ELEMENTAL LEARNING AS A FRAMEWORK FOR E-LEARNING

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ABSTRACT

Analysis of learning outcomes can be a complex and esoteric instructional design process that is often ignored by educators and e-learning designers. This paper describes a model of analysis that fosters the real-life application of learning outcomes and explains why the model may be needed. The Elemental Learning taxonomy is a hierarchical model composed of two primary types of learning: (a) elemental learning composed of actual and simulated elements; and (b) synthetic learning, composed of procedural understanding, conceptual understanding, and related knowledge. The importance of iteration and intuition in learning analysis is also discussed.

KEYWORDS

E-learning models, situated learning, learning analysis, instructional design, pedagogical models

1. INTRODUCTION

A primary assumption of meaningful e-learning is the fidelity of design to learning outcomes. The focus of this paper is that the primary design of assessment and learning activities that match learning outcomes should emphasize elemental (real-life or simulating real-life) learning. The emphasis on real-life learning outcomes is proposed from the perspective of a simpler taxonomical model that with five levels that can be easily grasped by non-instructional designers and applied to the analysis of meaningful learning outcomes.

More than ever it is possible to define learning progress along a “trajectory of experience” (Greeno, 1997). For more than a century, a conceptual approach related to guiding the learning experience has been argued along a loose continuum. One approach, beginning perhaps with Thorndike’s specific transfer theory of identical elements (Thorndike & Woodworth, 1901), has emphasized situated learning outcomes. This approach emphasizes task-based learning and probably because of its early association with logical positivism and ‘objective’ use of data has been overly vilified by the overgeneralization of early behaviorists. The other end of the continuum supports the transfer of general skills and principles to promote learning. This was characterized early on, for example, by Gestalt psychologists such as Wertheimer (1945) and Katona (1940). Because of the decontextualized nature of the general skills and principles approach, inductive learning philosophies (e.g., constructivism and connectivism) the common sense inclination of many educators is to see the merit in both positions (e.g., by De Corte, 1999). Few would argue, however, that learning activities and assessments that provide a situated context are more likely to retained in long-term memory and more able to be applied in a real-life environment. Although we keep reinventing it, the theory and research supporting these ideas have been very well-defined as early as the days of Thorndike and Dewey. The challenge is to apply these ideas in a simpler approach for analyzing teaching and learning outcomes in such a complex, information-bloated environment as e-learning.

2. LEARNING ANALYSIS AND LEARNING TAXONOMIES

Learning analyses are formal approaches to clarify the rational relationships among learning outcomes. In terms of intentional learning environments, such as higher education or technical training, two methods have been employed with some effectiveness: taxonomies and rule-based frames.

Using a learning taxonomy is appropriate when content is characterized by rational relationships. Classic learning taxonomies include those by Bloom (1956) and Gagne' (1985). The approach here is to ask in effect, "If you were to assess what the learner knows or can do, how would know?" The taxonomies of Bloom and Gagne' provide an rational way to approach that question by defining learning outcomes as abstract concepts and identifying the nature of the intentional or incidental (or unintended) learning outcomes that provide the learning as well as the relationships among the learning outcomes. Figure 1 illustrates Gagne's intellectual skills subdomain.

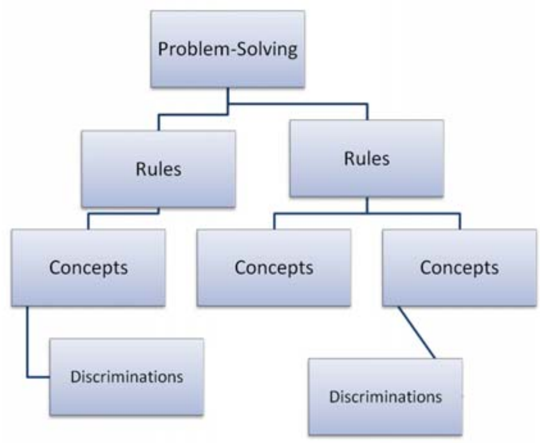

Figure 1. Gagne's Intellectual Skills Subdomain

As you can see, in this taxonomy problem-solving or higher-order skills depend on rule or procedural prerequisites; rules depend on concepts, both abstract (e.g., love or identity) and concrete (e.g., table or dog); and concepts require discriminations. This approach is hierarchical and deductive. It has been used routinely by skilled instructional designers to analyze what must be learned or assessed. It is very effective in indicating the essential prerequisites for a course or e-learning module (Gagne and White, 1978)

Another approach to learning analysis is a rule-based frame. A rule-based frame is a superb way to structure intelligent computer-based learning scenarios or examples and has increasingly been employed in computer-adaptive examinations. Figure 2 illustrates a matrix of related content that has been used for structuring question-based or declarative examples, case studies, identifying misconceptions, and so forth. When designed in rationally appropriate algorithms for computer software, rule-based frames (sometimes referred to as Type 2 Frames) identify specific classification problems, such as misconceptions or overgeneralizations) and adapt by providing classification examples that emphasize appropriate levels of discrimination (telling the difference between rationally related content) and generalization (applying to increasingly complex or divergent examples).

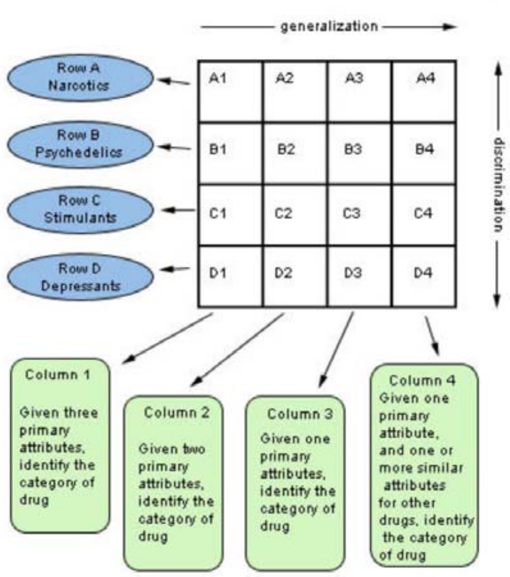

Figure 2. An example of a rule-based frame (from Dempsey & Driscoll, 1996)

The advantages of using classic learning taxonomies or rule-based frames to analyze frames are several. They provide a systematic approach to thinking about learning content for assessment or structuring rational relationships including essential prerequisite knowledge and skills. They can be empirically verified by learner responses. In addition they have relevance for advanced e-learning software applications including artificial intelligence, computer-based testing, computer-based testing, and systems-type wizards. Unfortunately, these approaches are not used at all or used ineffectively by most educators. Simply put, they are just too complicated to be easily applied by content experts and even less-skilled instructional designers.

3. ELEMENTAL AND SYNTHETIC LEARNING

Another approach to learning analysis and design is to emphasize elemental (real-life or simulating real-life) outcomes and, when these are identified, look for those synthetic outcomes that support their learning. Elemental Learning refers to the actual or real tasks applied in a real or close proximate environment in which the learning outcomes will be used. They are context- and content-specific. They can also contribute to learning similar elemental outcomes by virtue of the learner's enhanced experiential schema. An obvious example for the need for elemental learning involves the training of airline pilots. Who would want to be a passenger in an airplane in which the pilot had not experienced learning in an actual passenger airliner?

By contrast, synthetic learning outcomes are the cognitive learning outcomes necessary to support elemental learning. Synthetic learning outcomes are less context-specific, and the learner's experience is often less important in acquiring these outcomes. Synthetic here refers to forming something new (elemental) by combining other, usually decontextualized, outcomes. These are the traditional learning outcomes. In taxonomies such as Bloom's (1956) or Gagné's (1985), these are traditionally believed to be hierarchical, i.e., learning rules requires learning concepts, some basic knowledge is required, and so forth.

Figure 3 illustrates a simpler, more direct taxonomy that focuses on elemental learning outcomes. After elemental learning outcomes are identified, synthetic learning outcomes that support them are added. Elemental learning provides the context. Synthetic learning outcomes support the context.

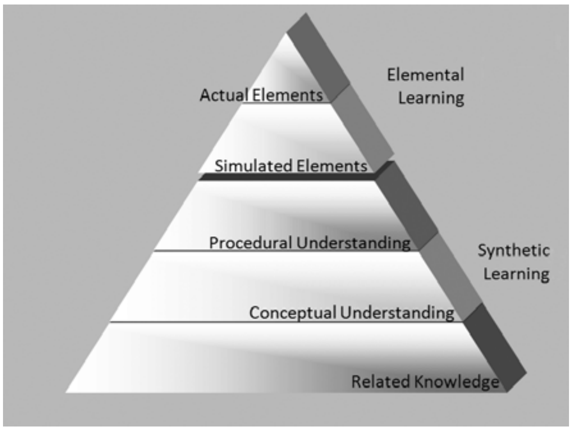

Figure 1. Elemental learning taxonomy represented as a pyramid culminating in actual elements. The top two levels are elemental learning outcomes. The bottom three learning outcomes are viewed as synthetic

3.1 Components of the Elemental Learning Taxonomy

Actual Elements are the most direct measures of the real learning outcomes required by the real environments in which the learner needs to use those learning outcomes.

Simulated Elements promote learning transfer. They reproduce reality or some version of reality "close enough" to actual elements. Although simulated elements may be lacking in some essential characteristics of reality, they retain the context of reality to some purposeful extent.

Procedural understanding requires that learners "walk the walk," not just "talk the talk." Even though procedural learning can be very complex it is missing essential features of the context. Even so, it is a "DO" learning outcome versus a "Know" outcome.

Conceptual Understanding can be abstract or physical. It can be learned (and assessed) by novel examples and nonexamples, by metaphors, and by inductive observation and reflection.

Related Knowledge associated information is intentional (e.g., from an Internet resource accessed via a handheld mobile device) or incidental (e.g., from a television program on another subject).

These categories are not exhaustive. For example, motor skills and affective learning are certainly important. Motor skills and affective learning are also contextual and almost always are highly associated with elemental learning. For example, how do we learn an attitude? One way we do is to intentionally or unconsciously emulate a human or human-like entity in our life (a mentor, perhaps) or in a simulated experience (e.g., an actor in a movie). It is the real or simulated experience that guides the choices we make that exhibit the attitude learning that has taken place.

3.2 Iteration and Intuition

Elemental learning has a theoretical foundation in the notion of spiral curriculum popularized by Jerome Bruner (1960). In a spiral curriculum, the learner revisits real or simulated learning situations iteratively and each time the learning deepens by building on prior experience (p.13). Complex learning outcomes (e.g., negotiating effectively in a foreign language in an alien culture) require the gradual scaffolding offered by iterative elemental learning scenarios. Experiential iterations of these sorts also subsume and give meaning to supportive synthetic learning outcomes. In a spiral curriculum challenge (difficulty) is increased as the learner's competence increases through iteration.

Iterative processes of elemental learning also promote "intuitive leaps." Bruner often referred to experts performing real tasks where they "leap intuitively into a decision or to a solution to a problem" (1960, p.62). In medicine and other areas, such as physics, intuitive leaps are referred to as the forward reasoning (from data to solution) applied by experts [7] versus the backwards (rigidly algorithmic) reasoning of novices.

4. CONCLUSION

The elemental learning model does not exist in a vacuum. Its goal is to provide a simpler method of analysis that result in significant learning outcomes. Established learning analysis models (e.g., Gagne's Taxonomy or rule-based framing) can be employed effectively to promote specific learning outcomes. Unfortunately, these models often result in decontextualized learning. They take some expertise to use in educative practices that result in increased learning retention. Additionally, they can be cumbersome to apply and thus the important practice of learning analysis is often neglected.

The elemental learning framework situates learning in reality (actual elements) or a mockup of reality (simulated elements), and does so iteratively to the extent that is possible. In analyzing a course or a module or some other e-learning situation, the challenge is to move beyond "giving" decontextualized knowledge and general principles (synthetic learning outcomes). The elemental learning framework provides a structure for contextual learning that is so often lacking in e-learning environments. Actual and simulated learning outcomes supported by synthetic learning outcomes create the structure without over-controlling the natural challenges of meaningful learning experiences.

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