Schmidt, 1992). A more extended notion of the organization of knowledge that includes not only conceptual knowledge but also other types of knowledge can be found in the concept of schema. Knowledge of a domain includes several schemata, tailored to typical task performance in the domain and organized in a systematic, often hierarchic way (Rumelhart, 1980). A schema contains the different types of knowledge required for task performance. In the case of problem solving, we can speak of problem schemata containing situational, conceptual, and procedural knowledge (de Jong & Ferguson-Hessler, 1986) that correspond to a particular problem type. The role of an efficient knowledge structure was demonstrated in an experiment where we investigated the knowledge structure of novice, first-year students of physics. The results showed that students who were good problem solvers (i.e., showed expertise at their own level) had a knowledge structure that was more similar to a set of problem schemata than students who were poor problem solvers (de Jong & Ferguson-Hessler, 1986). In a theoretical analysis of the subject matter of a first-year course on electricity and magnetism (Ferguson-Hessler & de Jong, 1987), we demonstrated how a set of problem schemata can be used as a basis for a hierarchic structure, forming the lowest level and being subsumed into the hierarchy as more knowledge is acquired.

It is evident from this discussion that depth and structure of knowledge are not independent. Only the introduction of deep elements makes possible the generalizations and abstractions that are required for the construction of (problem) schemata and the building of a hierarchical structure. However, it is possible to build a structure on superficial characteristics, and such a schema would also be remembered and used in applications. It might contain incorrect elements and relations and would thus lead to faults in the application. Such a structure could be described as a noncanonical schema. It lacks the functionality of schemata belonging to a well-structured knowledge base (Taconis & Ferguson-Hessler, 1993).

The relation between depth and structure is found in strategic knowledge as well. Superficial elements can be chained into a strategy we named "kick-and-rush": Find a formula, fill in, calculate, ready (de Jong & Ferguson-Hessler, 1984). A well-structured strategy contains a logical series of actions, such as analyzing information, constructing a problem representation, selecting tools for the solution, and planning the various steps to be carried out to reach the solution. Together, these actions form a strategy, but they cannot be isolated from that strategy and carried out independently.

In the mechanics problem, we can distinguish elements of conceptual knowledge that are either loosely connected (e.g., force equals mass times acceleration, friction equals μ times normal force, normal force equals normal component of weight) or structured in a logical way (e.g., the net force acting on a system equals its mass times the acceleration of the center of mass, thus in case of linear motion, net force normal to the direction of motion equals zero).

Automated (Compiled) Versus Nonautomated Knowledge

Task performance of a beginner can be a conscious, step-by-step process of choice and execution based on fairly general methods. For an expert this changes into a continuous, fluid, and automatic process based on strong domain or situation specific methods, a deep representation of the given task, and well-structured knowledge of principles and procedures. Such a knowledge base is described as being compiled—that is, tailored for a certain type of application (Anderson, 1983). Hereby attention is freed for the continuous parallel checking of the task execution, which is characteristic of expert performance. The total effect of automation is fast and reliable task performance.

The distinction between automated and nonautomated knowledge is strongly related to the distinction between tacit and explicit knowledge. Wagner (1991), following the Oxford English Dictionary, defined *tacit knowledge* as "practical know-how that is usually not openly expressed or stated" (p. 173). According to Wagner, it "typically is acquired through informal learning, either from one's own experience or from that of a mentor or colleague" (pp. 173–174). Gelman and Greeno (1989) denoted this type of knowledge as implicit knowledge. Broadbent and colleagues were among the first to emphasize the existence of tacit knowledge (Berry & Broadbent, 1984, 1988; Hayes & Broadbent, 1988). Tacit knowledge is seen by these authors as knowledge that is not open to being verbalized. In a series of experiments, Berry and Broadbent (1984) had subjects interact with a simulation (e.g., controlling a sugar factory), gave them a specific assignment (e.g., to reach a certain level of sugar production), and questioned them afterward. Results from this study showed that the ability to answer questions on a written posttest was not correlated with the ability to control the factory successfully. Apparently, people possess knowledge that enables them to perform a task, but it is tacit, implicit, or not easily expressed. On the other hand, explicit knowledge is not by definition transformed into knowledge that may drive task performance.

Schmidt and Boshuizen (1993) applied the idea of compiled knowledge to conceptual knowledge. In their research of medical problem solving they introduced the idea of knowledge encapsulation, which means "the subsumption or packaging," of lower level detailed propositions, concepts, and their interrelations in an associative net under a smaller number of higher level propositions with the same explanatory power" (p. 340). The idea of encapsulation indicates more than just a knowledge organization in which higher order concepts are introduced and lower level elements disappear or are encapsulated in the higher order concepts. By comparing the concepts used in recall and explanation of clinical cases, Schmidt and Boshuizen concluded that experts have encapsulated knowledge, whereas medical students (intermediates) rely more on biomedical knowledge.

Looking at the mechanics problem from Figure 1, we see that the levels of automation are relevant for different types of knowledge. Procedural knowledge, for instance, could be automated (e.g., directly drawing force diagrams for each of the two blocks) or used in a step-by-step process (e.g., starting with a check on the points of contact of the systems with the surrounding to identify all forces acting on the systems). Compiled situational knowledge makes it possible to interpret the given situation as a whole, whereas nonautomated knowledge forces the problem solver to interpret the elements of information one by one (e.g., tension in string means force on block means string pulls upward). The level of automation thus influences the whole process of solution, starting with the perception of the information given and the building of a task representation.

Modality of Knowledge

Knowledge can be stored in long-term memory as a set of either propositions (i.e., an analytic representation) or images (i.e., an analogous representation). Paivio (1975), in his dual coding hypothesis, suggested that concrete words tend to be represented in both types of codes, whereas abstract words are represented only in the analytic code. Imagery will lead to the construction of a rich analog representation, and, in general, it will be easier to remember input that is represented in multiple codes. We follow Paivio in distinguishing two modalities of knowledge: verbal (analytic) and pictorial (analog).

Diagrams have a central role in problem solving in science. They can be used to structure and give meaning to large amounts of knowledge, thereby reducing the load on memory. In domains where spatial relations play an important role, for instance physics and chemistry, the use of pictorial representations is essential for task performance. Whereas it is evident that a pictorial representation of elements of knowledge can be efficient for the construction of a problem representation, Larkin and Simon (1987) also stressed the importance of diagrams for computational efficiency in problem solving. The mechanics example illustrates this: The force diagrams have an important function in the solution, comparable to noting down intermediate results in a multiplication of tree-figure numbers. Anzai (1991) stressed not only the well-organized and abstract knowledge of experts, but also their use of this knowledge for constructing abstract problem representations from the viewpoint of underlying principles. These representations, according to Anzai (1991), often take a visual form. Similarly, Bowen (1990) emphasized the significance of pictorial representations for problem solving in chemistry.

In the mechanics problem, the modality of conceptual knowledge, for instance, could be analogical–verbal (e.g., a series of equations such as $F = ma$, $F_f = \mu F_n$, $F_n = mg \cos \alpha$) or pictorial (a standard force diagram; see Figure 2).

General Versus Domain Specific Knowledge

The quality *general* versus *domain specific* is often applied to knowledge of strategies and procedures. Problem-solving strategies are often described at a general level. Many authors describe a general problem-solving strategy as consisting of four steps or stages: analysis or description, planning or illumination, execution, and checking or verification (Polya, 1957; Schoenfeld, 1979). Heuristics, which are often part of a strategy, may be general and domain independent (e.g., means–ends analysis), but frequently they are bound to a domain (e.g., check all forces acting on system). A number of

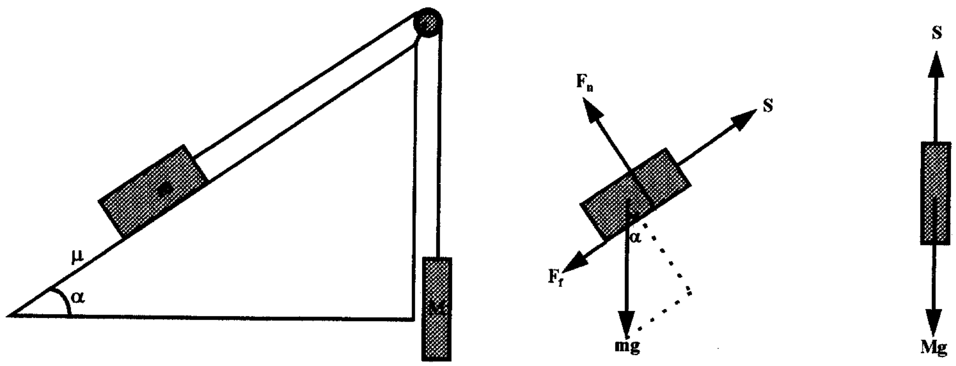

FIGURE 2 The given situation (left) and the force diagrams for the example given in Figure 1.

studies claim success in training problem-solving skills. These programs all work with domain specific strategies, whereas programs concentrating on general problem-solving strategies have had limited success (Larkin, 1989). Examples of successful programs are Schoenfeld's (1985) teaching of heuristics for problem solving in mathematics and a university physics course in which students were trained in modeling (Halloun & Hestenes, 1987). Also, in a secondary mechanics course, students were trained to use cognitive tools tailored to the type of problems where they had to be applied (Caillot & Dumas-Carré, 1991). Larkin (1989), in her search for knowledge that is a good candidate to be taught as a basis for transfer from one (sub) domain to another, defined a generality level between very general and completely domain specific. As examples, Larkin (1989) presented a decomposition strategy (dividing a problem situation into separate meaningful parts) and the use of general concepts such as "field" for the description of a situation, thereby taking advantage of the property of lines or surfaces where an entity has a constant value (i.e., equipotential lines or isobars).

Conceptual knowledge can also be described as being more or less domain specific. Both conceptual and situational knowledge may be abstracted and thus generalized. In physics, knowledge of laws of conservation of energy, charge, mass, and so on, may lead to a general concept of conservation law but may also specialize into a more domain specific form, such as the law of conservation of mechanical energy in a conservative force field. Characteristics of problem situations may be expressed in general terms such as time-independent, homogeneous, or spherically symmetrical. This type of generalization is usually combined with the construction of a hierarchic structure, which facilitates remembering and recall (Reif, 1984).

For the solution of our example mechanics problem, elements of both general and domain specific knowledge are needed: for instance, being able to conclude that this is a case of linear, accelerated motion of each of the two objects and knowing that the pulley changes the direction but not the magnitude of the force in the string.

THE KNOWLEDGE MATRIX AS A DESCRIPTIVE SYSTEM

The discussion of the previous sections distinguished ontological types of knowledge relevant for problem solving and different qualities that can be attached to the knowledge types. By combining these two dimensions it is possible to construct a knowledge matrix, suited for the description of a knowledge base relevant to a certain type of task performance. Table 1 gives such a description of a knowledge base that is relevant for problem solving, in which examples of different qualities for the various types of knowledge have been entered into the cells of the matrix.

As indicated in the previous section, the qualities in Table 1 are not all independent, and some qualities refer not only to separate types of knowledge but also to larger units of the knowledge base, for instance to schemata. The examples in Table 1 illustrate that qualities such as level, automation, modality, or generality can be attached to an individual type of knowledge separately, whereas structure is a characteristic that refers not only to an individual type of knowledge but also to the relatedness of knowledge types.

CONCLUSION

Several analyses of aspects of a knowledge base are relevant to cognitive theories, and they introduce general classification schemes for types of knowledge. As a complement to these analyses, we have introduced in this article a more specific perspective: *knowledge-in-use*. In this article, we have chosen problem solving as the context of analysis, and different analyses would have resulted from choosing another context such as troubleshooting, medical diagnosis, or programming. A knowledge-in-use perspective enables us to describe a knowledge base in terms of the two dimensions *type* and *quality* of knowledge, in which the types are defined on the basis of a detailed task analysis. A knowledge base that is adequate for the solution of a given type of problem at a given

TABLE 1
Example Descriptions of Knowledge as a Function of Type and Quality

	Types			
Qualities	*Situational*	*Conceptual*	*Procedural*	*Strategic*
Level Surface ↔ deep	Case-based reasoning ↔ translation into domain concepts	Symbols and formulae ↔ concepts and relations	Rules/recipes/algebraic manipulation ↔ meaningful action	Symbol-driven search for formula ↔ analysis and planning
Structure Isolated elements ↔ structured knowledge	Isolated features ↔ grouped together (i.e. models of situations)	Independent concepts and laws ↔ meaningful (hierarchical) structure	Isolated algorithms ↔ action related to concept or principle	Isolated actions ↔ Coherent set of sequential actions
Automation Declarative ↔ compiled	Conscious and stepwise ↔ automatic translation to domain concepts	Verbalizable principles, definitions, etc. ↔ intuitive, tacit understanding	Conscious choice and step by step execution ↔ automatic access and routine execution	Step by step choices and planning ↔ automatic analysis and planning; parallel checking
Modality Verbal ↔ pictorial	Words and symbols ↔ pictures and diagrams	Propositions and formulae ↔ pictures, diagrams	Sets of production rules ↔ pictorial (diagrams, figures, graphs)	Sets of production rules ↔ pictorial (diagrams, figures, graphs)
Generality General ↔ domain specific	General properties (e.g., homogeneous, time independent) ↔ domain specific characteristics	General structures of domains ↔ a specific domain, and also: conservation laws ↔ specific cases thereof	Define system for application of conservation laws ↔ check points of contact for forces	General steps (analysis, planning, etc.) ↔ specific steps (thermodynamics: system, interaction, process, etc.)

level is complete in the sense that it possesses all the necessary content *and* all the necessary types of knowledge. This knowledge should also have the required qualities, such as adequate structure and depth (e.g., organization according to problem schemata) and a combination of general and domain specific elements.

The approach we have taken has a number of advantages compared to existing approaches to describing the knowledge base. First, the knowledge-in-use perspective leads to an epistemological analysis of knowledge that renders ontological knowledge types. Several authors have emphasized the importance of ontological classifications in the analysis of knowledge, problem solving, and learning phenomena (Chi & Slotta, 1993; Chi, Slotta, & de Leeuw, 1994; diSessa, 1993). Hammer (1994) pointed to the fact that students may possess epistemological beliefs about physics that are not beneficial for a good understanding of the domain. For example, students may believe that physics is a set of separate pieces of information and that problem solving should be done by entering numbers into formulas. An analysis such as the one in this article may help instructors realize what are the relevant types and qualities of knowledge in a specific context, so that they can communicate these characteristics to learners. As Hammer (1994) suggested, these characteristics could well be instructional objectives in their own right.

Second, our analysis as reflected in Table 1 offers an overview and a new perspective for the discussion of a number of questions in the field of problem solving, such as knowledge assessment techniques (see, e.g., Snow, 1989), expert–beginner differences (Glaser & Chi, 1988), and instructional design (Romiszowski, 1981).

This article is a summary of an extended report (de Jong & Ferguson-Hessler, 1995) in which, as an example application of the matrix, we used the matrix for classifying assessment techniques. In that work we indicated the suitability of assessment techniques such as reproduction, thinking aloud, discontinuous thinking aloud, stimulated process recall, conversations, logfiles, card sorting, concept association, external material, explanations, reconstruction, speed tests, and transfer for measuring specific types and qualities of learning.

In the context of expert–beginner differences, Glaser and Chi (1988), for instance, wrote of "an organized body of conceptual and procedural knowledge." In this description we recognize several qualities of knowledge introduced in this study: abstract, containing the underlying principles of the domain—that is to say deep; well-organized or structured according to the needs of typical tasks; containing general visual elements (as distinguished from copies of surface elements) as well as verbal elements. The knowledge base of unsuccessful beginners, on the other hand, could be characterized by the same qualities: superficial elements of knowledge that are direct copies of external information that have not been related to fundamental principles of the domain or to each other and which are dominantly of a verbal–algebraic kind, with few general visual elements.

In the area of instructional design, our analysis can be used to design instructional measures that train specific knowledge types, qualities of knowledge, or both. An example of such an approach can be found in van Merriënboer, Jelsma, and Paas (1992), who listed a number of instructional techniques related to types of knowledge.

Third, by combining types and qualities in the form of a matrix, a parsimonious description of knowledge can be achieved. There are many examples of introductions of new types of knowledge that could be described more easily as combinations of existing types and qualities.

Fourth, use of the knowledge matrix may point to weaknesses in the current state of science. For example, in our inventory of knowledge assessment techniques (de Jong & Ferguson-Hessler, 1995) we found very few assessment techniques that are suitable for measuring the modality of knowledge.

It is our hope that the framework presented in this article will simplify discussions on knowledge by offering a parsimonious description of its types and qualities. Researchers investigating task performance, human errors, and learning and instruction, and teachers and trainers involved in the design and execution of curricula, instruction, and training might benefit from this analysis. Still, the concept of knowledge is very rich, and we are convinced that many other approaches are possible to the classification we have undertaken. We are aware of the fact that the framework presented here might be extended and improved. For example, the qualities we have defined here sometimes overlap or are not independent. We hope this article invites others to continue the discussion in order to find an efficient and parsimonious system for the description of knowledge-in-use. Such a description would be valuable for many researchers and educators.

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