Online ill-structured problem-solving strategies and their influence on problem-solving performance

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Online ill-structured problem-solving strategies and their influence on problem-solving performance

by

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in partial fulfillment of the requirements for the degree of

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2007

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ABSTRACT

Ill-structured problem-solving ability is key to success in our personal and professional lives. A small but growing body of research has investigated ill-structured problems; however, little if any research has examined strategies that individuals use while solving ill-structured problems in the context of a web-based problem-solving environment. Further, this research has not addressed the relationship between these strategies and problem-solving performance. Two objectives were addressed in the current study. The first objective was to characterize students’ ill-structured problem-solving strategies in a Web-based problem-solving environment. Cluster analysis revealed four groups of students who approached the same online problem-solving task in considerably different ways. Some students tended to focus on writing tasks, while others focused on exploring resources. Students also differed on their resource use, and the degree to which they discriminated relevant from irrelevant resources. The second objective was to examine the effect of these problem-solving strategies on students’ problem-solving performance. Forced-order hierarchical regression showed that the problem-solving strategies students used were significant predictors of problem solving performance when learner characteristics had been controlled. Results of the current study are discussed in light of previous research, and implications of the study for educators and for problem-solving researchers are presented.
CHAPTER 1. INTRODUCTION

Ill-structured problem-solving ability is key to success in our personal and professional lives because most of the real-life problems we encounter tend to be ill-structured in nature. We are constantly challenged by problems that may be as simple as deciding what to cook for dinner; or as complex as developing a strategy for addressing discipline problems that one’s child might have. Our ability to solve these problems is an important criteria for success and well-being. In fact, some have suggested that solving complex, ill-structured problems is a critical intellectual skill and the most important “learning outcome” in human life (Gagne, 1985; Jonassen, 2000).

In light of this, solving problems has become a key component of classroom instruction in the U.S. educational system. However, most school tasks are designed to engage learners in solving well-structured problems that are found at the end of textbook chapters or on standardized tests (Jonassen, 2000). Well-structured problems, unlike the kinds of problems typically encountered in real-life, are situated in artificially constructed and constrained problem contexts. These kinds of problems have single, definitive solutions that students can reach by simply applying previously learned concepts, rules, and/or principles (Bransford & Stein, 1984; Jonassen, 1997; Kitchener, 1983). Despite efforts to change them (NCTM, 1989; NRC, 1996), mathematics and science instruction continue to focus on reinforcing rules, principles, or facts by drilling these kinds of problems (Hiebert, Carpenter, Fennema, Fuson, Human, Murray, Olivier, & Wearne, 1996; Moreno, 1999). Many may still remember from their schooling experience calculating the area of a square when given the perimeter, applying Ohm’s law to find the
current passing through a conductor given the voltage and resistance of the conductor, or trying to balance a given chemical equation.

Many educators and researchers have recognized shortcomings with the use of well-structured problems with students (Jonassen, 2000; Kitchener, 1983; Lave, 1988; Rogoff & Lave, 1984; von Glasersfeld, 1995), after several decades of research on well-structured problem-solving (Alexander, 1992; Kuhn, 1991; Perkins & Salomon, 1989). Early problem-solving research typically focused on well-structured problems (puzzles, logic, and algorithm problems, etc.) in an attempt to generate universal problem-solving strategies (e.g. Ernst & Newell, 1969; Newell & Simon, 1972; Polya, 1957). General problem-solving strategies, or heuristics they identified were then taught directly to individuals in an effort to help them become better problem solvers. The researchers, however, found that these context-independent problem-solving strategies rarely transferred to novel real-life situations (Glaser & Chi, 1988; Pressley, Snyder, & Cariglia-Bull, 1987; Spiro, Feltovich, Jacobson, & Coulson, 1991). In fact, scholars indicated that the de-contextualized and oversimplified nature of well-structured problems has little or no resemblance to the problems individuals deal with in real-life contexts (Jonassen, 2000; Kitchener, 1983; Lave, 1988; Rogoff & Lave, 1984). In other words, findings from well-structured problem-solving research did not inform educators about how to improve their students’ problem-solving skills for the complex ill-structured problems they would likely encounter in their everyday lives.

Previous research suggested that performance on solving well-structured problems was independent of performance on solvers’ ability to solve complex, real life problems (Schraw, Dunkle, & Bendixen, 1995), and that the skills necessary for solving
well-structured problems were not sufficient when trying to solve ill-structured problems (Shin, Jonassen, & McGee, 2003). This means that solving complex real-life problems requires more than the application of the general heuristics that are used for solving well-structured problems. Real-life problems require the use of higher-level critical thinking and argumentative reasoning skills (Kuhn, 1991; Schraw et al., 1995; Shin et al., 2003).

Complex, real-life problems came to be known as ill-structured problems. These types of problems, set in realistic contexts, may require application of several concepts and/or principles from a variety of disciplines (math, science, social studies, etc.) rather than being constrained to a specific chapter of a textbook (Jonassen, 2000). Ill-structured problems typically involve conflicting viewpoints that may lead to several workable solutions (Kitchener, 1983). This means that there is no single correct way to approach the problem and a variety of different solutions or answers may be equally justifiable given one’s goals. For instance, a seemingly straightforward problem like buying a car when one is on a tight budget can become quite complex and challenging when one considers the many dynamic factors involved. One must consider initial cost, financing terms, gas mileage, price of insurance, as well as many other factors. The car with the lowest initial cost may seem like the best option because maximizing the down payment could minimize the amount of interest paid. However, when one has to keep the car for a longer period of time, paying more at the beginning might be a better option if the vehicle has a better gas mileage and is less likely to have costly mechanical problems.

Solving problems like the one above is fundamentally different from solving mathematics or science textbook problems. When solving a textbook problem, one needs to remember the right algorithm and use it correctly in order to find the single variable.
Solving ill-structured problems, on the other hand, requires one to attend to multiple contextual constraints and co-dependent factors that dynamically emerge from the problem context, approach the problem from multiple perspectives, and justify the proposed solution relative to competing alternative ones.

The fundamental differences between well-structured and ill-structured problems mean that solving ill-structured problems calls for different skills, strategies, and approaches (Schraw et al., 1995; Shin et al., 2003). A small but growing body of research has investigated the differences between solving processes of well-structured problems and ill-structured problems. However, little if any research has examined ill-structured problem-solving performance directly. Thus, research has not addressed individual factors that might influence ill-structured problem-solving performance, such as cognitive flexibility and argumentative reasoning skills (Schraw et al., 1995) or epistemological beliefs (Shin et al., 2003).

Problem-solving activities have also been integrated into web-based environments. Research has examined browsing strategies (Barab, Bowdish, & Lawless, 1997; Lawless & Kulikowich, 1996) or the role of epistemological beliefs and metacognitive awareness while learning with hypermedia (Bendixen & Hartley, 2003). However, the tasks in which students were asked to engage were well-structured in nature. There is little or no research investigating learners’ online behaviors and strategies that they use while solving ill-structured problems in the context of a web-based problem-solving environment. The present study was an examination of problem-solving strategies students used while solving an ill-structured problem in a web-based
environment, and how these strategies and individual factors influenced ill-structured problem-solving performance.

Gaps in the previous research pose at least two major questions. It is currently unclear a) what strategies individuals might use when solving an ill-structured problem in a web-based problem-solving environment or b) how these problem-solving strategies might influence ill-structured problem-solving performance when individual factors are controlled. If we are to better understand ill-structured problem-solving process, researchers must examine the influence of problem-solving strategies and intrapersonal factors in the ill-structured problem-solving processes.

The main purpose of this study is to examine students’ online problem-solving strategies and intrapersonal factors that influence their ill-structured problem-solving performance in the context of a web-based problem-solving environment. This purpose leads to the following research questions:

1. What kinds of problem-solving strategies do students use when solving ill-structured problems in a web-based environment?

2. How do students’ online problem-solving strategies relate to ill-structured problem-solving performance when learner characteristics such as domain knowledge, reading abilities, argumentative reasoning skills, metacognitive awareness, and epistemic beliefs are controlled?
CHAPTER 2. LITERATURE REVIEW OF RESEARCH ON PROBLEM-SOLVING

Problem-solving performance has been an important topic for educational researchers for several decades. A careful review of the literature on problem-solving reveals three major strands of research. The first major strand deals with problem types. Some investigators have adopted an analytical approach to understand and classify different types of problems based on a number of defining attributes. Researchers have also attempted to understand how individuals go about solving problems. Existing research suggests that solution strategies tend to differ based on the type of problem one is attempting to solve. Finally, a number of individual factors have been thought to influence problem-solving performance; i.e. domain knowledge, structural knowledge, cognitive flexibility, argumentative reasoning skills, metacognitive awareness, and epistemological beliefs, etc. In the remainder of this chapter these strands will be developed in more detail.

**Problem Types**

Researchers have analyzed problems based on the information distribution in their problem spaces and the nature of the task environments. Examination of problem spaces and task environments of problems has revealed several defining attributes to help understand and classify different types of problems (see Goel, 1992; Jonassen, 1997; Kitchener, 1983; Reitman, 1964; Simon, 1973). In fact, Goel (1992) examined task environments and problem spaces of different types of problems and explained them in
terms of these defining attributes. Moreover, based on a cognitive task analysis of hundreds of problems, Jonassen (2000) has identified 11 problem types including:

- logical problems,
- algorithmic problems,
- story problems,
- rule-using problems,
- decision-making problems,
- trouble-shooting problems,
- diagnosis-solution problems,
- strategic performance problems,
- case analysis problems,
- design problems,
- dilemmas.

(Five of the above problem types: logical, algorithmic, story, decision-making, and design problems will be further discussed later in this chapter.)

Defining attributes usually indicate a continuum along which different problem types reside. The distinction however is not absolute, meaning that aspects of the same types of problems may be at varying levels, and that different types of problems may overlap in certain attributes. However, in general these attributes help us classify problems in certain way. In the problem-solving literature the defining attributes of problem types are explained in terms of structuredness (information distribution in problem space), context-dependency, problem constraints, and success criteria (the nature of the task environment).

**Information Distribution in Problem Space**

Problem space includes the components of the problem and the solver’s interactions with them (Wood, 1983). Every problem has components such as beginning state, goal state, and series of transformation functions that help in the solution process.
Structuredness

Structuredness is related to information distribution in the problem space. In some problems, the beginning (initial) state clearly describes what is known while in others this is vaguely implied or left for solver to identify. Similarly, some problems may have well-defined goal states, which inform the solver of the nature of the solution (what the solution should be like). However, in other problems it may not even be obvious that there is a problem to be solved let alone define how the solution should look (Jonassen, 1997).

Moreover, each problem requires a set of operations to be carried out to reach the solution. These operations are often called transformation functions because they are used to transform the beginning state into the goal state (Goel, 1992). Again, problems differ in terms the transformation functions, on a continuum from well-defined to ill-defined. Some problems could be solved by employing a constrained number of straightforward operations that are well-specified as in algorithmic problems, whereas others may not have any specified functions to help solve the problem, as in deciding how to teach a certain topic.

Nature of the Task Environment

Task environment involves how the problem is presented to the solver, the nature of the solution process, and the solution.
**Context-dependency**

Problems show varying characteristics on the continuum from context-independent to context-dependent. Context dependency is the degree to which the context affects the problem-solving. All types of problems could be presented in a context to some extent but some problems are inherently context-dependent. In other words, some problems are quite abstract in nature while others tend to be situated in realistic contexts.

For example, puzzles and logical problems are context-independent and usually do not require application of any domain-specific knowledge for solution. Story problems are usually set in a shallow context and require constrained amount of domain knowledge for a solution (Jonassen, 2000). Conversely, medical diagnostic problems not only involve a significant amount of medical domain knowledge but also the medical history of the patient at hand and many other environmental factors.

**Problem constraints**

Another defining attribute for problems is the constraints inherent in the task environment. These constraints could be related to the nature of the solution process and/or the solution itself. The constraints in some problems are definitional and imposed by the problem space and explicitly stated in the beginning or goal state (Goel, 1992). For instance, in puzzles or logical problems rules and logical procedures are inherent to the problem and the solver must abide by these rules in order to solve problems. For example, in chess one is constrained by the rules of the game, otherwise he/she is not playing chess (Perkins & Salomon, 1989). Algorithmic and story problems usually have
well-specified constraints that are either definitional or forced by some natural law (Goel, 1992).

However, the constraints encountered in other problem situations can be loosely specified or unspecified but are only suggested by the problem context: social, economic, cultural, etc. (Goel, 1992). For example, medical diagnostic and treatment have contextual constraints that could be negotiated based on the patient’s age, physical condition, medical history, insurance plan, etc.

Success criteria

Problems also differ in terms of how the success of the solution is determined. Some problems have certain preferred solution paths that lead to the only right answer. The only way to succeed is by following an effective solution pathway and arriving at the right solution (Kitchener, 1983). For example, solving an arithmetic problem requires using specific math procedures correctly so that the right solution could be found.

However, some problems could be fairly ambiguous when it comes to determining the success of the solution because there can be multiple effective solutions. For instance, deciding what university to apply for a computer engineering graduate program depends on many factors. Likewise judging the success of one’s decision could be fairly challenging because there is no right or wrong solutions depending on one’s priorities and contextual constraints (financial aid availability, distance from home, focus of the program, etc.).
Problem-Solving Strategies

Some researchers have argued that there are certain general problem-solving strategies that effective problem solvers use to tackle different problems from a variety of subject domains (Ernst & Newell, 1969; Polya, 1954, 1957). This premise encouraged early problem-solving researchers to focus on understanding how these individuals deal with problems without paying much attention to the specific problem type or knowledge domain. The motivation mainly stemmed from an attempt to find these general problem-solving strategies and model them for novices to help them become effective problem solvers.

For example, Polya (1954) analyzed solving processes for mathematics problems. He argued that actual mathematics knowledge had little to do with solving mathematics problems: rather heuristics or general problem-solving strategies played a major role in finding the solution (Perkins & Salomon, 1989). These heuristics usually include recalling a familiar problem and applying the same solution strategy to the new problem, using visual aids to represent the problem in more comprehensible terms, and breaking the main problem into smaller and more manageable sub-problems. Researchers claimed that these heuristics were general enough that they could be applied to solve any kind of problem regardless of the problem type or knowledge domain.

Cognitive information processing researchers have also addressed this idea. Building on Polya’s work, other researchers have proposed general problem-solving strategies such as General Problem Solver (Newell & Simon, 1972) and IDEAL (Bransford & Stein, 1984). For example, the General Problem Solver (GPS) model was
based on using a means-end analysis to solve problems. This technique included several search strategies within the problem space that helped the problem solver decide which transformation functions to use in reducing the difference between the beginning state and goal state. This work helped support the idea that problem-solving was a general skill that could be taught to everyone.

These early heuristics then progressively developed into intelligent tutoring systems like ACT-R, Adaptive Control of Thought – Rational (Anderson, 1993), alongside the advancements in computer technology. ACT-R used sophisticated computer algorithms to simulate how humans execute higher-level cognitive tasks such as solving problems. The system was designed to solve problems by transforming declarative knowledge (encoding of examples) into procedural knowledge (production rules). When a problem was entered into the system, ACT-R checked for operations (transformation functions) that might help in the solution process, stored the successful operations and eliminated the ineffective ones. This process eventually led to a database of flexible heuristics. Thus, the next time a problem was encountered, the system started searching for similar problems and their solution strategies to use in solving the new problem.

Although contemporary intelligent tutoring systems like ACT-R are much more advanced than the early heuristics of Polya, the basic theory underlying them is fairly similar. They are grounded in the notion that general problem-solving strategies can be used to solve all types of problems. Conversely, scholars have provided a counter argument against the power of general strategies in solving all types of problems. They have shown that teaching general problem-solving strategies did not help individuals in
transferring their skills to unique situations (Glaser & Chi, 1988; Pressley et al., 1987; Spiro et al., 1991; von Glasersfeld, 1995). Moreover, different types of problems have been reported to call for different kinds of problem-solving strategies (Jonassen, 1997; Shin, Jonassen, & McGee, 2003).

**Individual Factors**

Besides the problem types and different strategies to solve them, there seems to be some intrapersonal factors that may influence the problem-solving performance.

**Domain Knowledge**

Research on cognitive psychology has noted that individuals’ problem-solving performance depended on what they already knew about the subject matter (Glaser, 1984). This knowledge is often referred to as domain specific knowledge. Domain knowledge combines the knowledge of facts or concepts (declarative or content knowledge) and the knowledge of how to carry out certain operations and procedures (procedural knowledge) in a specific domain (e.g., geography, mathematics, medicine, etc.)

Although some problems tend to be domain independent and do not rely on domain specific content knowledge like puzzles or logical problems, most problems require solvers to possess a certain amount of domain knowledge.

Another aspect of domain knowledge that is addressed by many researchers is structural knowledge. Cognitive scientists have extensively investigated human cognition and knowledge structure in terms of schemata (e.g. Anderson, 1981; Rumelhart, 1980).
Researchers claimed that schemata are the basic units of human knowledge. A schema is defined as an organized web of knowledge. Schema research has demonstrated that an existing web of knowledge (schemata) influences the way new information is interpreted and acquired; new knowledge in return causes the existing schemata to change in order to accommodate discrepancies (Pichert & Anderson, 1978).

Based on this theory, individuals not only need to know the concepts and procedures in a specific domain but also they need an organized web that meaningfully connects their domain knowledge together (schemata) in order to solve problems effectively. Rich and well-organized schemata in a specific domain will help individuals access appropriate concepts and procedures when searching for solutions to problems in the respective domain (Greeno, Collins, & Resnick, 1996). Jonassen (2000) defines this connected web of domain knowledge as well-integrated domain knowledge.

**Cognitive Flexibility**

Cognitive flexibility is defined as the ability to flexibly reconstruct and modify one’s knowledge in an effort to satisfy the dynamic needs of a complex problem-solving situation (Spiro & Jehng, 1990). The main premise of the cognitive flexibility theory is that in complex knowledge domains knowledge acquisition can be accomplished by visiting and revisiting the subject matter several times coming from multiple directions with different purposes in mind (Spiro, Vispoel, Schmitz, Samarapungavan, & Boerger 1987; Spiro et al., 1991). It has been thought that cognitive flexibility is an important skill in solving real-world problems where there are contradicting perspectives that lead to multiple interpretations of the problem (Jonassen, 1997). Individuals must attend to all
these alternative viewpoints and consider several different solution options to be a successful problem solver.

**Argumentative Reasoning Skills**

Argumentative reasoning is regarded as the ability to critically evaluate one’s own thoughts, beliefs, or decisions to justify their legitimacy. In fact, “thinking as argument is implicated in all of the beliefs people hold, the judgments they make, and the conclusions they come to. It arises every time a significant decision must be made” (Kuhn, 1991, p.3). However, such ability to formulate and evaluate well-reasoned arguments with regard to competing alternatives is an exception in most individuals (Kuhn, 1991).

Argumentative reasoning skills are thought to be important in solving complex real-world problems. The fact that there is not one right answer and typically little immediate feedback to confirm the solution in real-world situations (Goel, 1992), learners have to justify their proposed solutions. The justification process forces learners to reflect on their decision making criteria and the consequences of proposed actions within a given problem context. This requires learners to use their critical thinking and argumentative reasoning skills throughout the problem-solving process.

**Metacognitive Awareness**

Metacognition, also referred as cognitive monitoring (Flavell, 1979) or executive processes (Brown, 1987), is defined as “second-order cognitions: thoughts about thoughts, knowledge about knowledge, or reflections about actions” (Weinert, 1987, p.8). While cognitive skills help individuals perform a task, metacognitive skills enable them
to understand and regulate their performance (Schraw, 1994). In other words, metacognitive awareness is one’s awareness of his/her cognitive skills (weaknesses or strengths) and strategies for monitoring and regulating those skills. Reading a passage to understand what the author is trying to say utilizes one’s cognitive skills whereas reading the same passage to determine how difficult it is or deciding when and why to use the information in the text to solve a problem is considered metacognitive level activity.

Metacognitive awareness has been reported to include two major factors: knowledge of cognition and regulation of cognition (Schraw & Dennison, 1994). Knowledge of cognition is one’s knowledge about his/her strengths and weaknesses, strategies, how to use those strategies, and when and why to use them. Regulation of cognition on the other hand helps regulate one’s knowledge about his/her cognition through planning, monitoring, and evaluation (Schraw & Dennison, 1994).

**Epistemological Beliefs**

Epistemological beliefs are the beliefs individuals hold regarding the nature of knowledge and knowing. These are somewhat personal theories that people come to develop regarding questions like “What is knowledge?” and “How do people come to know?”

Perry (1970) described epistemological beliefs as being nine developmental stages individuals may go through. He claimed that these stages were clustered into three periods: simplistic (dualistic), more complex (multiplicity), and contextual (relativistic). Initially people hold naïve beliefs about knowledge as being either right or wrong. Eventually, this dualistic view develops into more complex reasoning where diversity of
viewpoints is valued and absolute answers are associated only with the authority. The last stage brings in more doubts and uncertainty about the absolute truth and notion of contextual relativism enters the stage (Hofer & Pintrich, 1997). Researchers speculated that the development of these beliefs was more related to the shifting nature of contextual exposures than cognitive skills (Louca, Elby, Hammer, & Kagey, 2004).

Extending Perry’s notion, Schommer (1990) proposed that epistemological beliefs consist of five independent dimensions concerning beliefs about knowledge: certain knowledge, simple knowledge, omniscient authority, quick learning, and fixed ability. In a study, Schommer (1990) asked 117 junior college and 149 university students to complete the Epistemological questionnaire. Four of the five proposed dimensions (innate ability, simple knowledge, quick learning, and certain knowledge) of epistemological beliefs emerged as factors.

As a follow up on the Schommer’s study Schraw, Dunkle, and Bendixen (1995) constructed the Epistemic Beliefs Inventory and tested it with 212 university students in a large Midwestern university. All of the dimensions Schommer suggested emerged as factors. There is on the other hand a note of caution regarding the fixed ability factor. Some have suggested that beliefs about the nature of intelligence or ability are not part of the construct of epistemological beliefs (Hofer & Pintrich, 1997).

**Conclusion**

In conclusion, the literature on problem-solving performance indicates a historical progression. Initially, a vast amount of research was conducted on puzzles, and on logical and algorithmic problems, in an attempt to produce general problem-solving strategies.
This research trend proved useful for teaching certain kinds of problem-solving skills. However, it was when researchers started investigating performance on solving real-world problems that they realized solving these kinds of problems required different kinds of problem-solving strategies and skills. This led investigators to classify problems in terms of two major category well-structured and ill-structured (i.e. Goel, 1992; Jonassen, 1997; Kitchener, 1983). Although Jonassen (2000) posited numerous, somewhat distinct problem types, these problems in general fall on either the well-structured or ill-structured side of the continuum in terms of the defining attributes discussed earlier. Literature on problem-solving strategies and individual factors that influence problem-solving performance also denote this distinction.

**Well-structured Problems**

The problems that are often found in standardized tests or at the end of textbook chapters such as logical, algorithmic, and story problems are mainly well-structured in nature (Jonassen, 2000). These problems have well-defined beginning states, goal states, and transformation functions (Goel, 1992). They are typically context-independent or situated in shallow and/or artificial contexts. Constraints are also artificial and usually stated in the problem statement. Finally, the success is determined by the effectiveness of the solution path and the accuracy of the solution, whether it matches the correct solution or not.
For example, consider the following problems:

Table 2.1: *Sample Well-structured Problems*

<table>
<thead>
<tr>
<th>Problem type</th>
<th>Sample problem</th>
</tr>
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<tbody>
<tr>
<td>Logical</td>
<td>You want to send a diamond necklace to a friend. You have a box to contain the necklace. The box has a locking ring that is more than large enough to have a lock attached. You and your friend have several locks with keys. But your friend does not have the key to any lock that you have, and vice versa. How do you do it? Note that you cannot send a key in an unlocked box, since it might be copied.</td>
</tr>
<tr>
<td>Algorithmic</td>
<td>The boiling point for water is 212 Fahrenheit at 0 ft altitude. Find the boiling point for water in Celsius degree at 0 meter altitude.</td>
</tr>
<tr>
<td>Story</td>
<td>John drops a brick off a chimney from the top of a roof located 20 meters above the ground. Determine the time required for the brick to reach the ground.</td>
</tr>
</tbody>
</table>

The problems in Table 2.1 seem quite different in nature. These problems vary in difficulty for different individuals because they require different kinds of skills, domain knowledge, and solution strategies. The first problem is logical and requires some analytical skills; the second one is an algorithmic problem that can easily be solved by converting Fahrenheit to Celsius. The third problem is a story problem that calls for basic physics knowledge and could be solved by simply applying the free fall formula.

However, when their problem spaces are examined (see Table 2.2), one can see that all of these problems have well-defined beginning and goal states (Goel, 1992). In other words, what is known, what the problem is, and the nature of the solution are all clearly described. Moreover, a constrained number of straightforward logical and/or mathematical operations (transformation functions) can simply be applied to transform their beginning states to goal states. Thus, well-structured problems are sometimes referred as application (Jonassen, 1997) or transformation problems (Greeno, 1978).
Table 2.2: Components of Well-structured Problems

<table>
<thead>
<tr>
<th>Problem</th>
<th>Beginning state</th>
<th>Goal state</th>
<th>Transformation function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logical</td>
<td>You have a box containing a diamond necklace. The box has a locking ring that is more than large enough to have a lock attached. You and your friend have several locks with keys. But your friend does not have the key to any lock that you have, and vice versa.</td>
<td>You want to send the diamond necklace to your friend. Note that you cannot send a key in an unlocked box, since it might be copied.</td>
<td>Number of logical operations</td>
</tr>
<tr>
<td>Algorithmic</td>
<td>The boiling point for water is 212 Fahrenheit at 0 ft altitude.</td>
<td>Find the boiling point for water in Celsius degree at 0 meter altitude.</td>
<td>[(F - 32) \times \frac{5}{9} = C] 0 ft = 0 meter</td>
</tr>
<tr>
<td>Story</td>
<td>John drops a brick of a chimney from the top of a roof located 20 meters above the ground.</td>
<td>Determine the time required for the brick to reach the ground.</td>
<td>[d = \frac{1}{2}gt^2] [g = 9.8]</td>
</tr>
</tbody>
</table>

These problems are artificially constructed and situated in shallow contexts. They are also constrained to a specific knowledge base so that a limited set of concepts, principles, and rules (Jonassen, 1997; 2000) are to be applied in the solution process.

The task environments impose the problem constraints. These constraints are either clearly stated in the beginning and goal states (as in the logical problem: “Note that you cannot send a key in an unlocked box, since it might be copied” and in the algorithmic problem: “find the boiling point of water in Celsius”) or dictated by natural law (as in story problem: acceleration of gravity for free-falling objects is 9.8).

In all three problems, a limited number of preferred solution paths and prescribed procedures can be identified to reach the definitive, correct solution (Kitchener, 1983).
This means that those who are able to choose the correct transformation functions (see Table 2.2) and follow them in the right sequence will most likely find the desired solution (successfully transform beginning state to the goal state) whereas those who do not know the required functions or do not know how to use them correctly will fail. In other words, all of these problems have certain, desired, logical solution strategies that lead to the only correct solution.

**Problem-Solving Strategies for Well-structured Problems**

Solving process for well-structured problems has been a central focus for many studies. In fact, problem-solving literature is replete with research conducted to understand how individuals solve well-structured problems (i.e., Ernst & Newell, 1969; Greeno, 1978; Polya, 1954). As mentioned earlier, the main motivation for these studies came from a hypothesis that emphasized the power of general problem-solving strategies.

Polya (1954) indicated that problem-solving involved a) understanding the problem, b) developing a plan, c) executing the plan, and d) checking the results. These problem-solving processes represent the basic structure for information processing models that were developed later to simulate how individuals solve well-structured problems, such as, the General Problem Solver (Newell & Simon, 1972), IDEAL (Bransford & Stein, 1984), and ACT-R (Anderson, 1993).

Based on these models, when faced with a problem individuals first try to understand the problem by analyzing its components, beginning and goal states. Since well-structured problems have well-defined beginning and goal states, solvers should be able to identify the givens, nature of the acceptable solution, and their task by
deconstructing the problem statement. This allows them to create their own mental models of the problem (problem space) and situate the problem within their existing schema (Voss, Wolfe, Lawrence, & Engle, 1991).

If the solvers can associate a given problem with a familiar problem type, they try to recall the solution strategies they used to solve similar problems. Then, they proceed with executing the plan by mapping known solution strategies onto the new problem (Jonassen, 1997). However, if the solvers have never dealt with a similar problem before or they fail to activate the relevant schema, then they start using some general heuristics. Means-end analysis and generate and test (weak methods) are some of the heuristics solvers use to generate different solution hypotheses while trying to eliminate the discrepancy between the beginning state and goal state. Solvers’ domain specific knowledge and their monitoring skills are central to their performance during this process (Glaser, 1984; Lester, 1994).

Finally, after generating appropriate operations and applying them to find the solution, solvers try to determine the success of the solution. If the solution exactly matches the one described in the goal state, then it is satisfied and the task is completed. However, if the solution does not satisfy the goal state, the solvers go back to repeat earlier steps to define and correct any mistakes made in the solution process. This continues until the right solution is found.

**Individual Factors Influencing Well-structured Problem-Solving**

Well-structured problem-solving performance, in general, is explained in terms of the solvers’ ability in using general problem-solving strategies. However, besides these
general problem-solving strategies, there appears to be a number of individual factors that mediate performance in solving well-structured problems.

**Domain Knowledge**

Further research on general heuristics eventually showed that individuals who possessed general heuristics for solving problems did not know how to use them when they did not have enough domain specific knowledge (Schoenfeld, 1985). In fact, Simon (1980) argued that expertise in problem-solving could not be achieved without domain knowledge. In addition, research on cognitive skills and problem-solving revealed more insights into the distinction between expert and novice problem solvers in terms of well-structured problem-solving performance (e.g. Chi, Feltovich, & Glaser, 1981; Rabinowitz & Glaser, 1985; Schoenfeld & Herrmann, 1982).

Experts were reported to have vast amount of well-integrated domain knowledge that leads to rich schema structures, including domain specific algorithm, concepts, principles, and rules (structural knowledge) (Jonassen, 1997). Thanks to their existing schema structures, experts successfully analyze problem situations and quickly recall appropriate domain specific patterns including concepts, principles, and rules within a particular domain and apply them effectively towards the solution of the problem (Perkins & Salomon, 1989).

Moreover, even when experts cannot find and activate an applicable solution strategy to map onto the current problem within their existing schema, they can still recall domain specific algorithms (strong methods) to use in solving the problem. Novices who did not possess enough domain knowledge were reported to use domain general
heuristics (weak methods) that did not guarantee a solution (Jonassen, 2000). This proved that domain knowledge was more important than general problem-solving strategies in problem-solving.

**Metacognitive Awareness**

Solvers use of cognitive skills depends on their awareness of those skills. For example, when encountering a problem, solvers need to assess what domain specific knowledge (algorithms, principles, rules, etc.) they possess applicable to this problem situation, then know how and when to apply this knowledge towards the solution of the problem (Schraw & Dennison, 1994). This is referred to as knowledge of cognition (Schraw, 1998). Besides knowledge of cognition, solvers also need to regulate their cognition (regulation of cognition) (Schraw, 1998) in order to succeed in problem-solving. For example, solvers need to monitor their problem-solving performance regularly, evaluate the effectiveness of the strategies used, and plan out new strategies relative to the success of previous plans, time, and other constraints.

Research with grade school students showed that metacognitive activities (planning and monitoring) were associated with improved use of problem-solving heuristics (Artzt & Armour-Thomas, 1992). It was also reported that students with high metacognitive skills were faster in solving problems than those with low metacognitive skills, even though they had lower aptitude and they did not differ in terms of strategy use (Swanson, 1990). However, in a study with 9th grade high school students, neither knowledge of cognition nor regulation of cognition (metacognitive awareness) was a significant factor in well-structured problem-solving performance (Shin et al., 2003).
Shin et al. concluded that this might be because well-structured problems were not challenging enough for students to use their metacognitive skills; rather they simply activated their existing solution schemas.

**Argumentative Reasoning Skills**

As mentioned earlier, argumentative reasoning skills are also referred to as justification skills (Kitchener, 1983). Although there is some indication that these skills mediate performance on solving well-structured problems (Shin et al., 2003), they are mainly attributed to ill-structured problem-solving because of the need for constructing arguments to provide justification for the proposed solution relative to alternative solution options.

In the Shin et al. study, 9th grade high school students were given a scenario related to an astronomy course content where they practiced solving several well- and ill-structured problems. The students then were asked to provide logical argumentation for the importance of given interview questions related to astronomy concepts as represented in the scenario. Based on students written responses to this task, researchers found that justification skills were significant predictor in students’ performance solving well-structured problems in the same domain.

However, Kuhn (1991) argues that justification (argumentative reasoning) skills indicate individuals’ ability to critically evaluate their own thoughts, beliefs, or decisions to justify their legitimacy. In other words, justification skills are related to students’ ability to provide rationale for their decisions and justification for their solution preference relative to alternatives. In the Shin et al. study, on the other hand, students
were expected to elaborate on how important concepts in the given scenario were related to one another in a narrative format. The fact that justification skills and domain knowledge were significantly correlated suggests that what the researchers measured in the Shin et al. study might actually be a component of structural knowledge rather than justification skills.

**Ill-structured Problems**

The problems that are encountered in real-life settings like decision-making and design problems tend to be ill-structured. The beginning state, goal state, and transformation functions are not well specified in these kinds of problems. Ill-structured problems are typically situated in realistic contexts rather than being constrained to a specific topic in a textbook. This means that the solving process of ill-structured problems often requires application of knowledge from diverse subject domains. Constraints are ill-defined or defined loosely in the problem statement. These constraints usually emerge from the problem context that may involve social, economic, cultural, etc. issues and are open to solvers interpretations and negotiation (Goel, 1992). Finally, the effectiveness of the proposed solution determines its success and relative merit compared to alternative solutions.
For instance, consider the problems in Table 2.3:

Table 2.3: Sample Ill-structured Problems

<table>
<thead>
<tr>
<th>Problem type</th>
<th>Sample problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision making</td>
<td>I inherited ten thousand dollars. Where should I invest it for the maximum gain: bonds, stock market, savings account, gold, or something else?</td>
</tr>
<tr>
<td>Design</td>
<td>I have a backyard with some trees. I want to design a swimming pool with the maximum possible length for practicing laps without having to cut down too many trees and going over a budget of eight thousand dollars.</td>
</tr>
</tbody>
</table>

When we examine the problem spaces of the problems in Table 2.4, we can see that these problems significantly differ from well-structured problems in terms of the degree to which the information (givens, rules, functions, etc.) is defined for the solver. For example, the beginning and goal states of these problems merely scratch the surface of the problem situations. The solvers need to gather a lot more information than what is disclosed in the problem statement in order to make any informed decision (Goel, 1992). In addition, there is no straightforward transformation function that could be applied to transform beginning states into the goal states. Solvers’ interpretation of the beginning state, goal state, and any other additional information regarding the problem context will help determine the kinds of operations they will use in solving these problems. While solving ill-structured problems, solvers even can manipulate the constraints and stakeholders’ expectations in order to construct a problem space that will better fit their existing schema (Goel, 1992).

These problems are situated in rich, realistic contexts and unlike well-structured problems, they are not constrained to a specific knowledge base. In fact, the solution process of ill-structured problems may require application of domain knowledge from multiple disciplines (Jonassen, 2000). For instance, deciding where to invest your money
for the best gain may require application of concepts, principles, and rules from math, 
statistics, and economics.

Solvers’ performance in solving these problems depends heavily on their 
understanding of the contextual constraints. These constraints are not completely 
described in the problem statement but they emerge from examination of the problem 
context. For example, in the decision-making problem only how much money is to be 
invested and that the maximum gain is desired are explicitly communicated as 
constraints. However, many other considerations are not communicated such as long- or 
short-term growth or whether or not immediate capital is needed. In the design problem 
for instance, timeline, how many trees are too many, the specifications of the backyard 
(length, width, where the trees are located) and how much of it the owner is willing to 
allocate for the pool are quite ambiguous. These constraints could only be identified 
through examination of the problem context and negotiation between the designer and the 
house owner.

In both problems, numerous valid solution paths and solutions can be identified 
(Kitchener, 1983) depending on one’s own goals, priorities, and problem constraints. 
Thus “there is uncertainty about which concepts, rules, and principles are required and 
how they are organized” (Jonassen, 2000, p. 67). In the decision-making problem, there 
are numerous factors that may influence the effectiveness of the solution. For example, 
the stock market seems like a profitable investment option, however one may have a hard 
time deciding in which stock to invest and can never guarantee how much and if there 
will be any profit from it. A savings account on the other hand might be a safe investment 
option in the long run but may not be the most profitable investment. This means that
solvers may have to make several value judgments during the problem-solving process. They must reflect on their decision making criteria and the consequences of proposed actions within a given problem context to provide justification for their actions. Since there is no right solution, each solution is evaluated based on its relative merit compared to alternatives and the soundness of justification provided by the solver.

Table 2.4: Components of Ill-structured Problems

<table>
<thead>
<tr>
<th>Problem</th>
<th>Beginning state</th>
<th>Goal state</th>
<th>Transformation function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision making</td>
<td>I have ten thousand dollars to invest.</td>
<td>How should I invest my money for the maximum gain: bonds, stock market, savings account, or gold? (Specifics are not clearly defined but rather are open for negotiation)</td>
<td>Functions related to arithmetic, statistics, economics, etc depending on the course of actions one might take</td>
</tr>
<tr>
<td>Design</td>
<td>I have a backyard with some trees.</td>
<td>How can I design a swimming pool with the maximum possible length for practicing laps without having to cut down too many trees and going over a budget of eight thousand dollars? (Specifics are not clearly defined but rather are open for negotiation)</td>
<td>Functions related to arithmetic, geometry, etc. depending on the course of actions one might take</td>
</tr>
</tbody>
</table>
Problem-Solving Strategies for Ill-structured Problems

Voss & Post (1988) and Sinnott (1989) conducted qualitative research using think-aloud protocols in order to understand the solving process of ill-structured problems. Similar to the solving process of well-structured problems, three major steps emerged in both studies that explained how individuals approach solving ill-structured problems. These include: a) constructing the problem space, b) generating solutions, and c) monitoring and evaluating the solution.

However, these studies have also provided insights into how the nature of ill-structured problem-solving process significantly differed from the solving process of well-structured problems. These researchers stressed the importance of reflective, dialectic nature of the ill-structured problem-solving process, as opposed to the solving process for well-structured problems that can be reduced to a systematic search for general problem-solving strategies to be used in solution (Sinnott, 1989; Voss & Post, 1988). In fact, the solving process of ill-structured problems is conceptualized as a “reflective conversation between the problem solver and the elements of the problem situation” (Jonassen, 1997, p. 79).

Jonassen (1997) developed a framework for solving ill-structured problems by further elaborating on Sinnott’s problem-solving process (see Table 2.5). According to Jonassen, while solving ill-structured problems, problem solvers first start constructing the problem space. They do this by interpreting the problem elements and contextual constraints and articulating the stakeholders’ alternative viewpoints. As discussed earlier, in ill-structured problems, problem elements (beginning state, goal state, and transformation functions) and constraints are not clearly specified in the problem.
statement for the solver (Chi & Glasier, 1985). Instead for the most part it is up to the solvers to confirm that there is in fact a problem. Then, they need to decide what information, concepts, or principles are relevant to the given problem context; and negotiate with the stakeholders regarding the goals and priorities in relation to problem constrains in order to construct the problem space. The dialectic nature of constructing the problem space leads to multiple possible problem spaces depending on the solvers interaction with stakeholders and their interpretation of the problem elements and constraints. Successful problem solvers consider several problem spaces that include all of the possible causes of the problem and contradicting perspectives concerning the problem.

Next, solvers generate possible solutions to alleviate causes of the problem at hand. They begin trying to situate the problem in their existing knowledge base in order to understand it in terms of what they know. They do this by creating their own mental representations of the problem (problem schema) through analyzing and interpreting the problem context, from which they propose alternative solutions (Jonassen, 1997).

Generating alternative solutions for ill-structured problems requires solvers not only to use their domain (conceptual) knowledge and prior experience but also to make reflective judgments (Kitchener & King, 1981) regarding the ambiguous nature of the problem space. When solving well-structured problems, solvers have comprehensible criteria to check their solution ideas against whereas in solving ill-structured problems “there are no right or wrong terminating states” (Goel, 1992). The evaluation criteria for alternative solutions are usually constructed through solvers’ negotiation with the stakeholders in light of the interaction between their problem schema and the causes and constraints of
the problem situation. In other words, solvers must make decisions regarding the validity
of alternative solutions based on not only their knowledge but also perceptions and
beliefs.

The existence of multiple alternative solutions, evaluation criteria, and
contradicting perspectives surrounding ill-structured problems force solvers to engage in
a recursive, reflective monitoring process. In fact, solvers try to “reconcile the uncertainty
of knowledge through the process of inquiry into their beliefs” (Jonassen, 1997, p.80).
Solvers evaluate the viability of alternative solutions and justify their decisions and
actions through argumentative reasoning in reference to their personal beliefs and values.
They iteratively eliminate alternative solutions and try to come up with a solution that
will alleviate all of the possible causes and be agreed upon by the stakeholders. After
implementing the solution or reflecting on possible consequences of the proposed
solution, they evaluate the relative merit of solution and adapt it in light of their
perceptions.

Table 2.5: Solving Process of Ill-structured Problems

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Construct problem space</td>
<td>Interpret problem elements and contextual constraints</td>
</tr>
<tr>
<td></td>
<td>Articulate stakeholders’ alternative viewpoints</td>
</tr>
<tr>
<td>Generate solutions</td>
<td>Generate possible solutions</td>
</tr>
<tr>
<td>Monitor solutions</td>
<td>Asses the viability of alternative solutions and elaborate on personal beliefs</td>
</tr>
<tr>
<td></td>
<td>Monitor the problem space and solution options</td>
</tr>
<tr>
<td></td>
<td>Implement and evaluate the solution</td>
</tr>
<tr>
<td></td>
<td>Adapt the solution</td>
</tr>
</tbody>
</table>
**Ill-structured Problems in Instruction**

Educators have realized the potential power of integrating ill-structured problems in teaching. Some suggested that knowledge is situated (Brown, Collins, & Duguid, 1989); thus, in order for individuals to be good problem solvers in real life, instruction should involve immersing them in authentic activities and culture in realistic learning contexts (Brown et al., 1989; Lave & Wenger, 1991). The notion of situated cognition maintains that the use of ill-structured problems in instruction may possibly enable teachers to enhance student learning through interconnected, meaningful, and intentional involvement in interesting and complex tasks situated in realistic problem contexts.

Teaching with ill-structured problems in universities is not a new concept. Numerous medical, business, engineering, and law schools have based their curriculum around ill-structured, real-world, problems in an attempt to prepare young professionals for their future occupation (Camp, 1996; Savery & Duffy, 1995). In this teaching method, called problem-based learning (PBL), authentic problems drive the learning. Learners are motivated to learn the content to solve problems a practicing professional in the field would encounter. They can utilize available resources and consult professors to comprehend the important concepts in the solution of the problem (Savery & Duffy, 1995).

Problem-based learning (PBL) has found many applications in technology-enhanced learning environments. Jonassen’s (1999) instructional design framework, Constructivist Learning Environments (CLEs), provides a guideline for technology-enhanced problem-based learning environments. The Jasper Woodbury project at
Vanderbilt (Cognition and Technology Group at Vanderbilt, 1996) is a good example: video clips are used to present mathematics problems embedded in real-life situations. This provides opportunities for using mathematical concepts, principles, and reasoning in order to offer a feasible solution to a realistic problem. Middle School Mathematics Through Application Project at the Institute for Research on Learning (Moschkovich, 1994; as cited in Greeno & Collins, 1996), and Interactive Multimedia Exercises (IMMEX) Project at the Center for Research on Evaluation, Standards, and Student Testing (CRESST) (Chung, de Vries, Cheak, Stevens, & Bewley, 2002) are some web-based learning environments where ill-structured problem-solving is at the core of the learning activities.

Investigators have examined browsing strategies employed while learning with hypermedia environments (Barab, Bowdish, & Lawless, 1997; Lawless & Kulikowich, 1996) but the task learners were asked to complete was mainly related to reading comprehension. Another study focused on the role of epistemological beliefs and metacognitive awareness in learning with hypermedia (Bendixen & Hartley, 2003). However, the nature of the task was well-structured (learners were asked to read text passages embedded in a hypermedia environment and then to respond to several short answer questions related to some factual information found on the hypermedia environment).

Additionally, researchers have investigated learners’ think-aloud protocols while solving an ill-structured problem using a web-based problem-solving assessment (Chung, et al., 2002). Even though Chung et al. used learners’ clickstream data for cognitive validation purpose, they did not analyze it quantitatively to examine learners’ browsing
strategies. Research is lacking that investigates learners’ online behaviors and the strategies they use while solving ill-structured problems in the context of a web-based problem-solving environment.

**Individual Factors Influencing Ill-structured Problem-Solving Performance**

Ill-structured problems have been reported to call for a different set of individual factors than well-structured problems. Careful examination of the ill-structured problem-solving process yields several important factors, i.e. cognition, argumentative reasoning, metacognitive awareness, and epistemological beliefs, that may mediate problem-solving performance (e.g. Jonassen, 1997, 2000; Kitchener, 1983; Kuhn, 1991; Schraw et al., 1995).

**Domain Knowledge**

Domain knowledge was found to be a significant factor in performance on solving ill-structured problems (Shin et al., 2003). It is also thought that structural knowledge might be a more important factor in solving ill structured problems than basic content (factual) knowledge (Jonassen, 2000). The importance of structural knowledge supercede that of factual knowledge because solvers not only need to know the principles and concepts in a specific domain but also must be able to establish the interrelationships among those principles and concepts to be successful in solving ill-structured problems.
Cognitive Flexibility

Being cognitively flexible means that the individual is aware that in any given problem situation there are multiple ways of approaching the problem and that alternative solutions are available (Martin & Rubin, 1995). Those who are willing to consider alternatives and adjust their strategies are thought to be more successful in problem-solving situations (Jonassen, 2000) specifically in ill-structured problem-solving.

Cognitive flexibility is an important skill especially solving problems in complex, ill-structured domains. In ill-structured knowledge domains, problems can be interpreted from multiple perspectives and solution proposals are evaluated based on a dynamic set of criteria. “It is only through the use of multiple schemata, concepts, and thematic perspectives that the multi-faced nature of the content area can be represented and appreciated” (Jacobson, as cited in Jonassen, 1997, p.80). This makes it necessary that the solvers understand the problem from multiple perspectives and consider alternative solution options before committing to any kind of solution. However, there is no empirical evidence to date linking cognitive flexibility skills in performance on solving ill-structured problems.

Argumentative Reasoning Skills

Argumentative reasoning skills, also referred as justification skills, are thought to be an important factor when solving problems that have no definitive, right solutions (Jonassen, 1997; Shin et al., 2003). These problems usually involve multiple viewpoints that sometimes may contradict with one another. This may require one to make value judgments concerning the viability and applicability of these differing viewpoints. Thus
the value of a solution depends heavily on one’s interpretation of the problem space and the evaluation of one’s own reasoning. The importance of argumentative reasoning skills are often discussed yet empirical data that demonstrates how they are related to problem-solving process is rare.

**Metacognitive Awareness**

Metacognitive skills are assumed to enhance performance in solving problems that are complex and ill-structured (Flavell, 1987; Jonassen, 1997; Jacobs & Paris, 1987). Because of the cognitive effort required by ill-structured problem-solving, solvers need to rely on their metacognitive skills in order to regulate their cognition effectively. Planning different strategies and evaluating them in relation to the problem situation are necessary skills in solving ill-structured problems (Jonassen, 1997). In fact, regulation of cognition was a significant predictor in high school students’ ill-structured problem-solving performance (Shin et al., 2003).

Despite the fact that metacognitive skills are mentioned frequently as an important factor of performance in the problem-solving literature, there is little research investigating the role of metacognition in solving ill-structured problems (Jonassen, 2000; Shin at al., 2003).

**Epistemological Beliefs**

Unlike Flavell (1979) who thought metacognition was the most important factor in understanding how people make conscious decisions while solving problems, Kitchener (1983) argued that there is even a meta level metacognition that operates when
people attempt to solve realistic problems that involve complex decision-making. Besides knowing what they know and what this knowledge means in terms of the problem and being able to plan and carry out strategies, solvers need to perceive the problem from a global perspective, and decide whether there is in fact a solution to this problem (Jonassen, 1997).

It was found that when asked to read a passage and provide a concluding paragraph, undergraduate students holding beliefs in simple knowledge and certain knowledge gave simple and inappropriate absolute conclusions (Schommer, 1990). Schoenfeld (1985) reported that even experienced students holding beliefs in quick learning who were asked to solve mathematics problems quit after five or ten minutes. Moreover, beliefs in simple knowledge were found to negatively affect complex problem-solving (Schommer, Crouse, & Rhodes, 1992).

**Chapter Summary**

In this chapter, three main strands of problem-solving research: (1) problem types, (2) problem-solving strategies, and (3) individual characteristics influencing problem-solving performance were reviewed. In light of these research strands, two major problem types – well-structured and ill-structured – were examined. The differences between the two types of problems indicated that solving strategies for well-structured problems did not sufficiently capture the essence of the strategies used to solve ill-structured problems. In addition, ill-structured problems were reported to call for different set of skills than those needed to solve well-structured problems.
Furthermore, the review of literature suggested that it is important to provide students with opportunities to develop their skills necessary for dealing with ill-structured, real-life problems. Yet the research investigating ill-structured problem-solving strategies and their effect on performance is limited. This study was conducted to build upon the existing research on ill-structured problem-solving and extend the previous research findings.

The research questions for this study involved understanding and characterizing the strategies individuals used to solve an ill-structured problem in a Web-based environment; and examine the effect of these strategies on students’ problem-solving performance. The following chapter will describe how this study was conducted.
CHAPTER 3. METHOD

Context of the Study

This study was implemented in an undergraduate course offered in the Curriculum & Instruction department at a large Mid-western university. The course is an Introductory Instructional Technology course that is required for those wishing to obtain teaching licensure at the secondary level. Course content covers both theory and practice concerning how educational technologies can be successfully integrated into classroom environments emphasizing meaningful learning for students.

Students attend two one-hour lectures and one two-hour lab sessions each week. The lecture instructor provides students with a pedagogical overview of the educational uses of technology in classrooms and introduces them to the theoretical underpinnings of lab assignments. Concepts taught during lectures include but are not limited to learning theories, information literacy, visual literacy, distance education, assistive technologies, universal design, equity & technology, and copyright issues.

There are four laboratory sections, which are usually taught by two lab instructors. The lab content (technology projects and software programs emphasized) is designed to flexibly address the needs of diverse content areas. Upon completion of projects, students are encouraged to go beyond the specific requirements of each assignment and make classroom connections by reflecting on how they can apply these newly learned skills in their own classroom. This enables students to focus on learning how technological applications can be integrated in their specific field of studies. Lab sessions allow students to apply the theories and concepts discussed during the lectures
into practice through several different technology projects. Lab instructors are responsible for creating learning activities for students to improve their instructional uses of computers for problem-based learning and facilitating their understanding as to how to integrate those in their lessons. Some of the projects that students create include desktop publishing, interactive multimedia, and video projects. Software applications used in the course include MS Word, MS PowerPoint, and iMovie.

**Participants**

The students who participated in the study were recruited from the course described above. Initially, 71 secondary education students were registered for the class. However, 7 students eventually dropped the class and thus were excluded from the study. From a total of 64 students who initially volunteered to participate in the study, 59 students completed all the materials and are included in the analyses. Participants included teacher education students from all grade levels (see Table 3.1): 18 freshmen (30.5%), 13 sophomores (22.0%), 21 juniors (35.6%), and 7 seniors (11.9%).

<table>
<thead>
<tr>
<th>Table 3.1: Year in School</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
</tr>
<tr>
<td>---------------</td>
</tr>
<tr>
<td>Freshmen</td>
</tr>
<tr>
<td>Sophomore</td>
</tr>
<tr>
<td>Junior</td>
</tr>
<tr>
<td>Senior</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

Participants came from several departments, including 11 students from agricultural education (18.6%), 10 from science education (17%), 9 from family and consumer science education (15.2%), 8 from language arts (13.5%), 8 from physical
education (13.5%), 7 from mathematics education (11.9%), and 4 from history (6.7%). There also was one student from elementary education and one from performing arts education.

Of the total of 59 students, 32 were female (54%) and 27 male (46%). This is not representative of the teacher education student population because the percentage of female students usually is much higher than the percentage of male students. This could be due to the fact that the participants of the study were recruited from the students majoring in secondary education. A majority (97%) of the participants were Caucasian American; there was also one Asian student (1.5%) and one Hispanic (1.5%) student.

**Research Design**

This was a non-experimental, correlational research study. The dependent variable (DV) is students’ ill-structured problem-solving performances (IPSP). Independent variables include domain knowledge, cognitive flexibility (CF), argumentative reasoning (justification) skills (AR), metacognitive awareness (MA), and epistemological beliefs (EB). Metacognitive awareness variable has two factors: knowledge of cognition (KoC) and regulation of cognition (RoC). Epistemological beliefs variable includes five factors: certain knowledge, simple knowledge, omniscient authority, fixed ability, and quick learning.

In addition, students’ online ill-structured problem-solving strategies were documented through their clickstream data of ill-structured problem-solving performance on the web-based problem-solving environment (Problem Solving Learning Portal). Exploratory Cluster Analysis (see p.63) was used to examine clickstream data. Problem-
solving strategies that emerged from the cluster analysis were treated as independent variables. See Table 3.2 for variables in the study.

Table 3.2: Variables in the Study

<table>
<thead>
<tr>
<th>Dependent variable (DV)</th>
<th>Ill-structured problem-solving performance</th>
<th>IPSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain knowledge</td>
<td></td>
<td>DK</td>
</tr>
<tr>
<td>Argumentative reasoning skills</td>
<td></td>
<td>AR</td>
</tr>
<tr>
<td>Metacognitive awareness</td>
<td></td>
<td>MA</td>
</tr>
<tr>
<td></td>
<td>Knowledge of cognition</td>
<td>KoC</td>
</tr>
<tr>
<td></td>
<td>Regulation of cognition</td>
<td>RoC</td>
</tr>
<tr>
<td>Independent variables (IV)</td>
<td>Epistemological beliefs</td>
<td>EB</td>
</tr>
<tr>
<td></td>
<td>Certain knowledge</td>
<td>CK</td>
</tr>
<tr>
<td></td>
<td>Simple knowledge</td>
<td>SK</td>
</tr>
<tr>
<td></td>
<td>Omniscient authority</td>
<td>OA</td>
</tr>
<tr>
<td></td>
<td>Innate ability</td>
<td>IA</td>
</tr>
<tr>
<td></td>
<td>Quick learning</td>
<td>QL</td>
</tr>
<tr>
<td>Cognitive flexibility</td>
<td></td>
<td>CF</td>
</tr>
<tr>
<td>Ill-structured problem-solving strategies</td>
<td></td>
<td>IPSS</td>
</tr>
</tbody>
</table>

**Materials**

**Instructional Materials**

A Web-based problem-solving environment, the Problem Solving Learning Portal (PSLP), was used as the instructional medium. PSLP was designed as a flexible template to present ill-structured problem-solving activities in a variety of content areas. Students are provided with problem scenarios grounded in authentic contexts so they can engage in the kinds of tasks they are likely to deal with in their future professions. Currently,
activities have been developed that include problems from engineering, education, and physics. The design of PSLP allows instructors to assign group or individual problem-solving activities to be done either during the class or as a long-term assignment outside the classroom.

For this study, an ill-structured problem was created to address several important concepts and principles including equity & technology, information literacy and concerns regarding Internet use in education (accuracy of the information, plagiarism, inappropriate sites). These topics are all typically taught in the Introductory Instructional Technology course from which the participants were recruited. The researcher has created the problem scenario in concert with the instructor of the course (see Table 3.3). At the center of the problem scenario is a conflict between a student and a teacher at a large inner-city high school. The teacher has assigned a multimedia project he believes the student has not only plagiarized but also used websites that are not credible. The student, on the other hand, had his own issues regarding time and resource constraints and did not understand the teachers’ concerns.

Research participants were provided with a variety of relevant and irrelevant resources, including brief background information about the key players in the problem scenario, the educational context of the problem (statistics about the school population, technology available to the students), teacher’s lesson plan for the project, the assignment in question, and portions of the questionable websites the student used.
Table 3.3: Problem Scenario

Mr. Whitman, an East High School science teacher, assigned a major multimedia project for his 9th grade students. Students selected a topic related to “Scientific Advancements in Space Research” and used the Internet to collect information. They then submitted a research paper for approval. With that completed, students had two weeks to complete a multimedia presentation that would be presented to the rest of the class. They were to use the information from the paper on their research topics as content for the multimedia presentations.

When Mr. Whitman began reading the research papers, he discovered a problem with what Mark had submitted. He saw two major problems: First, he had been reading Mark’s papers all semester and this did not look like his writing. Parts of it seemed okay, but some of it included advanced writing techniques and elaborate language that was inconsistent with his previous work. In addition, Mr. Whitman was quite concerned about the argument Mark was presenting in the paper. Mark was trying to make a case that the 1969 Moon Landing never actually happened. Mr. Whitman decided to consult the principal, Dr. Jones, regarding the situation. Principal Jones suggested that he meet with Mark to discuss his concerns.

Mark was excited to begin working on his multimedia project before he met with Mr. Whitman. At the meeting Mr. Whitman raised his concerns and told Mark that he would have to completely rewrite the paper. Mark was quite ashamed to be accused of plagiarism and had no idea that his paper would create this much trouble. He did not see how he could possibly have enough time to rewrite the paper and create the multimedia project in just two weeks. He had already skipped lunch every day that week so he could go to the media center to work on the research paper, and, even with that, it was not enough time. In fact, not having enough time was how the whole problem had started. Further, Mark did not see why the web sites that said moon landing was a hoax were not as credible as the ones that said it was true.

Before designing the PSLP version of the problem, all the materials were reviewed by a group of designers; including two professors (engineering and physics) who have implemented several problem-solving activities on PSLP, a professor and two graduate assistants who have involved in the design of the environment. Based on their suggestions, materials were revised and the problem embedded into the PSLP environment.

Then two former laboratory instructors of the course were asked to review the problem scenario and fill out a validation form (Appendix A) to see a) whether or not it is an ill-structured problem, b) if the problem scenario is clearly stated, and c) if the problem-solving tasks are aligned with the course content. They were also asked to
indicate whether or not enough relevant information is provided in order for students to be able to offer a valid solution.

Based on the comments and recommendations given by the reviewers, necessary modifications were made before using the environment in the study. Following are the modifications:

1. The initial task description was less than authentic (asking students to write a written report addressing the problem). It was reworded to reflect authenticity of the ill-structured problem (see Table 3.3).

2. There were not enough key players involved in the scenario (the student, his mother, and the science teacher). Another player (Principal Jones) was included to make the problem scenario more complex.

3. Some resources were too lengthy for the time provided to solve the problem, so they were shortened.

4. There was a “working memory” function that was included in the environment to allow students to take notes online. However, it opened up every time a resource was accessed which was a hindrance to the actual problem-solving process. This function was inactivated for the current study.

5. Some resources were in pdf format which did not open on certain computers so all resources were converted to html pages.

In order to best address the research questions of this study, the problem was set up as an activity to be completed individually during a two-hour lab session. This enabled the researcher to measure individual problem-solving performance, which was used as
the dependent variable, and to track students’ individual clickstream data to examine their navigation behaviors and online problem-solving strategies interacting with PSLP.

Table 3.4: Problem-solving Tasks

<table>
<thead>
<tr>
<th>Task Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>You recently applied for a science teacher position at East High and got invited to interview for the position. This afternoon you came in for the interview. The principal briefly met and told you about the incident Mr. Whitman had to deal with last year and is very concerned that something like this does not happen again. He has provided you with a folder including several resources with additional information and asked you to provide a written report to be used during the actual interview. To do this, read through the relevant resources, then use the progress bar above to analyze the problem, propose solutions, and reflect on your solutions.</td>
</tr>
<tr>
<td><strong>Analyze Problem:</strong> After reading the problem scenario and exploring the resources, please describe, in your own words, what you see as the problem in this scenario, examine possible causes of the problem and explain the key issues, constraints, and position of key players.</td>
</tr>
<tr>
<td><strong>Propose Solutions:</strong> Generate 3 possible solutions. Write a paragraph or two describing each solution and evaluate their merit relative to key issues and constraints.</td>
</tr>
<tr>
<td><strong>Reflect on Solution:</strong> Decide which of your proposed solutions you think will be the best way to revise Mr. Whitman’s activity to avoid incidents like this. Then, reflect on possible consequences of your proposed solution and explain the relative benefit of your solution compared to the alternative ones.</td>
</tr>
</tbody>
</table>

PSLP allows students to access the problem scenario, resources, and other necessary information for the solution of the problem (located on the navigation bar on the left-hand side) at any time during the problem-solving process in a non-linear manner (see Figure 3.1). However, the task bar across the top of the screen is navigated in a more linear fashion. That is, students needed to complete tasks in a given order to proceed forward with the problem-solving process (see Table 3.4). For example, after reading the problem scenario and exploring the resources, students needed to provide an analysis of the key issues, constraints, and key players in the problem context and identify possible causes of the problem. Then, they generated a range of possible solutions, evaluated their merit relative to key issues and constraints and proposed a viable solution for the problem.
situation. Finally, they were supposed to reflect on possible consequences of their proposed solution and explain the relative benefit of their solution compared to the alternative ones. This structure was based on Jonassen’s ill-structured problem-solving process (1997), which provided scaffolding for the students to progress through the problem in a systematic manner. Upon completion of each task students submitted their responses by clicking the submit button located on the bottom of the task page.

Figure 3.1: Screenshot showing the PSLP homepage, navigation bar, and problem scenario

Ill-structured Problem-Solving Scoring Rubric

Problem-solving performance served as the dependent variable in this study. The scoring rubric was developed in an iterative manner. First, a tentative rubric was developed by adapting “The Holistic Critical Thinking Scoring Rubric” (Facione & Facione, 1994) to reflect Jonassen’s (1997) ill-structured problem-solving model.
Drawing on Sinnott’s (1989) think-aloud protocols for solving ill-structured problems, Jonassen (1997) proposed that solving ill-structured problems involves: (a) articulation of problem space and contextual constraints, (b) elaboration of alternative viewpoints of stakeholders, (c) generation of possible problem solutions, (d) assessment of the viability of alternative solutions, (e) monitoring the problem space and solution options, (f) implementation and evaluation of the solution, and (g) adaptation of solution.

Each step was included as an element or broken down into elements in the rubric except for the last two steps, which involved implementation of the proposed solution. In educational settings, it is not always possible to try out the solution. Thus, reflecting on possible consequences of the proposed solution and justifying the solution compared to alternatives are sufficient to “engage learners in higher order, problem-solving learning” (Jonassen, 1997, p. 82). This is addressed through the last two elements in the rubric (reflecting on the proposed solution and relative benefits of the proposed solution).

Students’ responses to the problem-solving tasks were scored using the initial rubric. During this initial scoring, specific items were added to the rubric and criteria were modified to reflect the range of possible solutions offered by the students. Upon examining all the responses, alternative solution options were added to the rubric (see Appendix B). Two graders scored five student responses together to ensure the consistency in their scoring process and to clear any uncertainties regarding the scoring rubric.

Finally, participants’ responses were divided into two groups, each of which was graded by two different graders independently using the final rubric. Then, 20% of all the students from each group were selected randomly and cross-scored by two different
graders. A high Pearson correlation coefficient (.94) was reported for the inter-rater reliability.

**Cognitive Flexibility Scale**

Cognitive Flexibility Scale (see Appendix C) was used to measure the level of students’ cognitive flexibility. The scale was designed by Martin & Rubin (1995) to tap into three components of cognitive flexibility; being aware that different options and alternatives exist in any given situation, being flexible and able to adapt to different situations, and having self-efficacy being flexible (Martin & Rubin, 1995).

The scale consists of 12 Likert type items with a 6-point scale (6-strongly agree, 5-agree, 4-slightly agree, 3-slightly disagree, 2-disagree, 1-strongly disagree). Example of the items for each component included respectively: “I can communicate an idea in many ways,” “I have many possible ways of behaving in any given situation,” and “I can find workable solutions to seemingly unsolvable problems.” Some items such as “I have difficulty using my knowledge on a given topic in real life situations.” were reverse scored.

The possible scores on this scale ranged from 12 to 72 with higher scores indicating a higher level of cognitive flexibility. In this study, a fairly high Cronbach’s Alpha (0.81) was found for this scale. Cognitive flexibility served as an independent variable in the study.
Domain Knowledge Measure

Short essay questions from an existing course midterm examination were used to measure students’ domain knowledge. Questions were written to measure students’ understanding of important concepts taught in the Introductory Instructional Technology course and were crucial in the solution of the ill-structured problem. Table 3.5 shows the questions that were used to measure students’ domain knowledge.

Table 3.5: Questions Used to Measure Domain Knowledge

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1)</td>
<td>List and explain three of the ways that website biases can be identified.</td>
</tr>
</tbody>
</table>
| 2) | (a) What is plagiarism?  
(b) How can you tell when a student has plagiarized?  
(c) Describe two ways that a teacher can prevent plagiarism. |

An answer key was developed by the course instructor to score student answers. During the initial scoring, additional possible right answers offered by students (not originally included in the answer key) were added to the answer key (see Appendix D). Two graders scored five exams together using the answer key and then divided the exam papers into two groups and each scored their half independently using the same answer key. Finally, 20% of all the students from each group were selected randomly and cross-scored by two graders. A high Pearson correlation coefficient (.95) was reported for the inter-rater reliability. Domain knowledge served as an independent variable in the study.

Argumentative Reasoning (Justification) Skills Inventory

The argumentative reasoning task adapted from an existing measure developed by Kuhn, Shaw, and Felton (1997) was used in the current study (See Table 3.6).
Participants were asked to write a short argumentative essay on Capital Punishment. Their argumentative reasoning skills were scored using an analytic coding scheme (see Appendix E) designed by Kuhn et al. (1997). Kuhn and her colleagues chose Capital Punishment as a discussion topic because several reasonable arguments could be made from opposing sides and parallels could be drawn between conflicting arguments. The analytic scheme was designed in an iterative, inductive manner. Reliability was tested through a two-step process. First, coders independently divided the arguments into segments and each segment was coded by using the argument types in the coding scheme. High percent agreement (.80) between the two coders was reported for the adult sample in Kuhn et al. (1997) study.

Table 3.6: Argumentative Reasoning Task

<table>
<thead>
<tr>
<th>Instruction:</th>
<th>The following task deals with your beliefs and feelings about Capital Punishment. Read the task carefully and respond in the box provided below.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>How do you feel about Capital Punishment (CP)? Take a position and write a brief argumentative essay that explains, supports, and justifies your view about this issue.</td>
</tr>
</tbody>
</table>

The scheme is hierarchical in a sense that some argument types are classified more advanced than others (Kuhn, 1991), which enabled the researcher to score students’ argumentative essays. For example, functional arguments were more advanced than non-functional because they considered functions or purposes of Capital Punishment (CP) and evaluated the value of any practice associated with it. Among functional arguments, those that considered alternatives and stated the relative benefit of Capital Punishment or the
alternative to the Capital Punishment were regarded superior than those that simply provided rationale for being in favor or against without any reference to the alternative practices. Thus, functional arguments that considered alternatives were given four points whereas functional arguments without any consideration to alternatives were assigned three points (see Table 3.7 for sample arguments and scoring guide). Arguments that focused on conditions that justified Capital Punishment with no consideration of its functions, and those that did not provide any justification were scored as two points and one point respectively.

Two graders first scored five arguments offered by students together using the scoring guide. Then, the sample was divided into two groups and each grader scored his or her half of the sample independently. To check the degree of agreement between the raters, 20% of all the students from each group were selected randomly and cross-scored by two different graders. Similar to the original study by Kuhn et al. (1997), a high inter-rater reliability was found with a Pearson correlation coefficient of .80. This is an acceptable reliability but, given the small sample size ($N = 59$) in the current study, small differences might have a large effect on the results. Thus, two graders reviewed all of the arguments together until they came to a consensus on all the scores resolving any discrepancies between their scoring. Argumentative reasoning served as an independent variable.
### Table 3.7: Sample CP Arguments and Scoring Guide

<table>
<thead>
<tr>
<th>Pro/Con</th>
<th>Argument type</th>
<th>Sample argument</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pro</td>
<td>Functional considering alternatives</td>
<td>Alternatives to CP are not effective as deterrents</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Functional no consideration for alternatives</td>
<td>CP deters people from crime</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Non-functional (focused on conditions that justify CP)</td>
<td>CP is justified only if the crime is sufficiently grave</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Non-justificatory</td>
<td>Crime exists and needs a remedy</td>
<td>1</td>
</tr>
<tr>
<td>Con</td>
<td>Functional considering alternatives</td>
<td>Alternatives to CP are better as deterrents</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Functional no consideration for alternatives</td>
<td>CP is not effective in deterring people from crime</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Non-functional (focused on defects in administration of CP)</td>
<td>CP may punish innocent people</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Non-justificatory</td>
<td>Appeal to authority without intervening argument</td>
<td>1</td>
</tr>
</tbody>
</table>

### Metacognitive Awareness Inventory

The 52-item Metacognitive Awareness Inventory (MAI), designed by Schraw & Dennison (1994), was used to measure students’ metacognitive awareness. MAI has a two-factor model: knowledge of cognition (KOC) and regulation of cognition (ROC) (see Appendix C). Factors were reliable ($\alpha = .90$) and inter-correlated ($r= .54$) (Schraw & Dennison, 1994). Items such as “I can learn best when I know something about the topic” (KoC) and “I ask myself periodically if I am meeting my goals” (RoC) are rated on a 5-point Likert scale from “5-strongly agree” to “1-strongly disagree”. Higher scores on the scale reflect higher metacognitive awareness. MAI had a high internal consistency in
this study; Cronbach’s Alpha was 0.93. Metacognitive awareness served as an
independent variable in the study.

**Epistemological Beliefs Inventory (EBI)**

Epistemological beliefs were measured using the Epistemological Beliefs
Inventory (EBI) (Schraw, Bendixen, & Dunkle, 2002). See Appendix C. EBI was
designed to measure five epistemological belief factors developed by Schommer (1990).
These factors are: certain knowledge; simple knowledge; omniscient authority; fixed
ability; and quick learning. Acceptable levels of reliability (test-retest correlations ranged
from .62 to .81) and factorial validity for the five-factor structure were reported. The
instrument consists of 28 items with a 5-point Likert scale from “5-strongly agree” to “1-
strongly disagree.” In the original scale, higher scores indicated naïve beliefs regarding
the nature of knowledge and knowing. In the current study, all the items were reversed so
that higher scores on the scale reflected more complex epistemic assumptions. See Table
3.8 for sample items for each factor. In the this study, Cronbach’s Alpha for this scale
was 0.77. Epistemological beliefs served as an independent variable in the study.

**Table 3.8: Factors and Sample Items from the EBI**

<table>
<thead>
<tr>
<th>Factors</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Certain knowledge</td>
<td>“What is true today will be true tomorrow.”</td>
</tr>
<tr>
<td>Simple knowledge</td>
<td>“Most things worth knowing are easy to understand.”</td>
</tr>
<tr>
<td>Omniscient authority</td>
<td>“People shouldn’t question authority.”</td>
</tr>
<tr>
<td>Innate ability</td>
<td>“Smart people are born that way.”</td>
</tr>
<tr>
<td>Quick learning</td>
<td>“If you don’t learn something quickly you won’t ever learn it.”</td>
</tr>
</tbody>
</table>
Background Information

ISU records were used to gather background information regarding the participants. The background information was used to account for some of the individual differences that may or may not be contributing to ill-structured problem-solving performance. Information was collected for the following items: major, age, gender, educational background, and ACT scores.

Procedures

In the seventh week of the 15-week semester, students received an informed consent form and were asked to participate in the study. Those who chose to participate were given 40 minutes to fill out the online questionnaires (Cognitive Flexibility Scale, Metacognitive Awareness Inventory, Epistemological Beliefs Inventory, and Argumentative Reasoning Skills Inventory) during their regular scheduled lab session. Students took an average of 25 minutes to complete the questionnaires, then they proceeded with their regular lab topic for that day.

Two weeks later, lab instructors introduced the Problem-Solving Learning Portal during their assigned lab hours and let students explore its features. Instructors also discussed possible educational implications of online problem-based learning environments. Then, they were asked to complete the ill-structured problem-solving task during a regular scheduled two-hour lab session. Students took an average of 63 minutes to complete the task. All students in the class were required to complete this problem-solving task as a regular class activity that would contribute to their final grade.
Since participation in the study was voluntary, only consenting students data were used for statistical analyses. Data sources included students’ background information (major, age, gender, GPA, and ACT scores) obtained from ISU records, domain knowledge scores, ill-structured problem-solving performance, and responses to the online questionnaires.

**Data Analysis**

Two objectives were addressed in this study. The first objective was to examine strategies individuals used to solve an ill-structured problem in a web-based problem-solving environment (see Table 3.9 for research questions and data analysis techniques). Students’ individual problem-solving strategies were documented in the form of clickstream data. Clickstream data is a collection of students’ navigational choices. This data helped track students’ progress through the problem-solving activity. To address the first research question, the clickstream data were analyzed using a multivariate technique called hierarchical cluster analysis. Cluster analysis allows for groupings based on similarities or dissimilarities among individuals or variables (Johnson & Wichern, 2002).

The second objective was to investigate the effect of the problem-solving strategies – identified through the cluster analysis – on ill-structured problem-solving performance when domain knowledge, reading ability, argumentative reasoning skills, metacognitive awareness, epistemological beliefs, and cognitive flexibility had been controlled. The focus was on determining whether or not problem-solving strategies could explain additional variance when controlling for learner characteristics. Thus, a
conceptually driven forced-order hierarchical regression analysis was used to systematically remove variance associated with several learner characteristics.

Table 3.9: Research Questions, Data Sources/Instruments, and Data Analysis

<table>
<thead>
<tr>
<th>Research question</th>
<th>Data sources / Instruments</th>
<th>Data analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. What types of strategies do students use when solving ill-structured problems in a web-based environment?</td>
<td>Students’ clickstream of ill-structured problem-solving task performance/ill-structured problem-solving task</td>
<td>Cluster analysis IV</td>
</tr>
<tr>
<td>2. How do problem-solving strategies affect ill-structured problem-solving performance when controlling for learner characteristics such as domain knowledge, reading ability, argumentative reasoning, metacognition, epistemic beliefs, and cognitive flexibility?</td>
<td>Domain knowledge exam questions/Scoring rubric, ACT Reading scores, Argumentative reasoning inventory/Scoring guide, Metacognitive awareness inventory, Epistemological beliefs inventory, Cognitive flexibility scale, Ill-structured problem-solving performance / Scoring rubric</td>
<td>Regression analysis</td>
</tr>
</tbody>
</table>
CHAPTER 4. RESULTS

The objectives of this study were two-fold; 1) to explore the types of problem-solving strategies students’ used when solving ill-structured problems in a Web-based problem-solving environment, and 2) to examine the relationships among students’ ill-structured problem-solving strategies and their online problem-solving performance.

To examine the first research question, *Hierarchical Cluster Analysis* was used to explore different profiles of students’ problem-solving strategies. The results of this cluster analysis suggested a 4-cluster solution. Examining the individuals’ problem-solving processes making up these clusters helped to name the clusters and explain different problem-solving strategies that emerged. *Forced-order Hierarchical Regression* was used to examine the second research question. In this analysis, students’ online problem-solving strategies were the variable of interest in predicting ill-structured problem-solving performance.

**Research Question #1: Types of Problem-Solving Strategies**

Students’ individual problem-solving strategies were documented in the form of *clickstream* data, which is a sequential log of students’ navigational choices. These data helped track students’ progress through the problem-solving activity and showed the sequence in which an individual student visited the resources and tasks, and how long he or she viewed each resource or worked on completing the task screens.

Fifty-nine participants’ clickstream data of the online problem-solving activity were included in this analysis. The average time spent working in the problem-solving
environment was 63.53 minutes ($SD = 16.13$). Maximum and minimum times spent were 28.32 and 100.35 minutes respectively.

Overall, participants spent the major proportion of their time (0.63) on writing tasks (see Table 4.1). An additional 0.23 was allocated to exploring the resources. Of that 0.23, participants spent 0.16 proportion of their time on relevant resources and 0.07 on irrelevant resources. Participants also spent 0.12 proportion of their time reading the problem scenario and the task description. Finally, a small proportion of time (0.02) was spent looking at the help section.

**Table 4.1: Mean Proportions of Time Spent on Specific Pages Online**

<table>
<thead>
<tr>
<th>Specific page</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem scenario &amp; Task description</td>
<td>0.12</td>
<td>0.03</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>Writing tasks</td>
<td>0.63</td>
<td>0.13</td>
<td>0.30</td>
<td>0.88</td>
</tr>
<tr>
<td>Relevant resources</td>
<td>0.16</td>
<td>0.11</td>
<td>0.00</td>
<td>0.52</td>
</tr>
<tr>
<td>Irrelevant resources</td>
<td>0.07</td>
<td>0.04</td>
<td>0.00</td>
<td>0.29</td>
</tr>
<tr>
<td>Help section</td>
<td>0.02</td>
<td>0.18</td>
<td>0.00</td>
<td>0.10</td>
</tr>
</tbody>
</table>

The following pie chart (see Figure 4.1) shows the breakdown of how participants spent their time during the problem-solving activity.
Figure 4.1: Pie chart showing mean proportions of time spent on specific pages

Large standard deviations were apparent in these data, especially for the proportion of time spent on writing tasks (0.13), relevant resources (0.11), and irrelevant resources (0.04). These large standard deviations indicated a wide distribution of problem-solving strategies that were difficult to classify based on specific characteristics because of the large amount of unaccounted variance within the variables of interest. In the current study, describing and classifying participants’ problem-solving strategies using the raw data presented in Table 4.1 was not feasible because of the considerable variation in the ways participants used their time during problem-solving activities. This prompted a search for smaller and more homogenous groups within the original dataset to better explain the variance in problem-solving strategies.
Cluster Analysis of Online Problem-Solving Strategies

Multivariate hierarchical cluster analysis was used to explore the different types of problem-solving strategies that emerged from the clickstream data. Then, three One-Way ANOVAs and three Tukey HSD post hoc analyses were carried out to determine how these clusters differed in terms of the problem-solving processes (proportions of time allocated for writing tasks, and their use of relevant and irrelevant resources). In addition, the sequence in which individuals accessed different types of pages (writing tasks and relevant/irrelevant resources) was analyzed to further define the characteristics of problem-solving strategies demonstrated by each cluster. Finally, MANOVA and post hoc analyses were performed to compare clusters based on reading ability (ACT reading), domain knowledge, and ill-structured problem-solving performance.

Phase 1: Cluster Identification

Cluster analysis allows for groupings based on similarities or dissimilarities among individuals or variables (Johnson & Wichern, 2002). This technique can be used to reduce a large group of diverse individuals into a smaller set of homogeneous clusters. In other words, cluster analysis is helpful in identifying trends based on certain key characteristics (clustering variables) to establish smaller groups of similar profiles of behavior or performance from a large number of individuals (Aldenderfer & Blashfield, 1984; Everitt, Landau, & Leese, 2001). Clustering techniques have previously been used to study individual differences like hypertext navigational choices (i.e., Barab, Bowdish, & Lawless, 1997; Lawless & Kulikowich, 1996).
In the present study each individual was able to choose a unique strategy to complete the online problem-solving activity. For example, they could choose to visit or not visit certain resources (relevant or irrelevant), and allocate different proportions of their time to visiting these resources and completing writing tasks. The sequence in which they accessed pages could also differ. However, there would likely be certain similarities in terms of how some individuals approached solving a problem in an online environment. For example, some people might follow links in a haphazard fashion while others may adopt deliberate and systematic approaches to accessing information and solving the problem (see Barab et al., 1997; Lawless & Kulikowich, 1996; Niederhauser, Reynolds, Salmen, & Skolmoski, 2000).

Clusters of problem-solving strategies were formed based on three variables that represented the problem-solving process. Variables included proportion of time spent on (1) writing tasks (analyzing the problem, generating solutions, and reflecting on the proposed solution), (2) visiting relevant resources, and (3) visiting irrelevant resources. Students spent the major proportion of their time $M = 0.86$ on these three types of activities within the online problem-solving environment and they did not differ in terms of the time allocated to other activities (i.e. reading problem scenario and task description). Ward’s Cluster Analysis method was used to maximize within-cluster homogeneity (Aldenderfer & Blashfield, 1984; Everitt et al., 2001; Sharma, 1996). Different from alternatives (e.g., average, complete, and single linkage), Ward’s method uses an analysis of variance approach to evaluate distances between clusters to minimize the Sum of Squares (SS) of clusters that can be formed. Ward’s method is “one of the more conservative” methods of hierarchical cluster analysis (Milligan & Cooper, 1987 as
cited in Lawless & Kulikowich, 1996). In the current study, Ward’s method revealed smaller but more uniform clusters compared to average linkage method.

Results of the cluster analysis suggested a 4-cluster solution that was theoretically meaningful. The number of clusters was determined by examining the *dendrogram* (see Figure 4.2), and the plot of fusion coefficients versus number of clusters (see Figure 4.3). A dendrogram or hierarchical tree is a graphical representation of the distance between possible clusters (Everitt et al., 2001). Deciding the number of viable clusters is achieved by partitioning the dendrogram at a certain level. Large changes in the distance (fusion levels) suggest where the partitioning should be performed (Everitt et al., 2001).

Examination of the *dendrogram*, which represents the current dataset, leads to the identification of four distinct clusters because the first major change in the fusion levels appears between the 4-cluster and 3-cluster solutions.
Figure 4.2: Dendrogram showing the cluster formations and distance between clusters.
A second way to verify the number of clusters was to examine the plot of the fusion coefficients (a value indicating the distance between clusters as shown along the x-axis in the dendrogram) versus the number of clusters (Aldenderfer & Blashfield, 1984). As seen in Figure 4.3, at the point where fusion coefficient drops to 2, the plot starts to flatten. This indicates that the variance between clusters in the 6-cluster solution (there was no 5-cluster solution) was not meaningful enough to suggest further partitioning. These verification strategies suggested that a 4-cluster solution was the best representation for these data. In the next phase of the analysis, the 4-cluster solution was further examined to determine if the clusters were theoretically meaningful.

![Figure 4.3: Plot of distance between clusters (fusion coefficients) versus number of clusters.](image)

*Figure 4.3: Plot of distance between clusters (fusion coefficients) versus number of clusters.*
Phase 2: Description and Interpretation of the Clusters

The clickstream data of online problem-solving activity captured students’ problem-solving strategies from multiple angles. For example, it not only represents the proportion of time spent on different screens to reflect the students’ task focus and their ability to identify relevant information, but also the sequence in which they accessed these screens, to offer more insight into different types of problem-solving strategies. It is especially important to examine these data from multiple perspectives when interpreting the results of the cluster analysis. Thus, to better understand and interpret different problem-solving strategies as reflected by the clusters, data were examined in multiple ways. First, clusters were analyzed based on the task focus and the resource use in solving the problem. Second, the clickstream data were analyzed to explain the sequence individuals in different clusters used to attack the online problem-solving task. Finally, clusters were compared to external variables to strengthen the prior interpretations.

Three One-Way analysis of variance tests (ANOVAs) were conducted to examine how individuals who made up of each of the clusters differed in the tasks focus of their problem-solving processes and the nature of their resource use. For all three analyses, the cluster membership was used as the between subjects factor (1, 2, 3, & 4) and proportions of time spent on (1) completing writing tasks, (2) visiting relevant resources, and (3) visiting irrelevant resources served as the dependent measures.

Results showed a main effect for the completing writing tasks ANOVA ($F_{[3,55]} = 136.09; p < .001; MSE = .294$). Further, Tukey HSD post hoc analyses revealed that the mean proportion of time allocated to writing tasks for Cluster 4 ($\bar{x} = 0.77$) was higher
than the mean for all other clusters (see Table 4.2) and the mean for Cluster 3 ($\bar{x} = 0.64$) was higher than Clusters 1 and 2 ($\bar{x} = 0.53$; $\bar{x} = 0.40$). Further, the mean for Cluster 1 was higher than the mean for Cluster 2. The high mean proportion of time allocated to completing writing tasks for Clusters 3 and 4 suggests that students in these clusters spent their time completing the task. These participants spent the available time working on completing the writing tasks (analyzing the problem, generating solutions, and reflecting on the proposed solution). Students in clusters who spent the majority of their time working on writing tasks were classified as *writers*.

Table 4.2: *Mean Proportions of Time and Standard Deviations by Cluster*

<table>
<thead>
<tr>
<th>Specific page</th>
<th>Cluster 1 ($n = 13$)</th>
<th>Cluster 2 ($n = 7$)</th>
<th>Cluster 3 ($n = 19$)</th>
<th>Cluster 4 ($n = 20$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Writing tasks</td>
<td>0.53</td>
<td>0.04</td>
<td>0.40</td>
<td>0.08</td>
</tr>
<tr>
<td>Relevant resources</td>
<td>0.22</td>
<td>0.05</td>
<td>0.41</td>
<td>0.07</td>
</tr>
<tr>
<td>Irrelevant resources</td>
<td>0.09</td>
<td>0.06</td>
<td>0.07</td>
<td>0.04</td>
</tr>
</tbody>
</table>

There was also a main effect for the ANOVA that was used to examine the proportion of time spent visiting relevant resources ($F [3,55] = 128.52; p < .001; MSE = .235$). Post hoc analysis revealed that the mean for Cluster 2 ($\bar{x} = 0.41$) was higher than the mean for all other clusters and the mean for Cluster 1 ($\bar{x} = 0.22$) was higher than the means for Clusters 3 and 4 ($\bar{x} = 0.14$; $\bar{x} = 0.06$ respectively). This indicates that students in Clusters 1 and 2 spent considerable proportion of their time exploring the information...
resources. Based on the focus of their activity, individuals in both of these clusters were labeled as *investigators*.

Finally, main effect was found for the ANOVA that was used to examine the proportion of time spent visiting irrelevant resources \( (F[3,55] = 5.47; p < .01; MSE = .009) \). Post hoc analysis showed that the mean for Clusters 1 and 3 \( (\bar{x} = 0.09; \bar{x} = 0.08 \text{ respectively}) \) were higher in terms of the proportion of time spent visiting irrelevant resources than that of Cluster 4 \( (\bar{x} = 0.04) \). While a higher mean proportion of time for exploring relevant resources may be helpful in solving the problem, a higher mean proportion of time for exploring irrelevant resources likely hinders the problem-solving process. Therefore individuals with a high mean for exploring irrelevant resources (Clusters 1 and 3) were labeled as *non-discriminating* because they were not particularly effective in distinguishing relevant resources from irrelevant ones. However individuals in Cluster 2 were highly successful in discriminating between relevant \( (\bar{x} = 0.41) \) and irrelevant \( (\bar{x} = 0.07) \) resources and spent considerable time examining relevant resources. Students in Cluster 2 were then classified as *discriminating*. Individuals in Cluster 4 had the lowest mean for visiting irrelevant resources as well as for visiting relevant resources. This indicates that these students made minimal use of resources which makes it difficult to classify them either *discriminating or non-discriminating* without actually knowing whether or not they revisited relevant and/or irrelevant resources. Therefore, sequential analysis of the clickstream data will be used next to further classify these students nature of resource use.

Further, sequential analysis of the clickstream data introduced another level of classification to the problem-solving strategies discussed earlier. This analysis helped
finalize the cluster labeling process. To conduct the sequential analysis of the clickstream data, the screens were numbered in the order that they appeared in the online problem-solving environment: the problem scenario, task description, writing tasks and resources. Each screen was assigned a certain color based on its type. For example, writing tasks were color-coded in blue, relevant resources in green, and irrelevant resources in red. Each navigational choice (single click at a given time) was then transformed into a numbered and color-coded cell in the spreadsheet. A complete session of the problem-solving activity for each individual was represented as a row including all of the numbered and color-coded cells in the sequence in which they were accessed. Finally, all of the rows corresponding to the individuals in a particular cluster were listed together to analyze the trends among their problem-solving strategies as reflected in the clickstream data. The following results were based on these visual representations of clickstream data.

Examination of the clickstream data for the Cluster 1 revealed that students in this cluster did not tend to navigate through the environment in a linear fashion. They typically went back and forth between resources and writing tasks and revisited not only relevant resources but also irrelevant resources even after they started working on the writing tasks (see Figure 4.4). This observation is consistent with the earlier analysis that categorized these individuals as non-discriminating. Although these individuals used resources extensively they were not effective at separating relevant from irrelevant resources. Because of their extensive use of resources and the fact that they cycled back and forth between writing tasks and relevant as well as irrelevant resources, the behavior that the individuals in Cluster 1 demonstrated was classified as extensive ineffective-
cycling. Non-discriminating nature of these individuals’ resource use is captured in the ineffective-cycling part of the classification. Therefore, building upon classification analyses discussed earlier, the cluster name for Cluster 1 is extensive ineffective-cycling investigators (see Table 4.3).

Figure 4.4: Cluster 1 clickstream showing resource cycling pattern

Table 4.3: Labels and Descriptions of the Clusters

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>Extensive ineffective-cycling investigators</td>
<td>Focused on exploring resources, did not discriminate relevant and irrelevant resources, and tended to go back and forth between writing tasks and relevant as well as irrelevant resources.</td>
</tr>
<tr>
<td>Cluster 2</td>
<td>Extensive effective-cycling investigators</td>
<td>Focused on exploring resources, discriminated relevant and irrelevant resources, and tended to go back and forth between writing tasks and relevant resources.</td>
</tr>
<tr>
<td>Cluster 3</td>
<td>Minimal ineffective-cycling writers</td>
<td>Focused on completing writing tasks, did not distinguish relevant from irrelevant resources, made minimal use of resources and occasionally cycled back to relevant as well as irrelevant resources while working on completing writing tasks.</td>
</tr>
<tr>
<td>Cluster 4</td>
<td>Minimal effective-cycling writers</td>
<td>Focused on completing writing tasks, made minimal use of resources, and rarely cycled back to resources (relevant) while working on completing writing tasks.</td>
</tr>
</tbody>
</table>
Individuals in Cluster 2 also tended to go back and forth between writing tasks and resources. Even though they did visit irrelevant resources in the beginning, these individuals tended not to go back and revisit them again (see Figure 4.5). This finding is consistent with the previous analysis that these individuals were discriminating investigators based on the proportions of time spent visiting relevant resources ($\bar{x} = 0.41$) and visiting irrelevant resources ($\bar{x} = 0.07$). In addition to the previous classification analyses, based on these individuals’ extensive use of relevant resources and the fact that they shifted their attention back and forth between writing tasks and relevant resources, they were classified as *extensive effective-cycling investigators*. The discriminating nature of their resource use was reflected in the *effective-cycling* part of the classification.

*Figure 4.5:* Cluster 2 clickstream showing resource cycling pattern

Individuals in Cluster 3 tended to visit resources in the order that they appeared on the Web-based problem-solving environment (see Figure 4.6). These individuals rarely went back and explored resources again once they started working on completing writing tasks. When they did cycle back to resources, they revisited relevant as well as irrelevant resources (non-discriminating). These students in general made minimal use of resources and based on the sequential analysis they were not effective at cycling to
relevant resources. The non-discriminating nature of their resource use was reflected in their ineffective resource cycling. Thus, building upon the earlier classification analyses, these individuals were labeled as *minimal ineffective-cycling writers*.

**Figure 4.6**: Cluster 3 clickstream showing resource cycling pattern

Similar to individuals in Cluster 3, those in Cluster 4 tended to move through the resources in a sequential manner and focused primarily on completing writing tasks (see Figure 4.7). The students in this cluster rarely revisited resources once they started working on writing tasks. This led them to allocate a considerable proportion of time for completing writing tasks (\( \bar{x} = 0.77 \)). This observation is consistent with the previous finding that classified these students as *writers* based on their task focus. Students in Cluster 4 made minimal use of resources like those in Cluster 3. However, unlike students in Cluster 3, these students tended to go back to relevant resources while working on completing writing tasks. As a result, these students were labeled *minimal effective-cycling writers*. 
Phase 3: Comparing Clusters to External Variables

Comparing clusters to some external variables (variables that are not used as clustering variables) can be used to enhance the interpretation of the clusters (Milligan & Cooper, 1987 as cited in Lawless & Kulikowich, 1996). A Multivariate Analysis of Variance (MANOVA) was conducted with clusters as the between subject factor, and domain knowledge, reading ability, and problem-solving performance as dependent variables. Results showed only the main effect for problem-solving performance reached significance ($F_{[3,55]} = 3.90; p < .05; MSE = 47.65$).

Further post hoc analysis (Tukey HSD) was conducted to determine how clusters differed in ill-structured problem-solving performance. It was found that individuals in Cluster 4, *minimal effective-cycling writers*, had significantly higher scores on the IPSP measures than those in Cluster 1, *extensive ineffective-cycling investigators* (see Table 4.4). Even though students in Cluster 2, *extensive effective-cycling investigators*, scored considerably higher than those in Cluster 1, *extensive ineffective-cycling investigators*,
this contrast probably did not reach significance due to the small number of students \((n = 7)\) making up the cluster.

**Table 4.4: Means and Standard Deviations by Cluster for External Criteria**

<table>
<thead>
<tr>
<th>External criteria</th>
<th>Cluster 1 ((n = 13))</th>
<th>Cluster 2 ((n = 7))</th>
<th>Cluster 3 ((n = 19))</th>
<th>Cluster 4 ((n = 20))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (\text{SD})</td>
<td>Mean (\text{SD})</td>
<td>Mean (\text{SD})</td>
<td>Mean (\text{SD})</td>
</tr>
<tr>
<td>DK</td>
<td>5.18 0.69</td>
<td>5.79 1.58</td>
<td>5.13 1.21</td>
<td>5.58 1.05</td>
</tr>
<tr>
<td>ACT Reading</td>
<td>23.25 3.80</td>
<td>25.78 2.49</td>
<td>23.50 5.00</td>
<td>25.44 3.71</td>
</tr>
<tr>
<td>IPSP</td>
<td>16.85 3.65</td>
<td>20.71 3.73</td>
<td>19.16 3.32</td>
<td>20.90 3.48</td>
</tr>
</tbody>
</table>

In conclusion, cluster analysis yielded four clusters of students, which demonstrated four different online ill-structured problem-solving strategies. One strategy was based on students’ task focus; writers vs. investigators. Other strategies involved the nature of students’ resource use and the degree to which they discriminated relevant from irrelevant resources: extensive ineffective-cycling; extensive effective-cycling; minimal ineffective-cycling; and minimal effective-cycling. It was also found that there were significant differences between problem-solving strategies demonstrated by clusters in terms of problem-solving performance. Next, these online problem-solving strategies were examined to determine whether or not they would be significant predictors of ill-structured problem-solving performance.

**Research Question #2: Relationship between Problem-Solving Strategies and Problem-Solving Performance**

The purpose of the second research question was to examine whether or not the online problem-solving strategies that the cluster analysis revealed would predict ill-
structured problem-solving performance after accounting for the variance associated with learner characteristics; reading ability, domain knowledge, argumentative reasoning, metacognitive awareness, epistemological beliefs, and cognitive flexibility. Therefore, a conceptually driven forced-order hierarchical regression analysis was used to investigate this research question.

Due to the relatively small sample size a correlate and aggregate technique was used before performing regression analysis because the correlate and aggregate is more sensitive to small changes in the data (Niederhauser et al., 2000; Rushton, Brainerd, & Pressley, 1983). The analysis was carried out on the complete Participant x Page matrix of data. There were 59 x 16, or 940, possible observations for the analysis, which included 59 participants accessing 16 total pages (writing tasks, relevant resources, and irrelevant resources).

**Variables in the Analysis**

The criterion measure for the forced-order hierarchical regression was the participants’ scores on the ill-structured problem-solving task. The variables of interest were ill-structured problem-solving strategies. Two variables were created to represent ill-structured problem-solving strategies. These variables were task focus and resource discrimination (see Table 4.5). Task focus variable indicated whether students’ task focus was on completing writing tasks or exploring resources. Resource discrimination reflected the extent to which individuals used resources and the degree to which they discriminated relevant from irrelevant resources.
Table 4.5: Description of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Interpretation of high score</th>
<th>$M$</th>
<th>$SD$</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criterion measure</td>
<td>High problem-solving performance</td>
<td>19.42</td>
<td>3.75</td>
<td>11</td>
</tr>
<tr>
<td>ACT Reading</td>
<td>Good reading comprehension</td>
<td>24.37</td>
<td>4.13</td>
<td>13</td>
</tr>
<tr>
<td>Domain knowledge</td>
<td>Good domain knowledge</td>
<td>5.37</td>
<td>1.11</td>
<td>2.50</td>
</tr>
<tr>
<td>Argumentative reasoning</td>
<td>Ability to construct sensible arguments</td>
<td>3.03</td>
<td>0.77</td>
<td>1</td>
</tr>
<tr>
<td>Knowledge of cognition</td>
<td>High awareness of one’s own cognitive processes</td>
<td>47.76</td>
<td>5.65</td>
<td>34</td>
</tr>
<tr>
<td>Regulation of cognition</td>
<td>High ability regulating one’s cognitive processes</td>
<td>87.39</td>
<td>15.55</td>
<td>41</td>
</tr>
<tr>
<td>Simple knowledge</td>
<td>Holding a belief that knowledge is complex</td>
<td>21.19</td>
<td>3.47</td>
<td>11</td>
</tr>
<tr>
<td>Certain knowledge</td>
<td>Holding a belief that knowledge is not absolute but relative</td>
<td>18.78</td>
<td>2.29</td>
<td>13</td>
</tr>
<tr>
<td>Omniscient authority</td>
<td>Authorities may have access to vast amount of knowledge but their opinions can be evaluated</td>
<td>11.39</td>
<td>2.90</td>
<td>5</td>
</tr>
<tr>
<td>Quick learning</td>
<td>Holding a belief that learning takes time</td>
<td>18.20</td>
<td>2.48</td>
<td>12</td>
</tr>
<tr>
<td>Innate ability</td>
<td>Holding a belief that ability to acquire knowledge is not fixed at birth</td>
<td>18.30</td>
<td>3.70</td>
<td>9</td>
</tr>
<tr>
<td>Cognitive flexibility</td>
<td>High ability in considering alternative viewpoints</td>
<td>44.58</td>
<td>5.78</td>
<td>33</td>
</tr>
<tr>
<td>Task focus</td>
<td>Focus on completing writing tasks as opposed to exploring resources</td>
<td>1.66</td>
<td>0.48</td>
<td>1</td>
</tr>
<tr>
<td>Resource discrimination</td>
<td>Extensive use of resources and effective resource cycling.</td>
<td>3.36</td>
<td>0.96</td>
<td>1</td>
</tr>
</tbody>
</table>

The order of the variables entered into the equation was specified to systematically remove variance associated with several learner characteristics.

Proceeding in this fashion allowed for removing some of the variance from individual differences in reading ability, domain knowledge, argumentative reasoning, metacognitive awareness, epistemological beliefs, and cognitive flexibility. Students’ ACT reading scores were used as a measure of their general reading ability. Student
scores on the ACT reading test; domain knowledge, and argumentative reasoning measures were entered into the equation together as a block to remove variance associated with their reading ability, prior knowledge, and ability to construct sensible arguments. Metacognitive awareness variables (knowledge of cognition and regulation of cognition), the five dimensions associated with epistemological beliefs (i.e., simple knowledge, certain knowledge, omniscient authority, quick learning, and innate ability), and cognitive flexibility variable were entered next as a block.

This made it possible to examine the effects of online problem-solving strategies to see if they accounted for additional variance beyond the reading ability, domain knowledge, argumentative reasoning, metacognitive awareness, epistemological beliefs, and cognitive flexibility.

Finally, two ill-structured problem-solving strategy variables were entered as a block in the final step of the regression analysis (see Table 4.5 for a description of the variables used in the analysis). Gender and year in school did not contribute significant variance so they were dropped from the analysis.

**Regression Analysis**

The normal probability plot of standardized residuals (see Appendix F) indicates that $p$-values are believable and thus predictions based on this regression analysis are significant. Table 4.6 shows the results of the forced-order hierarchical regression. As anticipated, *Block One* including students’ reading ability, domain knowledge, and argumentative reasoning skills accounted for considerable proportion of the variance ($R^2 = 0.180$).
Also as expected the variables in block two including metacognitive awareness, epistemological beliefs, and cognitive flexibility variables accounted for a considerable amount of variance ($R^2 = 0.174$).

Metacognitive variables were strong predictors of problem-solving performance. Even though high awareness of cognitive processes (knowledge of cognition) was positively related to problem-solving performance, high ability in monitoring, regulating, and planning one’s own cognitive processes (regulation of cognition) translated into low scores in ill-structured problem-solving task. This is an interesting finding, which contradicts previous research (Shin et al., 2003) and will be discussed in the next chapter.

Table 4.6: Forced-order Hierarchical Regression Predicting IPSP

<table>
<thead>
<tr>
<th>Variable</th>
<th>$R$</th>
<th>$R^2$ Change</th>
<th>$\beta$</th>
<th>$F$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domain knowledge</td>
<td></td>
<td></td>
<td>.255**</td>
<td>$F(3,940) = 68.62**$</td>
</tr>
<tr>
<td>Argumentative reasoning</td>
<td></td>
<td></td>
<td>.222**</td>
<td></td>
</tr>
<tr>
<td>ACT Reading</td>
<td>.424</td>
<td>.180</td>
<td>.189**</td>
<td></td>
</tr>
<tr>
<td>Regulation of cognition</td>
<td></td>
<td></td>
<td>-.423**</td>
<td></td>
</tr>
<tr>
<td>Knowledge of cognition</td>
<td></td>
<td></td>
<td>.314**</td>
<td></td>
</tr>
<tr>
<td>Cognitive flexibility</td>
<td></td>
<td></td>
<td>-.191**</td>
<td></td>
</tr>
<tr>
<td>Certain knowledge</td>
<td></td>
<td></td>
<td>.144**</td>
<td></td>
</tr>
<tr>
<td>Simple knowledge</td>
<td></td>
<td></td>
<td>.091*</td>
<td></td>
</tr>
<tr>
<td>Omniscient authority</td>
<td></td>
<td></td>
<td>-.056</td>
<td></td>
</tr>
<tr>
<td>Quick learning</td>
<td></td>
<td></td>
<td>.003</td>
<td></td>
</tr>
<tr>
<td>Innate ability</td>
<td></td>
<td></td>
<td>.058</td>
<td></td>
</tr>
<tr>
<td>Block two</td>
<td>.595</td>
<td>.174</td>
<td>.224**</td>
<td>$F(8,932) = 31.33**$</td>
</tr>
<tr>
<td>Resource discrimination</td>
<td></td>
<td></td>
<td>.155**</td>
<td></td>
</tr>
<tr>
<td>Task focus</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block three</td>
<td>.656</td>
<td>.077</td>
<td></td>
<td>$F(2,930) = 63.01**$</td>
</tr>
<tr>
<td>(Problem-solving strategies)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Block One contains the variables ACT Reading, Domain knowledge, Argumentative reasoning. Block Two contains the variables Knowledge of cognition, Regulation of cognition, Simple Knowledge, Certain Knowledge, Omniscient authority, Quick learning, Innate ability, Cognitive flexibility. Block Three contains Task focus and Resource discrimination.

*p < 0.5. **p < 0.001.
Two of the five variables associated with epistemological beliefs (simple knowledge, certain knowledge) reached significance. Simple knowledge and certain knowledge were positively correlated with problem-solving performance indicating that students who held more complex and relativistic beliefs did better at solving the ill-structured problem. Omniscient authority, quick learning, and innate ability variables did not reach significance.

Cognitive flexibility correlated negatively with problem-solving performance. That is, students with high cognitive flexibility did poorly on the ill-structured problem-solving task. Although this finding contradicts theoretical assumptions (e.g. Jonassen, 1997; 2000; Spiro et al., 1991), it is consistent with the Niederhauser et al. (2000) study. This also will be discussed more fully in the following chapter.

Even after removing variance from all of the variables in blocks one and two, block three including problem-solving strategies variables still accounted for additional variance ($R^2 = 0.077$). The task focus finding indicates that spending more time on writing was positively related to ill-structured problem-solving performance, which is not a surprising result. The resource discrimination variable also positively correlated with ill-structured problem-solving performance, meaning that students who discriminated relevant from irrelevant resources and those who cycled back to relevant resources while working on completing writing tasks did well on the ill-structured problem-solving task.
CHAPTER 5. DISCUSSION

Two objectives were addressed in the current study. The first objective was to characterize strategies students used to solve an ill-structured problem in a Web-based problem-solving environment. The second objective was to examine the effect of these problem-solving strategies on students’ problem-solving performance when individual characteristics had been controlled. Results revealed four different online problem-solving strategies. In this chapter, characterizations of problem-solving strategies and predictors of ill-structured problem-solving performance, as highlighted in the regression analysis, will be discussed in light of previous research. Finally, implications of the study for education and problem-solving research are presented.

Online Problem-Solving Strategies

Cluster analysis revealed four groups of students who approached the same online problem-solving task in considerably different ways. The clusters were compared and contrasted against the (1) task focus, (2) resource use, and (3) sequence of the problem-solving process. This helped define four different online problem-solving strategies represented by four clusters. Then, a MANOVA revealed that some problem-solving strategies were more effective than others.

Task focus highlighted the differences in the proportions of time allocated to completing writing tasks and the proportions of time allocated to visiting resources. Based on task focus, there were two different strategies. One strategy was mainly task-oriented. That is, students’ main focus was on completing writing tasks and not on
exploring resources (Clusters 3 and 4). Thus, these individuals were classified as *writers*.

The second strategy was more information collection oriented or investigative in which students were more involved in visiting resources and less in completing writing tasks (Clusters 1 and 2). These students were named as *investigators*. The way investigators approached the online problem-solving task is consistent with what Lawless & Kulikowich (1996) characterized “information seekers” in their study of navigational strategies used while reading to learn in a hypertext environment.

Examination of proportion of time spent visiting relevant resources, the proportion of time spent visiting irrelevant resources, and the sequence of the problem-solving processes revealed the degree to which students in a given cluster successfully identified relevant resources and referred back to them while working on constructing their solutions. This is crucial especially when collecting information to solve an ill-structured problem because irrelevant resources may distract students from the original problem. Based on this, the behavior individuals in Cluster 1 demonstrated was classified as *extensive ineffective-cycling*. These individuals made extensive use of resources but navigated back and forth between writing tasks and irrelevant as well as relevant resources. The strategy individuals making up Cluster 2 used was characterized as *extensive effective-cycling* because they spent significant proportion of their time visiting resources ($\bar{x} = 0.48$) and they were effective in revisiting relevant resources while working on completing writing tasks. Those in Clusters 3 and 4 made minimal use of resources and rarely revisited them once they started working on writing tasks. However, when they did revisit resources, students in Cluster 3 did not show any clear sign of resource discrimination whereas those in Cluster 4 tended to refer back to relevant
resources. Therefore the strategies individuals in Clusters 3 and 4 used were categorized as *minimal ineffective-cycling* and *minimal effective-cycling* respectively.

Finally, to conclude the categorization of the clusters, individuals in Clusters 1, 2, 3, 4 are labeled as *extensive ineffective-cycling investigators; extensive effective-cycling investigators; minimal ineffective-cycling writers; and minimal effective-cycling writers* respectively (see Table 5.1).

Table 5.1: *Cluster Labels Based on Resource Discrimination and Task Focus*

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Resource discrimination</th>
<th>Task focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>Extensive ineffective-cycling</td>
<td>Investigator</td>
</tr>
<tr>
<td>Cluster 2</td>
<td>Extensive effective-cycling</td>
<td>Investigator</td>
</tr>
<tr>
<td>Cluster 3</td>
<td>Minimal ineffective-cycling</td>
<td>Writer</td>
</tr>
<tr>
<td>Cluster 4</td>
<td>Minimal effective-cycling</td>
<td>Writer</td>
</tr>
</tbody>
</table>

MANOVA showed a main effect for ill-structured problem-solving performance between clusters. Based on the post hoc analysis *minimal effective-cycling writers* (Cluster 4) were more effective problem solvers than *extensive ineffective-cycling investigators* (Clusters 1). These students chose a convenient path through the problem space. They visited resources in the order that they appeared on the Web-based environment from top to bottom and then focused their attention mainly on completing writing tasks. This coincides with the hypertext navigation strategy discussed in Niederhauser et al. (2000) study. Researchers concluded that this sequential, systematic way of navigating through the hypertext environment was effective because students minimized their use of cognitive resources associated with making conscious decisions about navigating the hypertext.
Even though extensive effective-cycling investigators (Cluster 2) scored considerably higher than extensive ineffective-cycling investigators (Cluster 1), this contrast probably did not reach significance due to the small number of extensive effective-cycling investigators \((n = 7)\). These students had the second highest average score on the ill-structured problem-solving tasks. They were effective problem solvers probably because they used resources well. They tended to go back and reconsider various issues presented in relevant resources to confirm their understanding of the problem space while constructing their solutions.

Another relatively effective group of problem solvers were minimal ineffective-cycling writers (Cluster 3). These students were not particularly effective in separating relevant resources from irrelevant ones. However, the fact that they received satisfactory scores on the problem-solving task indicates that while they might have taken longer to identify relevant information, they eventually did so. Also, these students seldom cycled back to irrelevant resources while working on constructing their solutions, the main difference from extensive ineffective-cycling investigators in terms of resource use.

The least effective problem solvers, as reflected in their lowest average score, were extensive ineffective-cycling investigators. These students failed to identify relevant resources and tended to refer back to irrelevant resources as well as relevant ones while working on their solution proposals. This was likely distracting and certainly not the best use of their cognitive resources. The strategy these individuals used is similar to the “prolific strategy” discussed by Steven & Palacio-Cayetano (2003). These investigators indicated that prolific strategy was an initial stage that was mainly used in the beginning of a problem-solving task. In this strategy, students begin visiting relevant and irrelevant
resources to construct their understanding of the problem space. However, students eventually distinguish relevant and irrelevant resources and focus on the most important information sources (Steven & Palacio-Cayetano, 2003). Otherwise, the prolific strategy was associated with low success rate – as was found in the current study.

**Predictors of Ill-structured Problem-Solving Performance**

Several findings of the present study were consistent with existing research – prior knowledge (Glaser, 1984; Greeno, Collins, & Resnick, 1996; Shin et al., 2003) and argumentative reasoning skills (Shin et al., 2003) played an important role in the ill-structured problem-solving performance. Reading ability was also an important factor that was positively related to performance on the ill-structured problem-solving task. This is not a surprising result considering the nature of the problem-solving task. In the current study, students were supposed to explore various information resources and identify relevant information to help construct their solutions. This is also consistent with numerous studies investigating the role of reading ability on learning in hypertext environments (i.e., Alexander, Klukowich, & Jetton, 1994; Bendixen & Hartley, 2003; Niederhauser et al., 2000).

Metacognitive awareness variables – knowledge of cognition and regulation of cognition – had considerable effect on ill-structured problem-solving performance. Knowledge of cognition was positively related to ill-structured problem-solving performance. However, regulation of cognition was negatively correlated with student scores on ill-structured problem-solving tasks. This means that students who were able to plan, regulate, and monitor their cognitive processes tended to score lower on ill-
structured problem-solving tasks. This unexpected finding contradicted existing research reporting positive correlation between regulation of cognition and ill-structured problem-solving performance in a high school science class (e.g., Shin et al., 2003).

However, a close examination of the literature suggests that there is limited empirical evidence connecting metacognitive variables to ill-structured problem-solving performance. Moreover, there is not a general consensus regarding the role of metacognition in achievement in general. Some researchers suggest that metacognition is a strong predictor of academic performance (Schraw, 1994; Swanson, 1990); others reported that academic achievement was not strongly related to metacognition (Bendixen & Hartley, 2003; Pintrich, Smith, Garcia, & McKeachi, 1991). Another study found a negative correlation between SAT math scores and metacognition (Sperling, Howard, Staley, & DuBois, 2004). These contradictory results suggest that the ways in which metacognition influences academic achievement in general, and ill-structured problem-solving performance in particular, is far from being completely understood.

Certain epistemological beliefs were related to success in the ill-structured problem-solving task. In particular, students holding more complex (captured by the simple knowledge variable) and relativistic (captured by the certain knowledge variable) beliefs regarding the nature of knowledge performed better on the ill-structured problem-solving task. This is consistent with previous research that connected epistemological beliefs to ill-structured, real-life problem-solving tasks (i.e., Schraw, Dunkle, & Bendixen, 1995; Schommer, 1990; Schommer, Crouse, & Rhodes, 1992). Theoretical assumptions that support this finding suggest that individuals are less likely to ignore or overlook interconnected concepts and principles, co-varying factors and constraints;
multiple, contradicting perspectives surrounding the problem space; and more likely to appreciate the ambiguous nature of the ill-structured problem-solving task when they do not see knowledge as fixed, absolute or as an accumulation of discrete facts. Therefore those who appreciate the complex and relativistic nature of knowledge likely feel more comfortable, and perform better when dealing with ill-structured problems (Hofer & Pintrich, 1997; Jonassen, 2000; Kitchener, 1983; Schommer, 1990).

Beliefs in omniscient authority did not seem have an effect on ill-structured problem-solving performance. This finding may be due to the limited nature of the omniscient authority variable measuring the “source of knowledge” dimension of the epistemological beliefs. The omniscient authority component of the self-report measure focused only on beliefs about the role of authority rather than addressing the shifting beliefs about the role of learner – from holder of knowledge to constructor of knowledge (Hofer & Pintrich, 1997).

Innate ability and quick learning were not related to ill-structured problem-solving performance. This is not a surprising result. Hofer & Pintrich (1997) suggested that beliefs about the nature of intelligence and beliefs about how quickly one can learn might be related to one another. They might also correlate with the beliefs about the nature of knowledge but they are different constructs from epistemological beliefs.

Cognitive flexibility correlated negatively with performance on ill-structured problem-solving. A similar result was found in an earlier study that examined the effects of navigational patterns in learning with hypertext (Niederhauser et al., 2000). Researchers integrated a compare and contrast function in a hypertext environment to reflect the use of cognitive flexibility theory through visiting and revisiting the content
multiple times coming from different directions. The use of compare and contrast links was hypothesized to increase students understanding of the content. Contradictory to their hypothesis, it was found that students who used the compare and contrast function to access the content were less successful. Niederhauser et al. (2000) attributed this result to the increased “cognitive load” that might have been posed by the complex nature of the tasks which was constructing meaning out of complex concepts, and the learner characteristics involving reading ability, prior knowledge, and experience with computers.

In the context of solving an ill-structured problem, cognitive flexibility could be a key factor because there are multiple perspectives, constraints, and solution options to consider. Individuals with high cognitive flexibility may be able to look at the problem from multiple angles, reflect on many co-varying factors surrounding the problem space while constructing a solution (Jonassen, 1997; 2000). As a cognitive process, solving an ill-structured problem obviously is not a mundane task. Rather it is a complex one that demands extensive use of cognitive resources. When first faced with an ill-structured problem, one needs to recognize the vagueness in the problem space as well as the need to collect information from multiple sources. Weighing and judging the relevance and validity of the information could also be crucial because there may be contradicting information. In addition, one needs to analytically compare and contrast competing evidence to offer a solution that could address most of the issues and resolve the problem situation. Feasibility and benefits of the proposed solution should be evaluated relative to alternative ones. This process raises several information processing issues. First, the nature of the tasks is complex, which creates an intrinsic cognitive load. Second,
individuals’ reading abilities, prior knowledge, and their ability to navigate through the problem-solving environment pose extraneous cognitive load.

Finally, the current study indicated that some strategies individuals chose to use in solving the ill-structured problem were significant predictors of their success even after controlling for several learner characteristic variables. Students who focused on writing, and students who chose to cycle back to relevant resources did well on the online ill-structured problem-solving task. Previous research indicated that information seekers (see Lawless & Kulikowich, 1996) were successful at reading to learn in a hypertext environment. However, the current study revealed two types of information seekers or investigators. One type not only focused on exploring resources, but was effective at separating relevant from irrelevant information when cycling back through resources to collect information while constructing their solutions. These information seekers tended to return to relevant resources and did well on the ill-structured problem-solving task. However, other information seekers were not effective when cycling back to resources. When they cycled through resources, they tended to review irrelevant as well as relevant resources. This finding highlights the importance of 21st century information literacy skills: evaluating the relevance and validity of information (Jonassen, Howland, Moore, & Marra, 2003; November, 2001).

**Implications for Education**

Results from this study indicated that reading comprehension and domain knowledge were not only strong predictors of performance on well-structured tasks in a hypertext or hypermedia environment as noted by previous studies (e.g., Bendixen &
Hartley, 2003; Niederhauser et al., 2000) but they also seemed to have a critical influence on the ill-structured problem-solving performance in a Web-based environment. Therefore, educators and instructional designers should take students’ reading abilities and domain knowledge into account when designing problem-solving tasks, especially in a Web-based environment that requires information retrieval and processing skills. In the present study, argumentative reasoning skills were positively related to ill-structured problem-solving performance. This finding is supported by the theoretical assumptions suggesting that argumentative reasoning skills are important skills in real-life where there is usually no single correct solution, but several possible ones to choose from (Kitchener, 1983; Kuhn, 1991). One needs to make conscious decisions based on sound reasoning, weighing all the possible options, because these decisions are sometimes of great importance. For example, deciding what house to buy, preparing a wedding party within a budget, and making dietary choices to lose weight and stay healthy are no simple tasks. As the present study indicated, even in an academic setting, ill-structured problem-solving tasks require argumentative reasoning skills. Educators and instructional designers should not overlook this finding while designing problem-solving activities for students. Challenging and complex problem-solving tasks may help students gain argumentative reasoning skills that are valuable not only in academic settings but in real-life as well.

The negative contribution of Cognitive Flexibility to the problem-solving performance once again brought up the “cognitive load” issue addressed in previous research (Niederhauser et al., 2000). Measures should be taken to alleviate the excessive burden on students’ cognitive resources while engaging them with complex, challenging
tasks. Cognitive load is the sum of extraneous, intrinsic, and germane cognitive load (Niederhauser et al., 2000). Therefore, limiting extraneous cognitive load and systematically mediating intrinsic cognitive load allow for increased *germane cognitive load*, which is more conducive to learning. For example, effective problem-solving strategies could be modeled in different elements of design such as embedding prompts to guide students’ thought processes by questioning them at different points, as well as including tools which allow students to take notes and help compare and contrast controversial information collected from diverse information sources.

Finally, problem-solving strategies influenced problem-solving performance even after controlling for several learner characteristic variables. The current study identified four groups of individuals and characterized four distinct problem-solving strategies they used in solving the ill-structured problem in a Web-based environment. Two effective strategies involved identifying relevant information. This finding once again reveals the importance of 21st century information literacy skills mentioned earlier. Every day, we are challenged to deal with messy, real-world problems. These problems usually involve multiple perspectives, constraints, and criteria; and they possess various solution strategies and solution options. More and more people are depending on information from the Internet to solve problems. Considering the vast amount and diversity of information available on the Internet, individuals need to be able to identify relevant information and validate its credibility. Also, the increasing number of online problem-based learning environments used in teaching and learning make it crucial to investigate how individuals approach solving ill-structured, real-life problems online. This is
especially important when designing such environments and helping individuals become better problem solvers.

**Implications for Problem-Solving Research**

The current study highlights the potential of using Web-based problem-solving environments as a tool for the analysis of problem-solving strategies. The use of cluster analytic techniques and examination of clickstream data made it possible to identify and characterize different problem-solving strategies individuals used while completing the online ill-structured problem-solving task. Although similar studies have been conducted to investigate the effects of navigational strategies on learning with hypertext or hypermedia (Barab et al., 1997; Lawless & Kulikowich, 1996; Niederhauser et al., 2000), little or no research is available examining ill-structured problem-solving strategies with the help of clickstream data. Analyzing clickstream data from multiple angles (cluster analysis and graphical representation) may help describe different types of successful and less successful online problem-solving strategies in an effort to help educators and instructional designers develop online problem-based environments conducive to learning and implementing effective problem-solving strategies. More studies conducted in this manner will likely help refine and verify the findings of the current exploratory study.

Examining the reasons that led students to four different problem-solving strategies was beyond the scope of this study. Further research is needed to investigate intrapersonal and external variables that might help better explain what kind of individuals may be more effective problem solvers. Although clusters were compared against domain knowledge and ACT reading scores, and it was found that higher scores
in domain knowledge and ACT reading translated into more effective ill-structured problem-solving strategies, these differences did not reach significance probably due to the small sample size. Therefore, larger samples may help better demonstrate the relationships between these variables and ill-structured problem-solving performance.

The current study indicated interesting relationships between metacognition, epistemic beliefs, and cognitive flexibility and ill-structured problem-solving performance. Given the small number of studies that investigated these variables in the context of ill-structured problem-solving, it is imperative that we conduct more research to understand how these variables influence ill-structured problem-solving performance.
REFERENCES


### APPENDIX A.

**ILL-STRUCTURED PROBLEM/TASK VALIDATION TOOL**

Using the rating below, please evaluate the problem scenario and given tasks. This will be used to help us validate if the problem is an ill-structured one and tasks address the intended skills.

5=Strongly Agree; 4=Agree; 3=Neither; 2=Disagree; 1=Strongly Disagree

<table>
<thead>
<tr>
<th>To what extent do you agree that</th>
<th>Expert Evaluation</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>the <em>Problem Scenario</em> is clearly stated?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>enough relevant information is provided for students to offer a valid solution?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>tasks are appropriate for the content of the class (CI 201)?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>the tasks require the use of concepts and principles addressed in the class?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>there are several ways to approach this problem?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>the solution will involve multiple perspectives?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>the solution will need justification or argumentation?</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
<tr>
<td>the problem or any of the tasks need to be modified? If so, please explain how in the space provided for comments.</td>
<td>5 4 3 2 1</td>
<td></td>
</tr>
</tbody>
</table>
## APPENDIX B. ILL-STRUCTURED

### PROBLEM-SOLVING SCORING RUBRIC

<table>
<thead>
<tr>
<th>ELEMENT</th>
<th>CRITERIA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td><strong>KEY ISSUES AND CONSTRAINTS</strong></td>
<td>Identifies and examines 4 or more possible causes of the problem. Presents an accurate and detailed description of key issues and constraints associated with the possible causes that is compelling and insightful.</td>
</tr>
<tr>
<td><strong>PERSPECTIVES</strong></td>
<td>Analyzes the problem from both key players perspectives. Shows concern to fully understanding position of both key players.</td>
</tr>
<tr>
<td><strong>INFO COLLECTING</strong></td>
<td>Presents a balanced and critical view of multiple sources of knowledge (facts, concepts, personal experience, theory and research, etc.) to make informed judgments.</td>
</tr>
<tr>
<td><strong>GENERATING POSSIBLE SOLUTIONS</strong></td>
<td>Generates 3 possible solutions that are well developed and elaborates on how these will address the causes of the problem.</td>
</tr>
<tr>
<td><strong>DEVELOPING A SOLUTION</strong></td>
<td>Assesses the viability of alternative solutions relative to 4 or more important issues and constraints associated with the causes of the problem.</td>
</tr>
<tr>
<td>Reflecting on Proposed Solution</td>
<td>Reflects on possible consequences of proposed solution relative to all of the important issues and constraints. Shows deep understanding of complex and interactive nature of educational actions and decisions.</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Relative Benefit with Proposed Solution</td>
<td>Offers a compelling explanation for the relative benefit with proposed solution compared to 2 viable alternative solutions.</td>
</tr>
</tbody>
</table>
## APPENDIX C.

### ONLINE QUESTIONNAIRE

**Instructions:** The following statements deal with your beliefs and feelings about your own behavior. Read each statement and check the number that best represents your agreement with each statement.

<table>
<thead>
<tr>
<th></th>
<th>6</th>
<th>5</th>
<th>4</th>
<th>3</th>
<th>2</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>strongly agree</td>
<td>agree</td>
<td>slightly agree</td>
<td>slightly disagree</td>
<td>disagree</td>
<td>strongly disagree</td>
</tr>
</tbody>
</table>

**Cognitive Flexibility Scale**

1. I can communicate an idea in many different ways.
2. I avoid new and unusual situations.
3. I feel like I never get to make decisions.
4. In any given situation, I am able to act appropriately.
5. I can find workable solutions to seemingly unsolvable problems.
6. I seldom have choices to choose from when deciding how to behave.
7. I am willing to work at creative solutions to problems.
8. My behavior is a result of conscious decisions that I make.
9. I have many possible ways of behaving in any given situation.
10. I have difficulty using my knowledge on a given topic in real life situations.
11. I am willing to listen and consider alternatives for handling a problem.
12. I have the self-confidence necessary to try different ways of behaving.

**Instructions:** The following statements deal with your beliefs and feelings about knowledge and learning. Read each statement and check the number that best represents your agreement with each statement.

<table>
<thead>
<tr>
<th></th>
<th>5</th>
<th>4</th>
<th>3</th>
<th>2</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>strongly agree</td>
<td>agree</td>
<td>neutral</td>
<td>disagree</td>
<td>strongly disagree</td>
</tr>
</tbody>
</table>

**Metacognitive Awareness**

11. I ask myself periodically if I am meeting my goals.
12. I consider several alternatives to a problem before I answer.
13. I try to use strategies that have worked in the past.
14. I pace myself while learning in order to have enough time.
15. I understand my intellectual strengths and weaknesses
16. I think about what I need to learn before I begin a task.
17. I know how well I did once I finish a test.
18. I set specific goals before I begin a task.
19. I slow down when I encounter important information.
20. I know what kind of information is most important to learn.
21. I ask myself if I have considered all options when solving a problem.
22. I am good at organizing information.
23. I consciously focus my attention on important information.
24. I have a specific purpose for each strategy I use.
25. I learn best when I know something about the topic.
26. I know what the teacher expects me to learn.
27. I am good at remembering information.
28. I use different learning strategies depending on the situation.
29. I ask myself if there was an easier way to do things after I finish a task.
30. I have control over how well I learn.
31. I periodically review to help me understand important relationships.
32. I ask myself questions about the material before I begin.
33. I think of several ways to solve a problem and choose the best one.
34. I summarize what I’ve learned after I finish.
35. I ask others for help when I don’t understand something.
36. I can motivate myself to learn when I need to.
37. I am aware of what strategies I use when I study.
38. I find myself analyzing the usefulness of strategies while I study.
39. I use my intellectual strengths to compensate for my weaknesses.
40. I focus on the meaning and significance of new information.
41. I create my own examples to make information more meaningful.
42. I am a good judge of how well I understand something.
43. I find myself using helpful learning strategies automatically.
44. I find myself pausing regularly to check my comprehension.
45. I know when each strategy I use will be most effective.
46. I ask myself how well I accomplished my goals once I’m finished.
47. I draw pictures or diagrams to help me understand while learning.
48. I ask myself if I have considered all options after I solve a problem.
49. I try to translate new information in my own words.
50. I change strategies when I fail to understand.
51. I use the organizational structure of the text to help me learn.
52. I read instructions carefully before I begin a task.
53. I ask myself if what I’m reading is related to what I already know.
54. I reevaluate my assumptions when I get confused.
55. I organize my time to best accomplish my goal.
56. I learn more when I am interested in the topic.
57. I try to break studying down into smaller steps.
58. I focus on overall meaning rather than specifics.
59. I ask myself questions about how well I am doing while I am learning something new.
60. I ask myself if I learned as much as I could have once I finish a task.
61. I stop and go back over new information that is not clear.
62. I stop and reread when I get confused.

**Epistemological Beliefs Inventory**

1. Most things worth knowing are easy to understand.
2. What is true is a matter of opinion.
3. Students who learn things quickly are the most successful.
4. People should always obey the law.
5. People’s intellectual potentials are fixed at birth.
6. Absolute moral truth does not exist.
7. Parents should teach their children all there is to know about life.
8. Really smart students don’t have to work as hard to do well in school.
9. If a person tries to hard to understand a problem, they will most likely end up being confused.
10. Too many theories just complicate things.
11. The best ideas are often the most simple.
12. Instructors should focus on facts instead of theories.
13. Some people are born with special gifts and talents.
14. How well you do in school depends on how smart you are.
15. If you don’t learn something quickly, you won’t ever learn it.
16. Some people just have a knack for learning and others don’t.
17. Things are simpler than most professors would have you believe.
18. If two people are arguing about something, at least one of them must be wrong.
19. Children should be allowed to question their parents’ authority.
20. If you haven’t understood a chapter the first time through, going back over it won’t help.
21. Science is easy to understand because it contains so many facts.
22. The more you know about a topic, the more there is to know.
23. What is true today will be true tomorrow.
24. Smart people are born that way.
25. When someone in authority tells me what to do, I usually do it.
26. People shouldn’t question authority.
27. Working on a problem with no quick solution is a waste of time.
28. Sometimes there are no right answers to life’s big problems.
Appendix D.

Domain Knowledge Questions and Answer Key

1) List and explain three of the ways that website biases can be identified.

- You can use link command on AltaVista.com and it will show who links to this site.
- Look at the URL (.gov, .edu), tilde=personal website...
- Use wayback machine to track certain changes in the website.
- Check the website on Overture.com to see if they pay to be listed on search engines.
- Use Easywhois.com to see who owns the website.
- Check for one-sided presentation of information.
- Examine phrasing for any ambiguities.

Alternative student answers:

- View other sites on the same topic.
- Check the original sources where the facts are derived. You need to see if the facts are presented in a way that manipulates the meaning.
- Pay attention to the use of superlatives (best, greatest, highest)

2) Use of the World Wide Web to conduct research by K-12 students has become increasingly widespread. This has made plagiarism a serious problem for educators. As future teachers, it is important that you know what plagiarism is, how to identify it, and how to prevent it.

(a) What is plagiarism?

Definition: Plagiarism is the practice of claiming, or implying, original authorship or incorporating material from someone else's written or creative work, in whole or in part, into ones own without adequate acknowledgement.

Alternative student answers:

- Plagiarism is using others text materials, writings, and such things that is not yours and not citing the information.
- Plagiarism is the stealing of other people’s ideas or work and presenting it as your own.
- Plagiarism is taking credit for others thoughts and ideas and passing them as your own.
Note: Plagiarism is different from copyright infringement. While both terms may apply to a particular act, they emphasize different aspects of the transgression. Copyright infringement is a violation of the rights of the copyright holder, when material is used without the copyright holder's consent. On the other hand, plagiarism is concerned with the unearned increment to the plagiarizing author's reputation. (Wikipedia.com).

The following answers indicate misunderstanding of plagiarism:
- Plagiarism is the unauthorized use of someone else’s copyrighted material.
- Plagiarism is using someone else’s work without sourcing or permission.
- Plagiarism is the unauthorized use of copyrighted or patented works.
- Plagiarism is when a copyrighted work has been over-used in terms of percentage or word count and is not properly cited.

(b) How can you tell when a student has plagiarized?
- Complex language and paraphrasing in a paper,
- You can submit the paper in question to Plagiarism.com and they will let you know.

Alternative student answers:
- The way a paper is written – students and professionals have noticeable differences in the way they each write.
- Using vocabulary that is out of their reach, different dialect than what the student usually writes with.
- You can type in certain words to a browser (or Google) which can show you if the student plagiarized.

Incomplete student answers:
- No citations to source the references.
- If the majority of work is from another work and is not cited.

(c) Describe two ways that a teacher can prevent plagiarism.
- Teach students what it is and why it is important to avoid it.
- Teach students how to cite sources appropriately.
- Let them know about the severe consequences of plagiarism.
- Take disciplinary measures failing the assignment, etc.

Incomplete answers:
- A teacher could use web sites where you type in the student’s work and it will show if there are any matches (this is a way to detect plagiarism not to prevent it - an answer for the previous question).
APPENDIX E.
CODING SCHEME FOR ARGUMENTATIVE REASONING

Pro arguments
1. Functional arguments
A. Alternatives to CP are ineffective or less effective than CP
   A1. Alternatives to CP are not effective as deterrents
   A2. Alternatives to CP are not effective in protecting society from criminals
   A3. Alternatives to CP are not sufficient punishment
   A4. Alternatives to CP fail to rehabilitate criminals
   A5. Alternatives to CP are too burdensome or costly a way to serve their purpose
B. CP reduces crime
   B1. CP deters people from crime
   B2. CP protects society from the acts of criminals
C. CP is an appropriate punishment
   C1. Eye-for-eye
   C2. Criminals have forfeited the right to life and privileges associated with it
   C3. Compensates victim or victim's family

II. Non-functional arguments (focused on conditions that make CP justified, without consideration of its functions)
A. CP is justified only if guilt is established beyond reasonable doubt
B. CP is justified only if criminal judged competent to be responsible for own actions
C. CP is justified only if it is applied consistently
D. CP is justified only if the crime is sufficiently grave
E. CP is justified only in the case of repeated crime

III. Nonjustificatory arguments
A. Justification based on sentiment
B. Appeal to precedent (CP has been in use for a long time)
C. Appeal to majority (many or most think it's a good idea)
D. Appeal to authority (without intervening argument)
E. Crime exists and needs a remedy

Con arguments
1. Functional arguments
A. Alternatives exist that are preferable to CP
   A1. Alternatives to CP are better as deterrents
   A2. Alternatives to CP are better in protecting society from criminals
   A3. Alternatives to CP are better punishment
   A4. Alternatives to CP allow rehabilitation of criminals
B. CP does not reduce crime or reduce it sufficiently
   B1. CP is not effective in deterring people from crime
   B2. CP is not effective in protecting society from the acts of criminals
C. CP is not an appropriate punishment
   C1. CP commits the same crime it is meant to punish
   C2. CP does not right the wrong (doesn't restore loss to victim of crime)
   C3. We lack the right to take life
   C4. We lack the right to make judgments of who should live or die
   C5. We lack the right to make judgments of other people's actions
   C6. CP violates the principle of forgiveness
C7. Any killing is wrong
C8. CP is violent, barbaric
C9. CP wastes lives
C10. CP serves no purpose
C11. Enforcers of CP themselves commit crime

II. Nonfunctional arguments (focused on possibly remediable defects in administration of CP, without consideration of its functions)
A. CP may punish innocent people
B. CP may punish people who are not responsible for their actions
C. CP is not administered uniformly (may be discriminatory against certain groups)
D. CP may punish people who committed crime accidentally or as victim of circumstances
E. CP is not administered efficiently (e.g., may be drawn out and costly)

III. Nonjustificatory arguments
A. Justification based on sentiment
B. Appeal to precedent (CP has not been widely used or as widely used as it once was)
C. Appeal to majority (many or most are against CP)
D. Appeal to authority (without intervening argument)

Note. CP = capital punishment Source: Kuhn, Shaw, and Felton (1997).
APPENDIX F.
PROBABILITY PLOT OF STANDARDIZED RESIDUALS

Dependent Variable: IPSP