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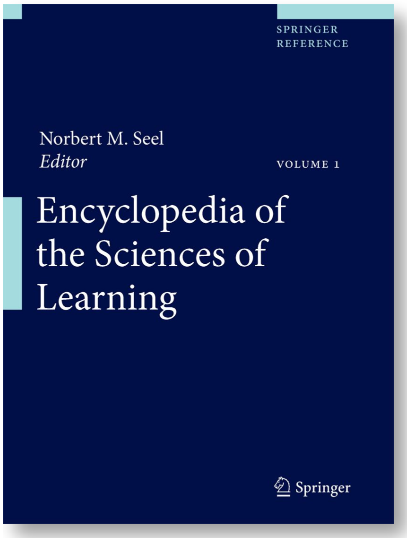

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Encyclopedia of the Sciences of Learning

- ▶ The first encyclopedia covering all sectors, paradigms and movements of the sciences of learning from their origins through the present
- ▶ Contributions from a wide variety of leading researchers in a wide variety of fields
- ▶ Provides up-to-date, broad and authoritative coverage of the specific terms used in the sciences of learning and its related fields, including relevant areas of education and computer science
- ▶ An indispensable reference for scientists, educators, students, and researchers active in understanding learning and the learning sciences

Over the past century, educational psychologists and researchers have posited many theories to explain how individuals learn, i.e. how they acquire, organize and deploy knowledge and skills. The 20th century can be considered the century of psychology on learning and related fields of interest (such as motivation, cognition, metacognition etc.) and it is fascinating to see the various mainstreams of learning, remembered and forgotten over the 20th century and note that basic assumptions of early theories survived several paradigm shifts of psychology and epistemology. Beyond folk psychology and its naïve theories of learning, psychological learning theories can be grouped into some basic categories, such as behaviorist learning theories, connectionist learning theories, cognitive learning theories, constructivist learning theories, and social learning theories. Learning theories are not limited to psychology and related fields of interest but rather we can find the topic of learning in various disciplines, such as philosophy and epistemology, education, information science, biology, and – as a result of the emergence of computer technologies – especially also in the field of computer sciences and artificial intelligence. As a consequence, machine learning struck a chord in the 1980s and became an important field of the learning sciences in general. As the learning sciences became more specialized and complex, the various fields of interest were widely spread and separated from each other; as a consequence, even presently, there is no comprehensive overview of the sciences of learning or the central theoretical concepts and vocabulary on which researchers rely.

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using simple actions such as shaking (Fitzpatrick 2003; Arsenio 2004a). These works show how object recognition and robot experimental manipulation evolve developmentally from human demonstration. By transferring the manipulation skill from human to robot, the latter can generate equally training data to the object recognition algorithm. For instance, (Arsenio 2004a) shows that by having the robot hammering on a table, the perceptual system extracts visual templates of the object which is thereafter recognized as the same object previously segmented from human demonstration.

Indeed, a large range of applications were investigated in which the humanoid robot Cog was taught as a child by a human caregiver, exploiting human–robot interactions for emulating cognitive capabilities on the robot. Such development was inspired both by Vygotsky and Margaret Mahler's child developmental theories, with several developmental milestones, as predicted by Mahler's theory, implemented on Cog (Arsenio 2004a).

Cross-References

► Cognitive and Affective Learning Strategies
► Cognitive Learning
► Cognitive Robotics
► Developmental Cognitive Neuroscience and Learning
► Developmental Robotics
► Human–Robot Interaction

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Cognitive Artifacts, Technology, and Physics Learning

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Synonyms

Concrete–abstract objects and cognition; Imagined worlds; Worlds from ideas

Definition

Certain types of computer software are powerful *cognitive artifacts* (Norman 1991). A cognitive artifact is a tool to enhance *cognition*, allowing the user to create and explore "concrete–abstract objects" and "worlds from ideas" and check how well these "worlds" can correspond to "real worlds," or make sense of "imagined worlds." Cognitive artifacts can become an essential tool in teaching and learning in physics education, making learning of complex abstract concepts and models more significative and epistemologically grounded.

What I cannot create I cannot understand (text found on Richard Feynman's blackboard at the time of his death).

Theoretical Background

Learning Physics, Conceptual Difficulties, Familiarization, and Reification

Physics is a relatively new subject in the secondary curriculum. Only in the second half of the nineteenth century did science education become part of the curriculum, and only in the second half of the twentieth century did physics, or physics and chemistry, commonly become an autonomous subject in the developed countries.

Teaching and learning physics has always been considered a difficult task by most teachers and students (see, e.g., Reif 2008). However, for Richard Feynman (1918–1988), a famous physicist and Nobel Prize winner, "subjects like philosophy and psychology are hard, but physics is easy and that's precisely why we know so much about it." But if physics is "easy," why is it difficult to teach and learn? Certainly, there are many reasons for that. One, surely not the least important, is that teachers soon face the harsh reality of how deep and extensive their students' difficulties are and how naïve it is to assume that kids are just as enthusiastic about the curriculum as they are.

Besides the many social-cultural problems teachers face in their teaching, it can be argued that learning science, and physics in particular, is like learning a new language – a language that uses many of the same words as ordinary language but with altered and far more precise meanings.

The essence of the problem of learning the language of physics is learning to make conceptual distinctions among related but distinct concepts. It is, essentially, a matter of *familiarization* with the lexicon of the language and its proper use in specific contexts. *Familiarization* is an important issue when learning science (and mathematics). And, for some eminent scientists, *becoming familiar with* is so important to the success of scientific ideas that new ideas only become triumphant because supporters of old ideas die, as Planck wrote in his autobiography (Planck 1950, pp. 33–34): "A new scientific truth does not triumph by converting its opponents and making them see the light, but rather because its opponents eventually die, and a new generation grows up that is familiar with it." Scientists frequently say that they do not understand some of the most fundamental concepts or theories in their own field. For example, Feynman confessed that he did not really understand quantum mechanics.

Experienced physics teachers also alert us to the fragile nature of our understanding. For example, many of the useful concepts of physics are, for teenagers, mysterious and difficult to grasp; the nature of an electrostatic charge, of a magnetic field, of electromagnetic wave propagation in vacuum, or of charm and color of quarks are examples. There is no absolute understanding or knowledge of the nature of these entities, yet any young adult will certainly wonder about their nature. In physics education, there is surely the need for the kind of humility shown by Feynman, when he felt he did not fully understand quantum mechanics. As Davies wrote (1997, pp. 420–421):

▸ If teachers continue to give the impression that they do have a better basic understanding of such fundamentals than their students, the students will see their own perplexity and uncertainty as a negative reflection on their own capabilities. Even in this group today there will be some of you who will remember the relief you felt when you could use some equation, and your mathematics, to answer a problem, rather than stay with your uncertainties regarding the concepts involved. We learn and teach others to use mathematics to manipulate the symbols associated with mysteries. This does not mean that we or they have a grasp of the mysteries themselves.

Physics deals with conceptual objects such as *force, velocity, energy, radiation*, etc. These are all words that are in common use in everyday language. In fact, many people will use words like momentum, force, and energy interchangeably in casual conversation. Nonetheless, in physics these concepts and the words we use to name these concepts are quite distinct. *Force*, in the language of physics, is the "rate of change of momentum." Energy or work can be related to force as can momentum, but neither force nor momentum is conceptually the same as energy. Power is yet a different concept.

Another important issue in learning such abstract concepts, and one that is intimately related to familiarization, is the issue of *reification*, that is, of *concretization of abstract objects.* According to Wright and Wright (1998, p. 128), "Reification is a central goal [... of learning science and mathematics]; it essentially defines scientific literacy. It is the foundation for common sense about how the world works (...)."

If we take the position that *reification* and *familiarization* are essential aspects of learning physics and mathematics, we are led to ask how can such learning be improved with technology and, specifically, with computers? Hebenstreit, writing about the role of computers in education, coined a term that provides an important insight into understanding how computers can help in the reification of knowledge. For Hebenstreit, computers allow us to manipulate a new type of object; a kind of object that he calls a *concrete–abstract* object (Hebenstreit 1987). *Concrete* in the sense that they can be manipulated on the screen and react as "real objects" and *abstract* because they might be physical or mathematical constructs such as vectors, equations, fields, etc.

Teachers tend to teach what they can teach, not necessarily what they think it would be useful to teach. This is what some authors call *technological determinism*. For example, most of the practical and theoretical teaching is dependent on the *limited* mathematics that students (and also teachers) can use: *simple analytical tools* that often need complex algebraic manipulation. But with computer tools, one can use *numerical approaches* that can turn out to be simpler than analytical ones and lead to improved familiarization and reification of physics by students.

A characteristic feature of using a computer as a cognitive artifact is that the emphasis is on *meaning* and *semiquantitative reasoning* instead of formulaic solving of well-classified problem types. A good example of what is semiquantitative reasoning can be done with a mathematical object such as $dx/dt = 4 \times t$. (For the sake of concreteness, assume that x is a distance and t is a time – in that case the 4 represents an acceleration.) What does this tell us? First, the rate of change of x is proportional to t and that means that the larger the value of t the larger the rate of change of x. More precisely, when t is 5 time units, for example, the rate of change will be, at that instant, $4 \times 5 = 20$ velocity units. If t is 10 time units, then the rate of change will be $4 \times 10 = 40$ velocity units. That is, if t doubles, the rate of change of distance doubles. Moreover, x always increases for positive values of t. Consider another example: $dx/dt = 4 \times x$. (NB in this case the 4 represents 1 divided by a time or a frequency.) Now we have a rate of change of x that is proportional to x at any instant of time. For example, if x is zero, then the rate is also zero. For a positive value of x, at any instant of time, the rate of change is positive and so x increases. Experts can readily do this kind of semiquantitative reasoning even if they do not know the specific details of a calculation.

Physics is a science in which visualization plays an important role, even when visualization is only used to show mathematical objects, such as vectors or field lines. It therefore seems reasonable to suppose that computer visualization can help learners create meaning from manipulations of abstract objects. This capability of the computer has been used extensively in many contexts and is stressed by many authors, who pointed out to the capability of making dynamic representations of non-concrete formal objects. This ability accounts, at least in part, for the increasing importance of computer visualization and simulation in science in general and in physics in particular. Galison (1997), for example, wrote about the new "epistemic position" of computers and simulations in the production of physics knowledge.

Nickerson (1995) pointed out that researchers had not focused on students as authors of simulations. He argued that "it is only difficult, not impossible, and the work that goes into the successful building of a microworld is likely to deepen one's understanding of whatever the microworld is intended to simulate" (p. 16). To build simulations, one can use programming languages, but these often require technical knowledge and skill outside of the domain being simulated. This is the reason why Nickerson proposed the development of specific tools that can be used by people without that knowledge (p. 16): "For student-developed simulations to be practical for educational purposes, it will probably be necessary to develop tools that are designated to facilitate the building of simulations by people without such language facility and programming experience." Such tools have been developed in the last decade (see, e.g., Teodoro 2003), and its impact has been assessed (see, e.g., Teodoro and Neves 2011). These tools have been used extensively as an "integral part" of new curricula, such as *Advancing Physics*, developed by the Institute of Physics in the UK (2000/2008).

In the early 1980s, it was not clear how important and ubiquitous computers would become in our society. Now computers have changed working practices and leisure activities, and everybody agrees that using computers is part of literacy and numeracy. The impact on science is so profound that, for the National Research Council (USA), scientific computation can be considered a third fundamental methodology of science – parallel to the experimental and theoretical approaches.

It has been pointed out that computers, like all technological innovations in schools, tend to follow a cycle of high expectations, rhetoric about the need to innovate, oriented policy and finally limited use. There have been many promises of radical change in education from technology enthusiasts. After intelligent tutoring systems, multimedia, Internet, etc., educators have become cautious of what can really make a difference. Educators increasingly tend to focus on supportive systems, on coaching and scaffolding. Groups such as the group that worked with the Education Technology Center in Harvard between 1985 and 1995 have initiated this perspective. The Harvard perspective was based on four principles (Harvard Educational Technology Center 1988):

Goals: Focus on key concepts and on the overall nature of knowledge, evidence, and inquiry in a discipline.
Teaching Approaches: Help students develop a deep understanding of the subjects they study by taking into account their prior theories and by integrating teacher-directed instruction with opportunities and challenges for critical inquiry.
Technology: Use technologies selectivity to make a distinct contribution to teaching and learning, for example, to present dynamic models of key ideas or to enable students to participate in disciplined inquiry.
Implementation: Design technology-enhanced teaching modules and approaches that can be gradually and gracefully integrated into existing curriculum and practice.

As we can see in these statements, *technology is not a goal in itself* but a selective contribution "to make a distinct contribution to teaching and learning." And it is the *teacher* that really can make the difference in creating powerful educational environments *with* technology.

Important Scientific Research and Open Questions

Embedding the use of computers as information delivery tools has been done in schools in the last decade. This use usually adds nothing fundamentally different from previous tools of delivering information. But integrating computers as powerful cognitive tools in the physics curriculum (as well as in mathematics and other scientific subjects) is a much more difficult endeavor. It needs a coherent view of the role of cognitive tools, a culture of teaching and learning close to the way science is done, and reasonable organizational conditions.

A properly balanced integration of computer cognitive tools in the curriculum remains to be found. Important open questions left for future research are, for example: Is there an optimal set of tools that minimizes cognitive opacity? If a course is organized into lectures, practical and laboratory work, what is the best way to integrate computer cognitive tools? How do these tools relate with interactive digital documents?

We are beyond the point of needing short-term programs that assume that innovation is guaranteed because it has proven to work with enthusiastic adopters. We need programs that encourage cumulative improvement committed to ongoing slow but clear change. Computer tools and computer networks have an enormous potential impact in learning, and it will increase as technology advances. But, as Seymour Papert pointed out 30 years ago, *there is a world of difference between what computers can do and what society will choose to do with them*. We all face the challenge of using technology to empower learning (as well as other human activities), and not to create a kind of Aldous Huxley *Brave New World* where machines control everything, dehumanizing schools and learning.

Cross-References

► Cognitive Artifacts and Developmental Learning in a Humanoid Robot
► Learning Through Artifacts in Engineering Education
► Models and Modeling in Science Learning

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Cognitive Aspects of Deception

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Synonyms

Intentional deception; Tactical deception

Definition

At the *behavioral level*, deception constitutes the misinterpretation of situations by one individual as a consequence of the behavior or signals of the other individual. Functionally, such a misinterpretation poses costs to the receiver and benefits the deceiver.

This operational concept refers to a variety of responses ranging from species-typical patterns given in a certain context, like the feigning of injury by ground-nesting birds or the false alarm calls of sentinel birds in mixed species foraging flocks, to a broad range of diverse behavioral patterns which are used very flexibly in different situations. The term "tactical" deception has been introduced to emphasize a contrast between short-term tactics (in which the deception flexibly uses elements from an honest counterpart in the individuals' repertoire) and long-term strategies (in which deception rests on fixed elements in the individuals' or species' behavioral repertoire).

From a *cognitive perspective*, tactical deception has been assumed to reflect *intentions* by the deceivers in the sense that individuals want to manipulate others. The critical question concerns the *degree of intentionality*, i.e., whether the deception aims to affect the other's behavior or the other's mental states. Deceptive interactions may thus be the result of a range of cognitive abilities such as reading behavioral cues, learning about and/or understanding behavioral maneuvers or even attribution of mental states.

In practice, it is difficult to distinguish between different orders of intentionality, as acts carried out to affect the beliefs of others do not look any different from acts that shall affect merely the others' behavior. To date, there is little evidence that nonhuman animals are capable of full mental state attribution (theory of mind), i.e., to understand that others have beliefs and desires, but there are some persuasive examples of precursor elements like visual perspective taking. Recently, attempts have been brought forward to specify *cognitive building blocks of deception*, which may underlie the transition from different orders of intentionality. The most promising among them are the ability to flexibly inhibit normal behaviors and the understanding that conspecifics can be manipulated.

Theoretical Background

In comparison to morphological and physiological traits, behavior is relatively easy and cheap to fake. Consequently, behavioral deception in the form of *withholding information* and *providing false information* can be found in variety of species and contexts ranging from predator–prey interactions to any form of intra- and interspecific communication, cooperation, and competition. To what extent these behaviors meet the functional definition and cognitive criterion of tactical deception and intentional deception, respectively, has received surprisingly little investigation.

To date, primates have been considered as primary candidates for intentional deception because their *complex social life* creates ample opportunities in which it would pay to flexibly conceal information, to distract others' attention, or to use others as social tools. Specifically, subordinate group members may use deceptive tactics to counter exploitation by dominants. However, *constraints* imposed by social structure, such as the risk of detection, punishment, and/or the need for cooperation, make deceptive tactics rare events that often work only for a short time period. Accordingly, deceptive tactics are difficult to study and much of the early literature on the topic consists of anecdotes. Nevertheless, progress in studying deceptive tactics and their cognitive basis has been made with experimental approaches that are based on ecological meaningful behaviors, such as outwitting conspecifics in competition for food. Moreover, species other than primates