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4. GENERAL VERSUS SPECIFIC INTELLECTUAL COMPETENCIES

The Question of Learning Transfer

INTRODUCTION

One major goal of education is to provide students with the knowledge and skills that will prepare them to be productive citizens and enable them to make informed decisions about work, family and societal issues. It is commonly believed that what we learn in school will be applied at appropriate times later in life. Unfortunately, research on transfer of learning raises doubts about the effectiveness of education to create transferable knowledge and skills.

The concept of transfer of learning has been a topic of study for many researchers. Bransford, Brown and Cocking (1999) argued that the ultimate goal of schooling is to help "students transfer what they have learned in school to everyday settings of home, community and workplace" (p. 73). Current views of transfer (Beach, 1999; Bransford & Schwartz, 1999; Greeno, Smith, & Moore, 1993) indicate that transfer occurs when students activate and apply prior learning. This activation and application of prior knowledge can foster productive as well as unproductive transfer (Royer, Mestre & Dufresne, 2005). It is during these transfer events that the state of awareness of one's thoughts plays an essential role.

Concerns about transfer of learning were virtually nonexistent prior to the early 1900s because the commonly accepted "theory of faculties" implied that if learning had occurred, then the application of that learning in new situations (i.e., transfer) would be automatic. Unfortunately, both "experience and experiment combine to prove that such an outcome is never achieved" (Bayles, 1936, p. 211).

A new perspective on transfer resulted from numerous psychological studies conducted by Thorndike and his colleagues in an attempt to understand how certain mental functions contribute to improvements in the performance of other cognitive processes (Thorndike, 1924; Thorndike & Woodworth, 1901). These studies revealed that successful transfer of learning depended on the degree of correspondence between the stimuli, responses and conditions of the learning setting and those same factors in the transfer setting. This finding led to the creation of Thorndike's "theory of identical elements." According to this theory, as long as a similarity exists between the context in which learning occurred and the new situation in which the learning should be applied, then the transfer will be automatic. When differences exist between

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the learning and application settings, then transfer is less likely to occur. While this basic concept holds true today, it fails to consider the role of learner characteristics and individual cognition in supporting transfer (Bransford, Brown, & Cocking, 1999).

In contrast to the theory of identical elements, Judd (1936) argued that similarity between the learning and application settings is not enough. Instead, he promoted the idea that learning generalized principles was the answer to the problem of transfer. Building on this perspective, if one can learn generalized rules and how to apply them in different situations, the chances of appropriately applying those rules in new situations will be greatly enhanced.

While both of these theories offer contrasting insights into the drivers that promote successful transfer of learning (e.g., identical elements vs. rule generalization), what is clear is that that the context of the learning environment is a critical factor and transfer does not generally occur automatically.

One area of schooling that is particularly relevant to the enhancement of learning transfer is engineering and technology education. This emerging field of study is historically based on vocational and technology fields, which by nature are hands-on and require high levels of creative and critical thought in order to design and problem-solve. While general schooling has tried to enhance creative and critical thought processes over the years, little progress has been made.

It is claimed here that engineering and technology education can be an effective vehicle for developing students' general competences, such as problem-solving, decision-making and creativity. It is through technical design and problem-solving experiences that students will create a deeper understanding of general concepts such as systems, control, feedback, design and optimization. As an added benefit, experiences through engineering and technology education will enhance learning in other closely related fields such as mathematics, science and technology. This form of learning benefits all students because practical hands-on experiences and principle-based understanding support the transfer of knowledge and skills from school to daily life and to the workplace as technologies advance and as careers change.

TYPES OF TRANSFER

The Role of Context in Supporting Transfer (Near vs. Far Transfer)

Over the years, scholars have attempted to categorize transfer from different perspectives and for different purposes. Probably the most common categorization is the dichotomy of near and far transfer (Clark & Voogel, 1985; Perkins & Salomon, 1996, 1988; Royer, 1986). The concept of near transfer is consistent with Thorndike's theory that emphasizes the contextual similarity between the learning situation and the situation in which the learning is later applied. In other words, the transfer situation is very near to (or similar to) the situation in which the knowledge and skills were originally learned. Near transfer occurs rather easily because of the similarity between the learning and application contexts and the learner's familiarity with the new situation as a result of prior experience. In this sense, learning has been contextualized for application in real-world settings (Resnick, 1987).

In contrast, far transfer relates to the application of knowledge and skills in situations that are significantly different from the context in which the original learning occurred. In other words, there is a far distance between the original learning context and the context where that learning is likely to be applied later. Because of this contextual difference, far transfer is more difficult than near transfer because the learner has not previously experienced applying the learning in the new context. Although it is more difficult to achieve, far transfer is becoming more critical because of the rapid growth and change in knowledge, technology and the workplace (Leberman, McDonald, & Doyle, 2006).

As an example, imagine a new technician on her first day at work being asked to repair a machine that is identical to the machines she practiced on at her technical institute. The technician's familiarity with the machine will allow her to be confident and proficient because the experience she gained at the technical institute can be applied immediately to her new work assignment. In contrast, imagine a second technician who is faced with a new computer-controlled machine that is drastically more modern than what he used in his technical training program. While the basic principles underlying the two technical systems remain the same, the details of the system layout and the component function are radically different from what was experienced at the technical institute. In this case, the technician is less likely to directly apply prior knowledge and skills because of the great difference (i.e., far transfer) between the learning situation and the context of application. This difficulty occurs because the technician has developed, through experience and deliberate practice, particular ways of working with familiar systems that easily map onto similar machines and systems. Unfortunately, the relevance of prior knowledge and skills is not readily apparent when dealing with machines and systems that differ in shape, form, or function. Clearly, more principle-based understanding is needed to support transfer of learning to new and different contexts and situations.

The Cognitive Effort Required for Transfer (Low Road vs. High Road)

A second common dichotomy of transfer types involves how transfer actually occurs, that is, either automatically or with considerable cognitive effort (Perkins & Salomon, 1996). Automatic transfer, often called low-road transfer, occurs when skills are developed to a high level of automaticity and are then applied in similar or familiar situations. The cognitive effort required for low-road transfer is minimal because it occurs subconsciously as a result of the extensive practice that led to conditioned and reflexive behavior. This form of transfer often involves procedural skills such as driving. Driving skills can be developed to a level of near automatic performance, and transfer occurs easily because there is little variation in one automobile to the next.

In contrast, high-road transfer involves purposeful and conscious analysis of a situation to determine what prior learning can be applied in novel situations. In contrast to the automatic performance that occurs for low-road transfer, high-road transfer requires the mindful search for knowledge and strategies that can be applied in an unfamiliar situation. For example, the Pythagorean Theorem is typically taught as an abstract equation with little consideration for its practical application. In this sense, learning is decontextualized and has little meaning beyond the specific application in which it is taught. The opportunity for far transfer might occur later when the student is working on a summer construction job and discovers that Euclidean geometry can be used to determine if a wall is square. This form of transfer requires a conscious search of past experience because the problem is novel and has little direct similarity to the abstract equation that was learned previously.

COGNITIVE CONCEPTS THAT CONTRIBUTE TO SUCCESSFUL TRANSFER

At the core of every engineering and technology educator's teaching strategy is the presentation of content and practice in a systematic manner that is conducive to effective near and far transfer. In fact, according to Sutton (2003) and the International Technology Education and Engineering Association (ITEEA), technologically literate people must be able to transfer their knowledge and skills from one situation to another. Employers, however, often complain about students' inability to transfer concepts and procedures learned in the classroom to situations that are very different from the context in which it was learned. Failure by students in this critical area has caused many to question the effectiveness of the teaching strategies used. It is argued here and elsewhere that instructional strategies and concepts in technology education need to focus on broader, more abstract levels of learning and metacognitive understanding (Johnson, 1995). By placing greater importance on teaching cognitive strategies and skills, technology education students will be better prepared to transfer successfully their learning to new situations. The following section highlights several important cognitive concepts that contribute to successful transfer. These include metacognition, mental representations and analogical reasoning.

Metacognitive Skills and Transfer of Learning

Transferability of knowledge is not limited simply to acquisition of knowledge or possessing a cognitive ability to invoke the memory of a task done in the past. It also requires the engagement of executive control processes (i.e., metacognition) so that students understand under what conditions a particular task is best suited, develop strategies for applying their knowledge, monitor or regulate progress and evaluate the quality of the process and/or product.

The study of metacognition has become one of the hallmarks of psychological and educational theory and research. Students with good metacognitive skills are more knowledgeable of and responsible for their own cognition and thinking (Pintrich, 2002), and as a result, tend to learn better (Bransford, Brown, & Cocking, 1999; Chambres, Bonin, Izaute, & Marescaux, 2002; Case, Gunstone, & Lewis, 2001; Mokhtari & Reichard, 2002; Phelps, Ellis, & Hase, 2002). The results from these studies also suggest that metacognition improves learning and helps one improve transfer of what was learned to new situations.

It is clear that successful learning and transfer depends not only on having adequate knowledge but also sufficient metacognitive ability that involves awareness and control of that knowledge. Despite numerous research findings suggesting that the use of metacognition is essential in learning (Bransford, Brown, & Cocking, 1999; Clark & Mayer, 2003), it is a challenge to adopt metacognitive activities as an integral part of students' routine academic activities in school. This section will briefly discuss metacognition, how it differs from cognition, and its role in improving learning transfer.

In simple terms, metacognition is one's awareness of his/her own thinking or thinking about one's own thinking. Metacognition is an active monitoring process of one's cognitive activity (Brown, 1978; Kluwe, 1982; Schoenfeld, 1987). It also involves a process by which the brain organizes cognitive resources (Cuasay, 1992) and involves overseeing whether a cognitive goal has been met. As specific tasks are performed, individuals use this awareness to control their actions.

Flavell (1976), an early researcher in metacognition, divided it into two aspects: (a) *metacognitive knowledge* and (b) *metacognitive experiences or strategies*. He described metacognitive knowledge as "knowledge concerning one's own cognitive processes and products or anything related to them" (p. 232). It can lead someone to engage in or abandon a particular cognitive enterprise based on its relationship to his/her interests, abilities and goals. Metacognitive experiences or strategies, on the other hand, help one to plan, evaluate and regulate cognitive activities. Flavell also identified three different types of metacognitive knowledge: *person* (the knowledge a person has about him or herself and others as cognitive processors); *task* (the knowledge a person has about the information and resources necessary to undertake a task); and *strategy* (the knowledge regarding the strategies that are likely to be effective in achieving goals and undertaking tasks). These three components of metacognitive knowledge interact with each other and shape one's engagement in tasks.

From a different point of view, Pintrich (2002) divided metacognition into metacognitive knowledge and metacognitive control. Metacognitive knowledge refers to strategies that might be used for a particular task and knowledge of the conditions under which these strategies might be used. Metacognitive control is a cognitive process that learners use to monitor, control and regulate their cognition and learning. Despite differences in defining and categorizing metacognition, common elements are present in those definitions.

The difference between cognition and metacognition is based on functionality. While cognition concerns one's ability to build knowledge, information processing, knowledge acquisition and problem-solving, metacognition concerns one's ability to control the working of cognition to ensure that cognitive goals have been achieved (Flavell, 1979; Gourgey, 1998). It is also a process by which one becomes aware of any knowledge deficiency and takes necessary steps to overcome it (Chi, 2000). Metacognitive activity usually precedes and follows cognitive activity.

Mental Representation and Transfer of Learning

The extent and quality of learning transfer to solve a problem is also dependent upon the quality of the mental representations that students have of the problem. Mental representation is germane to the issue of learning transfer, especially when transferability is required within a context that is quite different from the context under which technological concepts and procedures were learned. It is therefore important that technology educators understand the underlying cognitive processes that support mental representation, (i.e., schema, naïve theories and mental models) and the role they play in the transfer of learning.

Schemata. Paivio (1990) describes schemata as mental structures that represent our general knowledge of objects, situations and events. According to Brewer (2001), as the mind is exposed to many different forms of content, the mind creates abstract cognitive representations that contain generic knowledge organized to form unconscious qualitative mental structures and processes. Hamilton and Ghatala (1994) indicated that schemata not only represent knowledge that can be verbalized about things and situations (declarative knowledge), but also general knowledge that guides our behavior (procedural knowledge).

Naïve theories. Like schemata, naïve theories are knowledge structures that are developed as people gain new knowledge. This coherent system of knowledge allows one to conceptualize causal explanations of phenomena, form questions about the unknown and make sensible predictions (Brewer, 2001). These cognitive structures are often referred to as intuitive, folk, naïve or common sense theories (Gelman, 1996). Naïve theories differ from scientific theories in that they are not as detailed, explicit, coherent or tested as scientific theories. Studies show that children use naïve theories to organize their experiences with the world into sensible and clearly delimited ontological groupings. Through naïve theories, students can make inferences about internal or invisible entities such as electron flow (Brewer, 2001). As schemata are modified with new episodic information, naïve theories are modified and improved as children gain knowledge that disconfirms their previously held theories.

Mental models. Mental models are subtypes of naïve theories. Brewer (2003) described mental models as cognitive representations of mechanical causal domains that allow students to explain and make predictions about these domains. They are unstable, subject to change and are often used to make decisions in novel situations. Various types of causal mental models can be used by the teacher to help students understand and predict the behavior of technical systems. These include general domain models, specific device models (Kieras & Boviar, 1984) and system models (Collins, 1985; Kempton, 1986).

General domain models are generic models that apply to a wide class of devices and systems within a domain. According to White and Frederiksen (1989), the electrical circuit depicted in Figure 1, which represents a general domain model, can accurately simulate the behavior of a large class of circuits, thus helping students solve a wide range of circuit problems. For example, the student can be asked to predict the state of a single device after a switch is closed, or to describe the behavior of the entire circuit as various switches are opened and closed, or to determine what faults are possible given the behavior of the circuit.

Specific device models have specific information about the physical characteristics of devices and their individual function. A drawing illustrating the location of buttons, levers, switches and indicators of a computer-controlled device, along with information that explains their functions, is a typical example of a device model. Figure 2 depicts the device model used by Kieras and Boviar (1984) in a study that examined how using a device model from the outset of instruction can facilitate better retention and reduce the time needed to execute a procedure.

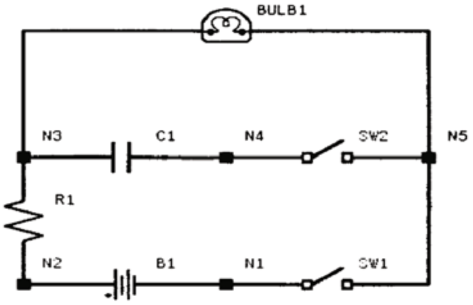

Figure 1. General domain model (White & Frederiksen, 1989).

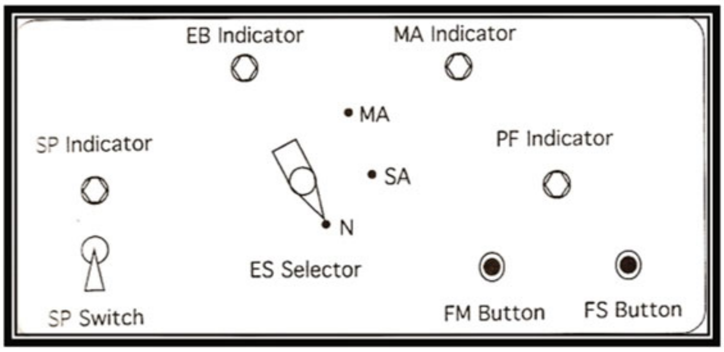

Figure 2. Device model used by Kieras and Bovair (1984).

Analogical Reasoning and Transfer of Learning

Analogical reasoning is regarded as a fundamental cognitive tool that supports transfer of learning (Ball, Ormerod, & Morely, 2004). Reasoning through the use of analogy occurs when similarities between two situations, concept, or phenomena are identified and the relevant information is mapped from the familiar to the less familiar (Mason, 2004). Analogies enable individuals to not only make connections to new phenomena but to also further elaborate their understanding of the known phenomena through a process called abstraction. This process is not only relevant to learning transfer in general, but is also particularly relevant during design problem-solving. The retrieval of prior knowledge to solve engineering design problems through the use of analogies is an important part of the design process. An example of the use of analogies during design problem-solving is George de Mestral's creation of Velcro® (Velcro Industries N.V., 2010). Noticing the cocklebur's ability to "stick" to clothing, de Mestral studied its features and was able to design a fabric fastener that contained similarities between cocklebur and the new design. This connection between known and new phenomena (in this context within design) is an important aspect of analogical reasoning.

Gentner's (1983, 1989) structure-mapping theory explains analogical reasoning through two primary processes: (a) structural alignment and (b) inference projection. Structural alignment enables learners to identify similarities between the familiar (base) and new (target) domains. Inferences about the target domain are based on what is already known about the base domain. Analogical reasoning is supported by the degree to which the base and target domains correspond (Markman & Gentner, 2001). Gentner's (1989) systematicity principle indicates that higher-order relationships, such as causal connections between the base and target domains, are preferable to isolated relations.

Transfer of learning through analogical reasoning "occurs when information and experiences from one known situation are retrieved and utilized in the search for the solution to an entirely different situation" (Magee, 2005, p. 33). Based on the structure mapping theory, Holyoak and Thagard (1997) developed a series of steps to explain how transfer of learning is accomplished through analogical reasoning. These steps include: (a) retrieval, (b) mapping, (c) inference and (d) learning. Previously learned analogies are accessed in the retrieval step and are mapped onto the target domain through the cognitive process of inference, which leads to understanding the new domain (i.e., learning). These general steps are applicable across most domains and can particularly inform the development of design abilities. For example, Dym and Little (2004) promoted the use of analogies to encourage creative, divergent thinking during engineering design. These basic analogical reasoning steps can be applied to the engineering design process. As Ball, Ormerod and Morely (2004) found in their study, engineering designers use analogical reasoning during the design process. Expert designers tend to use a specific type of analogical reasoning process called schema-driven analogizing, where they apply abstract knowledge to familiar problem types, developing a design solution.

Analogical transfer in problem-solving. Researchers have examined the role of analogical reasoning to support learning transfer in problem-solving contexts more generally. Magee (2005) argued, for example, that analogical transfer is "particularly well suited for problems whose solution requires creative thought" (p. 34). Studies examining analogical transfer in problem-solving have largely focused on spontaneous transfer (e.g., no hints are given to the subjects) or by using a base exemplar as a hint (Reeves & Weisberg, 1993). Subjects are typically presented with a novel problem and an analogous story that shares a solution principle (Clement, 1994).

Gentner and Markman (1997) summarized three generalizations that have emerged across these types of studies. The first is that transparency between the target and base domains appear to make analogical mapping easier for individuals. Second, subjects that possessed greater understanding of the base domain (i.e., experts) were better able to transfer their understanding under adverse conditions. Third, different types of similarities require individuals to rely on different sub- processes of transfer. According to Anolli et al. (2001), the evidence indicates that "people fail to transfer spontaneously the solution procedure described in the source to the target if they are not instructed about the source-target relationship" (p. 238). In addition to being aware of the analogous relationship, content and context appear to play a crucial role in the process (Markman & Gentner, 2001). Subjects are more likely to use analogies that share similar or overlapping content and contexts, resulting in a tendency toward near, rather than far, transfer (Reeves & Weisberg, 1993).

EDUCATIONAL IMPLICATIONS FOR USING COGNITIVE STRATEGIES TO SUPPORT TRANSFER

Whether students' prior knowledge is coherent or fragmented, the high level of awareness that students have of their own understanding helps them recognize when their knowledge can or cannot be reconciled with new data, ideas, concepts, conditions or contexts. In many instances, students try to understand new phenomena by creating a mental model that helps them predict how things will behave. Students often use analogical reasoning to bridge the known to the unknown. It is in this context that cognitive and metacognitive skills play an important role in the transfer of learning. Students who possess domain knowledge but monitor and control their cognition poorly may fail when solving problems; however, in contrast, metacognition can help compensate for lack of experience in solving problems (Schoenfeld, 1999). Thus, helping students gain cognitive skills and the ability to monitor their thinking and understanding of new concepts is essential for achieving successful transfer of learning.

Enhancing Transfer through Improved Metacognition

As with other knowledge, metacognitive understanding develops with age and experience (Garner & Alexander, 1989). It is an ongoing process that leads to an understanding of self as agent (McCombs & Marzano, 1990). Metacognition plays an important role in human learning at any level (e.g., K-12, post-secondary, organizations) and for any knowledge domain (e.g., language, science, technology, engineering and mathematics) to do all kinds of cognitive enterprises (e.g., reading, troubleshooting, case-study, design). Research shows that metacognition is teachable (Chan & Moore, 2006; Paris, 1986), and with proper instruction and practice, students are able to improve their degree of control over learning and master complex transfer problems (Takahashi & Murata, 2001). In this study, students in the metacognition instruction group were asked to evaluate the problem-solving process, the goal and the strategy to solve the problem. The findings suggested that by activating student metacognition, students in the metacognition group are better able to understand their degree of progress and require less time to solve transfer problems compared with those in the control group. In another study, Steif, Lobue, Kara and Fay (2010) found that having students taught through discussion about salient problem features in statics improves students' problem-solving skills. The use of metacognitive prompts that initiate systematic discussion helps students develop a better mental representation and monitor their problem-solving process. This finding is consistent with research on self-explanation, where students who generate more explicit and deeper explanations of the process outperform students who generate fewer or shallower explanations (Chi, de Leeuw, Chiu, & LaVancher, 1994). These abilities are essential for engineering and technology education, particularly for solving design problems.

Design problems are ubiquitous, complex and ill-structured, and they offer substantial challenges to students and professional engineering designers. Solving an engineering design problem is a structured and staged process. The ways in which students use strategies, observe what transpires and search for alternative solutions illustrate how metacognition is applied in design activities. Furthermore, metacognitive skills "help students become active participants" (Paris & Winograd, 1990, p. 18) to solve problems that involve ambiguous specification of goals with no predetermined solution path and often require the integration of multiple knowledge domains (Reitman, 1965; Simon, 1973). Instructional strategies that provide scaffolding (e.g., cooperative learning, peer-tutoring, reciprocal teaching, self-explanation) encourage students to experience and practice using both cognitive and metacognitive strategies and evaluate the outcomes of their efforts, which may improve their degree of control over learning and performance.

Teaching for transfer involves linking new knowledge to existing schemata, naïve theories and mental models of students, and reorganizing these cognitive structures where necessary. This adds relevance to the new information that is being learned and also enables students to begin the process of modifying their inaccurate models and theories. An effective way to link new knowledge with existing knowledge and procedures is through concept maps. Concept maps are used to improve problem-solving in many knowledge domains (Lee & Nelson, 2005). They have been used successfully to enable learners to interpret problems (Zhang, 1997), remember important information while solving problems and become aware of new relations among the concepts that are embedded in a problem (Hayes, 1989). For example, if the instructor is teaching about the concept of energy and its use in technology, she could brainstorm with the class while generating a concept map of the different ideas on a flip chart or on the whiteboard. An alternative approach would be to place the students in groups and allow them to generate their own concept maps of energy and its use in technology (see Figure 3).

Teaching students about complex systems and their inter-related components can also be challenging. Barak and Williams (2007) found that by exposing students to block diagrams, they can learn to identify basic variables within a system, such as input, output, feedback and distortion; explore dynamic phenomena in a system; distinguish between dynamic analysis and steady-state analysis; and recognize the difference between the real system and the model. However, as these authors stated, describing a system through a model is not an easy task. Using schematic diagrams is also challenging, because their level of detail can detract the students from understanding the general concept of the system's operation. A variation of concept maps, called functional flow diagrams, can remove or reduce the complexity of schematics and improve students' overall mental representation and conceptual understanding of the causal behavior of systems (Johnson & Satchwell, 1993; Satchwell, 1996). An example is illustrated in Figure 4.

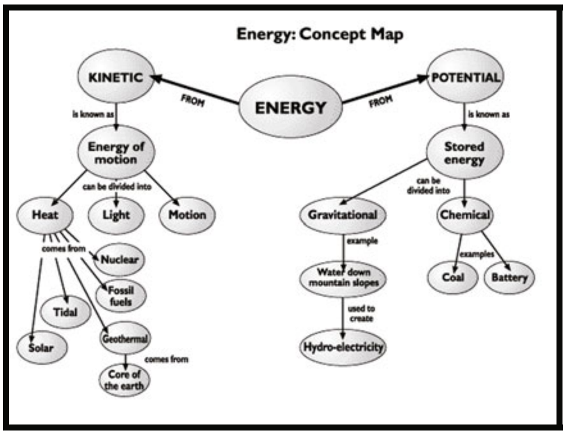

Figure 3. Concept map of energy (retrieved from www.hydro.com.au/education/discovery/concept1.html)

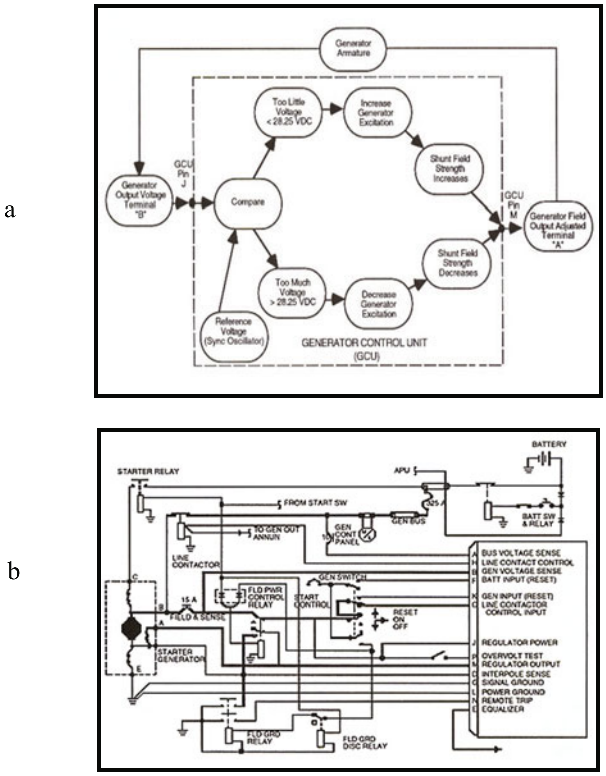

Figure 4. A functional flow diagram (a) and schematic diagram (b) of a system (Johnson & Satchwell, 1993; Satchwell, 1996).

Hands-on experience with troubleshooting and problem-solving is important in order for students to develop mental representations of similar systems they will encounter later in the real world and at their workplaces. For example, the understanding of system concepts such as feedback and control can be deepened by inviting students to design and assemble a real pneumatic or hydraulic system in similar or related contexts. In addition, the expertise and creativity of students will improve with increased hands-on, deliberate practice at designing, problem-solving and troubleshooting. Using simulation to supplement hands-on activities can also enhance students' mental representation of complex systems. According to Spector (2000), simulation provides an opportunity for students to analyze systems of different levels of complexity, explore dynamic phenomena that are difficult to follow in real conditions, and examine models and conditions that cannot be physically created.

Research shows that experts represent problems by their conceptual features while novices represent problems primarily by their surface features. In fact, in designing, Ball, Ormerod and Morely (2004) found that experts use more schema-driven analogies (i.e., analogies that have similar conceptual structures) while novices primarily use case-driven analogies (i.e., analogies that have similar surface features). These findings underscore the importance of exposing students to a variety of problems that have different surface features, but bear the same underlying conceptual structure, in order to develop proper mental representations of concepts that govern the operation of systems. For example, a technology teacher could teach the concepts of mechanical advantage and velocity ratio by allowing students to experiment with gears, pulleys, clutches, hydraulic and pneumatic systems. A similar pedagogical strategy can be used when teaching ill-structured problems such as engineering design. Solving ill-structured problems help students learn to think systematically and qualitatively. Transfer of general principles can be enhanced by teaching multiple cases that have different surface features, but require similar underlying concepts for solution. By explicitly comparing various cases, students can abstract the underlying concepts that make them similar and develop the ability to transfer general principles to real-world problems (Gentner, Leowenstein, & Thompson (2005).

Enhancing Transfer through Improved Analogical Reasoning

Many scholars have pointed out the benefits of analogical reasoning as a cognitive tool across many different educational contexts, including science (Gibson, 2008), technology (Daugherty & Mentzer, 2008), computer programming (Lai & Repman, 1996), grammar (Vokey & Higham, 2005) and auditing (Marchant, 1989). Teaching via analogical reasoning "facilitates the coding and organization of knowledge, improved access and retrieval of knowledge from memory and reduction of misconceptions" (Mason, 2004, p. 295). Numerous instructional strategies have been developed to support analogical reasoning, including teaching-with-analogy (Glynn, 1989), bridging analogies (Brown & Clement, 1989), multiple analogies (Spiro, Feltovich, Coulson, & Anderson, 1989) and student-generated analogies (Wong, 1993).

These instructional strategies all recognize that learners should first have a clear understanding of their existing base domain knowledge so they can access the relevant information that is structurally similar to the new target domain. Mason (2004) cautioned that if learners do not have a sufficient understanding of the base domain, misconceptions can result by mapping non-relevant or surface features to target domains that are either incorrect or lead to inappropriate comparisons. Also, many studies have shown that individuals have trouble transferring knowledge between vastly different analogous situations. This is largely due to the challenge that individuals face in accessing the relevant knowledge from memory (Clement, 1994).

Mandrin and Preckel (2009) argued that learning through analogical reasoning "requires a high level of guidance and learning hints" (p. 135). Instructional approaches should thus stimulate comparisons and develop learners' awareness of similarities in their pursuit of learning. For example, Reeves and Weisburg (1993) advocated for the use of concrete examples and scaffolded analogical transfer problems that become increasingly more abstract and different in terms of content. Instructors can help students map newly learned principles to surface feature similarities. Subsequent problems should be increasingly different in content to lead toward more abstract understanding of the principles. Similarly, case-based reasoning is a pedagogical technique for developing cognitive understanding to assist students in making useful analogical inferences (Kolodner, 1997). Case-based reasoning uses computational modeling to understand the roles of encoding, retrieval and adaptation in analogical reasoning processes. This line of research has educational implications including the need for students to be motivated to learn by applying their learning to real-world problems. Cases can provide this motivation by suggesting "issues to focus on and solutions to problems, warn of potential pitfalls, support projection of the effects of a chosen solution and so on, facilitating solution of more complex problems" (Kolodner, 1997, p. 62).

Daugherty and Mentzer (2008) explored the viability of instructional strategies that utilize analogical reasoning within a technology education context. They argued that instructors could model analogical reasoning for their technology education students. For example, a schema for systems theory (input → process → output with feedback loops) can be used to transfer understanding through analogical reasoning. By understanding how system components are interconnected, students can transfer that understanding to how the components of other technological devices interact. Daugherty and Mentzer offered inter-modal transportation as an example, wherein students can be encouraged to map the inputs (cargo), the processes (containerization) and the outputs (shipping, globalization, economic growth, etc.). Such explicit modeling of cognitive processes and analogical reasoning could significantly improve thinking and understanding in a technology education context.

CONCLUSIONS

This chapter highlighted the importance of fostering transfer of learning by focusing on cognitive and metacognitive principles. Building a deep understanding of knowledge and skills, with a base in underlying principles, is critical for learning that transfers to new and unfamiliar situations. By providing students with carefully selected learning experiences accompanied by scaffolded and problem-based instruction, engineering and technology education can serve as a vehicle for addressing the many challenges of learning transfer.

As highlighted by Perkins and Saloman (1992), the research on transfer is discouraging because most studies suggest that transfer is difficult to achieve for many reasons. However, upon closer examination of the conditions under which transfer occurs and the cognitive mechanisms that support learning transfer, we are left with a much more positive perspective. Education through engineering and technology education can achieve significant success in promoting transfer if it is properly designed in ways that support learning beyond superficial understanding.

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