

UC Riverside

UC Riverside Electronic Theses and Dissertations

Title

The Relation Between Reasoning and the Structure of Knowledge When Solving Mechanical Problems

Permalink

<https://escholarship.org/uc/item/94f4t1h6>

Author

Reisz, Z

Publication Date

2015

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
RIVERSIDE

The Relation Between Reasoning and the Structure of Knowledge When Solving
Mechanical Problems

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Psychology

by

Z Reisz

August 2015

Dissertation Committee:

Dr. Mary Gauvain, Chairperson

Dr. Daniel J. Ozer

Dr. H. Lee Swanson

Copyright by
Z Reisz
2015

The Dissertation of Z Reisz is approved:

Committee Chairperson

University of California, Riverside

Acknowledgements

This dissertation marks the end of a journey, and as is the nature of any good journey the path was seldom straight or easy. It is during these times of challenge that we ask the most of those close to us. With my deepest gratitude, I would like to recognize the support I have received, and the sacrifices that I have asked of those closest to me. Any claims I make to success during this journey are a tribute to the support and sacrifice of my family, friends, and mentors.

Melissa, my love, you have been beside me throughout the transitions from student to professional and back to student. You have remained in steadfast support of my aspirations. In times of trial you have been an ever-giving source of security, encouragement, and compassion. Whenever my light, my ambition, my aspiration waned you never failed to take up my burdens. When my eyes were downcast and my shoulders slumped you carried me through to raise my head, to stand straight, to persevere. I have leaned on your support, and asked more of you than anyone else in these past years.

Gerald and Suellen, my parents, you have given years of sacrifice and support. From tying my skates to exploring the nuances of knowledge and problem solving you have made my goals a part of your own. Gerald, you worked tirelessly to provide for Ash and me. Through your actions you instilled the values and work ethic that has allowed me to overcome challenges that would otherwise have been beyond me. Suellen, you were my first teacher. Through your eyes I learned to appreciate the strength and beauty that is inherent in human variety. Together you provided the foundation from which this dissertation was built.

Ash, Ho, Ned, and Jasa, from skiing to barbecue you never let me forget there is time to relax. In these times you encouraged my curiosity and concern for education. Thank you for the good times, good food, and good conversations. When I was exhausted you always reminded me of the reasons to persist.

To my roommates, Nick, James, and Lizzie, commiseration and good stories were always near at hand. Thank you for making our house a place of rest, support, comfort, and delicious family dinners.

To Faye and Renee, from deadline to deadline, I have always depended on your help. Thank you for your compassionate ears, advice, and the broader perspective you have provided in our conversations. Thank you for helping me in all my times of marginal timeliness and last minute near-tragedies. You made many tough times better.

Lastly I would like to thank my dissertation committee members, Drs. Mary Gauvain, Dan Ozer, and Lee Swanson; without your support and guidance the research presented in this dissertation would not have been possible. Dan, thank you for seeing potential in me, working with great flexibility to help me define my research interest, and teaching me to value and appreciate the rigor and methodological sophistication that is central to behavioral science. Mary, thank you for the opportunity to work in your lab and to benefit from your research and experience. Your advise, support, and skill at burgeoning creativity and clarity in our discussions ensured that frustration was short lived and followed with productivity and focus. Lee, thank you for your service on my committees, and the advice you provided throughout my qualification exam and during the development of this dissertation.

In dedication to the teachers that opened the doors to a world of awe and wonder

Suellen Bowersock

The world is vast, the world has variety, this is wonderful

Tim Wehner

To teach is to support, to teach is to care, to teach is to change a life

Roger Sweet

A thing is beautiful not in the end, but in the emotion of its creation

Leo Webber

One way or another we will build it, we will fix it

Dan Ozer

There is elegance in the world's numbers

Mary Gauvain

In research we extend ourselves, to learn, to teach, to create, to fix, and to appreciate

ABSTRACT OF THE DISSERTATION

The Relation Between Reasoning and the Structure of Knowledge When Solving Mechanical Problems

by

Z Reisz

Doctor of Philosophy, Graduate Program in Psychology
University of California, Riverside, August 2015
Dr. Mary Gauvain, Chairperson

An important outcome of formal education is the acquisition of knowledge that will facilitate domain specific problem-solving skill. Theories of human intelligence identify general reasoning as a cognitive ability that is strongly associated with solving novel problems where learning about the problem is necessary. This dissertation investigates individual differences, such as general reasoning, that may influence how an individual structures knowledge within a domain, such as bicycle gears, and subsequent problem-solving skill. Special focus is given to identifying the structural characteristics of the acquired bicycle gear knowledge and relating these characteristics to general reasoning and skill at solving bicycle gear problems. College participants (N = 174, 111 female) completed a general reasoning test, reported the bicycle parts they knew, and their mechanical self-efficacy was assessed before they watched a training video on bicycle gear adjustment. After training, the extent of their procedural knowledge was tested, the structure of their knowledge was elicited, and then their skill at fixing bicycle gear problems was tested. Professional bicycle mechanics (N = 3) were recruited to provide a

criterion for evaluating the structural characteristics of bicycle gear knowledge. The results from regression analysis indicated that bicycle gear problem-solving skill had a stronger relation with how knowledge was structured, as compared to the extent of procedural knowledge, general reasoning, mechanical self-efficacy, or problem-solving effort. Regression analysis of knowledge structure indicated that general reasoning was associated with acquiring an expert-like knowledge structure, as was learning effort and pre-training bicycle part knowledge, but not mechanical self-efficacy. These results support the view that general reasoning is associated with problem solving because it facilitates the acquisition of knowledge that is structured similarly to experienced professionals. If it is the structure of knowledge that facilitates or hinders problem-solving, as suggested by this study's results, mechanical training may be enhanced by an explicit focus on structuring knowledge to replicate that of experts. A focus on using educational materials that impart the desired knowledge structure may significantly reduce the need of general reasoning in achieving mechanical expertise.

Table of Contents

Abstract	vii
Introduction	1
Methods	28
Results	38
Discussion	55
References	80
Tables	84
Figures	91
Appendices	96

The Relation Between Reasoning and the Structure of Knowledge When Solving Mechanical Problems

How does the process of solving novel problems, such as those seen on IQ tests, differ from solving problems where previous experience and training is relevant, such as fixing a bicycle's gears? Many of the problems on IQ tests are purposefully designed to be independent of previous experience and knowledge. For example, Raven's Advanced Progressive Matrices (APM; Raven, 2000) presents a sequence of images that follow a pattern and the respondent is asked to identify from a set of related images the image that would continue the pattern. Neither the images nor the problem structure are assumed to reflect prior experiences of the respondent. In contrast, the types of problems that arise in everyday life are usually related with previous experience and knowledge. For example, why is the water faucet dripping, or why does the bicycle chain keep skipping between sprockets? These two everyday, mechanical problems are fundamentally different from the more stripped-down types of problems found on IQ tests such as the APM. Solving everyday mechanical problems is often highly dependent on referencing experiential knowledge, whereas APM problems are more independent from any particular experience even though they may have embedded cultural meaning. In this study, the relation between individuals' knowledge, particularly the organization of knowledge in a specific domain, and their skill at solving related problems is examined. The aim is to discover how the knowledge base and the organization of that knowledge contribute to

skill at solving mechanical problems, the types of problems that many tradespeople and professionals confront in their work. As background, literature pertaining to human cognitive abilities and problem solving is reviewed. It is emphasized that the current understanding of intelligence and human cognitive abilities is insufficient to explain problem solving, especially in the type of problems confronted in everyday life. It is argued that individual differences in knowledge are central to understanding problem solving, and the supporting literature is reviewed.

Human Intelligence, Explaining Problem Solving Independent of Knowledge

For over a century psychologists have been interested in understanding the various cognitive processes that underlie problem solving. Although every problem is unique in its own way, much of the research has focused on identifying the cognitive processes that are common to the successful resolution of problems in general (Newell & Simon, 1972). An underlying assumption in this research is that the successful resolution of one problem shares a commonality with the resolution of other problems. For many psychologists, this generalized ability to solve problems is a central characteristic of intelligence (Gottfredson, 1997; Wasserman, 2012). Those who are intelligent will be able to solve a broad array of problems, while those who are less intelligent will be more limited in the problems they can solve. However, the research supporting this idea focuses on problems stripped of relevance to specific experience or knowledge, except in a few cases where general cultural knowledge is being tested by the problems. This research emphasizes how intelligence and the related cognitive abilities support novel problem solving, but it provides minimal understanding of how intelligence is involved in

solving problems where previous experience and knowledge is relevant.

Over the last century, a great deal of effort has gone into identifying and assessing human intelligence, as seen in the work of researchers such as Binet, Wechsler, Spearman, Thurstone, Cattell, Horn, and Carroll (Wasserman, 2012). The extensive research into identifying the general cognitive abilities that underlie performance and problem solving on IQ tests has recently reached a general consensus about the nature of these abilities (Carroll, 1993; Horn & Blankson, 2005; Schneider & McGrew, 2012). These general cognitive abilities are undeniably important to solving problems. However, this approach to examining problem solving lacks consideration of the role that specific experiences and related knowledge have in problem solving. Domain-specific knowledge has aptly been described as the “dark matter” of adult intelligence because it is precisely this domain specific knowledge that is most likely to explain the type of problem-solving skill that most adults demonstrate (Ackerman, 2000).

In the following sections we review one prominent theory of human cognitive abilities as it relates to differences in problem solving, and then turn our attention to review the research that has examined the relation between knowledge and solving related problems. This background is used as a framework for understanding the roles of general cognitive abilities and domain-specific knowledge in how everyday, experience, and knowledge-related problems are solved. By integrating an understanding of general cognitive abilities with an understanding of domain-specific knowledge, we hope to extend the explanation of problem-solving behavior to problems other than those seen on IQ tests.

Because domain-specific knowledge can be expansive, we take the position that the better organized this knowledge is, the better someone will be at solving problems in that domain. This claim suggests that examination of the organization of knowledge content is important for advancing understanding of how knowledge is involved in problem solving. In addition to reviewing three broad types of knowledge, we review a method for assessing how an individual has organized and structured their knowledge within a domain. We will also review several findings using this method that support the claim about the importance of the structural organization of knowledge for solving the everyday types of problems that adults often confront. This background literature provides the foundation for examining how the organization of knowledge contributes to problem solving.

General cognitive abilities and problem solving. Cattell (1943) introduced the theory of fluid and crystallized intelligence asserting that, “Adult mental capacity is of two kinds, the chief characteristics of which may be best connoted by the use of the terms ‘fluid’ and ‘crystallized’” (Cattell, 1943, p.178). Fluid intelligence was conceptualized as the general ability to discriminate and perceive relations; it predicts performance on novel problem solving tasks such as the Raven’s APM. Crystallized intelligence was conceptualized as “... discriminatory habits long established in a particular field, originally through the operation of fluid ability, but no longer requiring insightful perception for their successful operation” (Cattell, 1943, p. 178). This quote highlights two important aspects of crystallized intelligence that are central to the purpose and design of this study. First, crystallized intelligence is the discriminatory habits of a

particular field. We propose that discriminatory habits are the established principles of a field and are expressed in the way an individual organizes the information from a problem in that field. Second, crystallized intelligence is acquired through the operation or investment of fluid intelligence. For the current study, the focus is on understanding the relation between general reasoning, one's organization of problem information, and skill at solving the problem.

Horn extended Cattell's theory of intelligence and developed the extended Fluid and Crystallized theory of cognitive abilities (Horn & Blankson, 2005). This theory builds from Cattell's work to identify the general cognitive abilities that constitute adult mental capacity, more commonly referred to as intelligence. The extended fluid and crystallized theory broadens the view of intelligence to include eight general cognitive abilities that are grouped into three classifications. Horn did not argue that these are the definitive eight general cognitive abilities, but that they are the general abilities with enough evidence to be formalized. These general cognitive abilities differ between individuals, display different developmental trends, and predict the types of intelligence test problems an individual can solve.

Support for the extended fluid and crystallized theory is based on structural evidence from factor analyses and from developmental research. The structural evidence is derived from research looking for common factor patterns among tests designed to assess human intelligence. It is argued that these kinds of test items are grouped by the cognitive abilities they tap. When a set of test problems are highly correlated, performance on one item predicts performance on the others, the correlation is argued to

result from a commonality in the cognitive ability being utilized when solving the problems. When a full IQ test is examined in this manner it is argued to provide evidence of the structural organization of human cognitive abilities. One exemplar of this type of research is Carroll's survey and analysis of over 460 cognitive ability test data sets (Carroll, 1993). The developmental research supporting the extended Gf/Gc theory is derived from observing trends in cognitive abilities across time using cross-sectional or repeated measures study designs. The convergence of these two methods of research provides the evidence for the general cognitive abilities and the three classifications of these abilities described in the extended fluid and crystalized theory of cognitive abilities.

The extended fluid and crystalized theory identifies eight broad cognitive abilities that are organized into three clusters: vulnerable, expertise, and sensory-perceptual abilities. Vulnerable abilities are the abilities that are most similar to Spearman's theory of intelligence and Cattell's concept of fluid intelligence. Expertise abilities are those abilities that are most similar to Cattell's concept of crystallized intelligence. The sensory and perception abilities are those abilities that have clear ties to the sensory modalities, such as visualization and auditory comprehension. The cognitive abilities within each cluster exhibit similar developmental trends (Horn & Blankson, 2005), and are theoretically important in solving different types of problems. For instance, the vulnerable abilities should be most extensively utilized when the problem is novel, while the expertise abilities should be utilized more in the type of everyday problem solving that relies on previous experience and is the focus of this study. We further develop the role of these abilities in problem solving in the next section.

We do not extend the discussion about the relation of general cognitive abilities and problem solving to the class of sensory and perceptual abilities. The focus of this study is to gain a better understanding of how vulnerable abilities, specifically general reasoning, interact with the acquisition and organization of knowledge and problem solving. Differences in the sensory and perception abilities are clearly connected with the ability to utilize the type of information provided by that modality. Yet, it is unclear how sensory and perception abilities are involved in the acquisition and application of knowledge in problem solving. A complete understanding of problem solving will include this class of abilities, but is the topic for future research.

Vulnerable abilities. Vulnerable abilities are the cognitive abilities that demonstrate a relatively early peak in adulthood followed by a steady decline; this vulnerability to earlier decline is the source of this cluster's name. These are the abilities that are reminiscent of Spearman's conception of intelligence as the capacity for apprehension and the education of relations and correlates (Horn & Blankson, 2005). The vulnerable cluster of abilities includes the broad cognitive abilities of fluid or general reasoning (Gf), short-term apprehension and retrieval (SAR), and processing speed (Gs). These abilities are most pronounced in solving novel problems that require the apprehension of the problem and an identification of the relations between the elements of the problem; problems where acquiring knowledge beyond the current base is necessary.

Raven's APM is an example of problems designed to assess vulnerable abilities. The problem content and design are likely to be entirely novel, and the experience from one APM problem to the next provides only limited aid for the next solution. The

examinee must recognize the pattern of relations between the images to solve the problem and previous knowledge is presumed to be of little use in doing so. This process requires holding the elements in memory, thus employing SAR, and recognizing the relations between the images, thus employing Gf. The test is timed, so Gs factors into overall performance as well.

The vulnerable abilities are considered necessary for solving problems where previous knowledge is not applicable; direct or immediate, as opposed to prior, experience with the problem is the only way to gain an understanding of the problem and solve it. In most applied and real world problems, knowledge from previous experience is relevant (e.g., Cornelius & Caspi, 1987; Diehl, Willis, & Schaie 1995), and may substantially reduce the need to use vulnerable abilities in problem solving. The need for vulnerable abilities in problem solving may be further reduced by access to problem related training materials, such as technical manuals, or more experienced individuals. Both the more experienced person and a technical manual provide other avenues to acquire the knowledge needed to solve particular problems. Access to such problem relevant information may substantially change the process of solving a problem, shifting the emphasis from vulnerable abilities to expertise abilities and training.

Problems that are common or important within a culture tend to have instructional supports developed to convey the knowledge of experts. For example, a novice cyclist with no mechanical experience is having problems with his or her gears. Several options are available for solving this problem. The cyclist may implement a trial and error process relying on their Gf and SAR cognitive abilities to develop an understanding and

solution to the problem. Or, the cyclist may seek out instructional material designed to convey the relevant knowledge of professional bicycle mechanics. For instance, a bicycle manual or information available on the Internet can be particularly powerful tools for learning how to solve a variety of problems. Such resources may provide a step-by-step guide and, in the case of the Internet, a video demonstration of how to adjust the gears on a bicycle and solve the gear problem. The use of cultural tools, such as instructional manuals and videos, to learn about problems and how to solve them may substantially reduce the importance of the vulnerable abilities in solving many problems.

To further illustrate the change in problem solving that is introduced when individuals are provided problem related instruction, consider the effect of training Raven's APM test takers. For example, if the examinee was given the following information: Each pattern of images is governed by a rule of change or a combination of several rules of change; the easiest problems will use only one rule of change, but harder problems will compound multiple rules of change; to solve APM problems you need to identify the rule(s) of change being used; and the solution to APM problems is even further aided if the rules of change are defined (e.g., if the pattern is governed by the rule of momentum then the pattern is one of either adding or subtracting parts). When examinees are not provided this information, Gf and SAR are necessary to solving a problem, and if the test is timed, Gs is important as well. However, when given information about how to solve the problem and its underlying principles, the process of solving these problems is fundamentally changed. The vulnerable abilities may no longer be needed to solve the problem because there is less need to learn from the problem and

organize this experiential information into problem knowledge. Thus, instruction may serve to reduce or remove the need to rely on vulnerable abilities during problem solving.

Expertise abilities. The expertise cluster of cognitive abilities is composed of those abilities that are much more closely tied to the knowledge acquired from experience. Expert cognitive abilities are the extension of Cattell's crystallized factor of intelligence (Horn & Blankson, 2005). The cluster is populated by acculturation knowledge (Gc), fluency of retrieval from long-term storage (TSR), and quantitative knowledge (Gq). The Gc cognitive ability is assessed with tests of general culture knowledge. In one Gc test, picture completion, a common object is displayed with a part missing, such as a car with no wheels. The examinee is asked to identify the missing element, testing their understanding of this general cultural artifact. The TSR cognitive ability is assessed with tests that require retrieving information. For example, an examinee may be asked to recall something that was learned an hour earlier, to provide as many synonyms as he or she can, or to rewrite a sentence using different words without changing the meaning of the sentence. The Gq cognitive ability is assessed with tests of mathematical abilities. For example, an examinee may be tested on the accuracy and speed she or he can perform arithmetic operations, or to identify the information needed to solve various mathematical problems.

The expertise cognitive abilities represent an understanding of the role of knowledge in human mental capacity and problem solving. These abilities are organized by their content, Gc and Gq, or the ability to reference stored knowledge, TSR. Focusing solely on the content of knowledge per se is inadequate for understanding problem

solving however. For example, a narrower ability within Gc is mechanical knowledge. Mechanical knowledge is an assessment of the ability to identify mechanical tools, equipment, and general principles for solving mechanical problems (Horn & Blankson, 2005). We argue that assessment of the content of mechanical knowledge provides an insufficient explanation of expertise and does not account for the flexibility professional mechanics demonstrate in the problems they can solve; knowledge is more than its content. The way that knowledge is organized is another characteristic that may be important in understanding expertise and skill at solving problems.

Characterizing Knowledge in Relation to Problem Solving

Knowledge can be characterized by its nature as either declarative, procedural, or structural (Jonassen, Beissner, & Yacci, 1993), and these differences may determine the utility of knowledge in problem solving. One characteristic difference between these three types of knowledge is in their organization. Declarative knowledge characterizes a type of knowledge that is not organized in any particular manner, but rather is a knowledge of largely independent facts. Procedural knowledge is characterized by its sequential organization and is usually directed at achieving one specific outcome, such as the steps an individual should follow to fix a specific bicycle gear problem. Knowledge that is characterized as structural has the potential to be utilized in the broadest array of related problems. This type of knowledge is not organized into a rigid sequence directed at one outcome, but rather is organized by the relations that are maintained between the concepts in that domain. For instance, having an understanding of how all the parts of a bicycle are functionally related in the transfer of pedal motion to wheel motion has the

potential to explain much of expert mechanic problem-solving skill in this domain.

Declarative knowledge describes knowledge that is primarily factual and descriptive, and is limited in its connections to other information (Jonassen et al., 1993). Declarative knowledge of a bicycle's drive train would include the names of the parts, a variety of facts about those parts such as pricing, specifications, options, and weight, but minimal to no information about how the parts are interrelated in a bicycle's mechanical system. This type of knowledge is important in solving the types of problems confronted by purchasing and supply clerks. For example, consider the problem of finding a replacement 8-speed rear derailleur. To solve this problem, the clerk needs to know the specifications of that part, if multiple brands fit the specifications, if the part is in the store's stock, if it is not in the store's stock what suppliers carry the part, and if there are any additional options that need consideration when ordering the part. Solving this problem does not rely on understanding how the part fits into the overall drive system, the solution rests in knowing a number of declarative facts.

Procedural knowledge is characterized by its sequential nature and typically describes the step-by-step process for resolving a specific problem (Jonassen et al., 1993). This type of knowledge is useful for solving well-defined problems. Instructional manuals are predominantly an effort to document and transmit procedural knowledge. The common problems seen by bicycle mechanics can be solved with an almost exclusive use of procedural knowledge. For example, the problem of the derailleur throwing the chain off the smallest sprocket can be solved with a four step procedure: shift to the smallest sprocket, tighten the high limit screw $1/8^{\text{th}}$ turn, check to see if the

adjustment fixed the problem, and, if not, continue to tighten in 1/8th turns until the problem is fixed. However, bicycles may present a wide variety of problems and learning the procedure to fix each one may not be feasible even after extensive practice. Learning procedural knowledge is often the focus of technical job training because it is considered an, or perhaps the most, efficient way to solve common problems. However, the utility of procedural knowledge is limited by its specificity to a single problem, and the complexity of the procedures required by some problems.

Structural knowledge refers to the way that knowledge content is organized and structured by its interrelations (Jonassen et al., 1993). Whereas declarative knowledge is factual and procedural knowledge is a rigid set sequential relations, structural knowledge is an understanding of how knowledge content is interrelated and used to perform a particular function. In the drive system of a bicycle, structural knowledge is the understanding of how the derailleur is related to the chain, the sprockets, the crank set, the wheel, and all of the other components that work together to transfer pedal motion into wheel motion and allow the selection of different gears. Figure 1 provides an illustration of three bicycle gear knowledge structures. It is a more holistic view of the problem that recognizes the important parts of the problem and how those parts are related to each other. The structure of knowledge has the potential to provide the most information about a knowledge set's utility in problem solving. A mechanic who understands how the drive system on the bicycle functions, and how that functioning is dependent on the numerous interrelations between parts, is more than likely well equipped to troubleshoot any problems within the system – in other words, an expert.

This assertion, however, is an empirical question, one that is central to this dissertation.

The Structure of Knowledge, Experience, and Problem Solving

The idea that it is the characteristics of how knowledge is structured that determine its utility in performance and problem solving has been supported in several lines of research. One such line of research began as part of an evaluation of pilot training programs in the U.S. Air Force (Schvaneveldt et al., 1985). It was observed that instructor and student pilots differ in the way they structure their knowledge about flight related concepts for combat situations. For instance, the student pilots had more complex structures that had on average 47% more links between concepts than the instructors' structure. It was also discovered that over the course of training as experience and skill increased, student-instructor differences in the structure of their knowledge decreased. Experience appears to define, constrain, and streamline how one organizes knowledge. Extensive experience in a domain may result in the development of efficiently structured knowledge that, in turn, improves performance (Schvaneveldt et al., 1985).

As this line of research continued different content areas were explored, such as troubleshooting electronics, but the main push was to identify the structural characteristics of knowledge that may determine its utility in performance and problem solving. Current evidence suggests that structural density, coherence, and similarity to an expert's knowledge structure may determine the utility of an individual's knowledge content in any one domain. The bulk of this evidence is derived from studies that assess knowledge structures before and after a training period, assess performance in the trained domain, and evaluate the structures of students' knowledge in comparison to that of

instructors or other experts.

One of the first studies to test a method of comparing two knowledge structures occurred in the setting of a psychology statistics course (Goldsmith, Johnson, & Acton, 1991). At the beginning and near the end of the course, students' knowledge structure of 30 important statistics concepts (e.g., variable, replication, significance) was elicited and compared to their overall class performance. It was found that structural similarity to the instructor's knowledge structure was predictive of final course grade. Furthermore, when between-student differences in structural similarity were examined at the end of the course, students in the high performer group structured their knowledge more similarly to each other than students in the group of low performers. This suggests that experience and training may restructure knowledge as one acquires a better understanding of the concept relations that are maintained by the environment and problem structure. Experience may drive an individual's knowledge structure to converge with the structure of more experienced individuals. A number of studies have replicated the relation between similarity to an expert's knowledge structure and domain performance, as well as higher structural similarity between higher performers than lower performers (e.g., Acton, Johnson, & Goldsmith, 1994; Cooke & Schvaneveldt, 1988; Davis, Curtis, & Tschetter, 2003; Gillan, Breedin, & Cooke, 1992; Schvaneveldt, Tucker, Castillo, & Bennett, 2002).

The structure of knowledge may determine its utility. There is growing evidence that the utility of one's knowledge may be determined by the way that the knowledge is structured. In a variety of different content domains it is seen that the closer

one structures his or her knowledge to experts' knowledge, the better his or her performance in that domain. This positive relation between performance and having an expert-like structure to one's knowledge has been observed in a computer-programming course and a financial accounting class (Acton et al., 1994; Davis et al., 2003). Similarity to an expert's knowledge structure predicted the ability to define essential concepts from an introductory psychology course after taking the course (Gonzalvo, Cafias, & Bajo, 1994). Other studies found that similarity to an expert's knowledge structure was associated with performance in a video game (Day, Arthur, & Gettman, 2001), therapist performance as rated by clients (Kivlighan, 2008), and skill at troubleshooting airplane electrical malfunctions (Rowe, Cooke, Hall, & Halgren, 1996). Similarity to an expert's knowledge structure appears to capture characteristics of knowledge that facilitate performance and problem solving above and beyond what a listing of knowledge content in the domain would yield.

Two additional properties of the structuring of knowledge are common to experts, uncommon to novices, and are related to performance and problem solving. These properties are the density and coherence of the knowledge structure (Schvaneveldt et al., 1985). Density refers to the complexity of the structure and coherence refers to the consistency of the inter-concept relations in the structure of knowledge. Both of these concepts are defined in more detail in the next section. Research on troubleshooting the cause of failures of automated spacecraft life-support systems indicates that the density and coherence of the knowledge structure are related to troubleshooting skill (Burkolter, Meyer, Kluge, & Sauer, 2010). High density is negatively related to performance,

indicating that making numerous connections between concepts reduces the usability of knowledge, hindering problem solving. In contrast, increases in coherence have a positive association with accurately diagnosing the cause of failures. The coherence of a knowledge structure has been shown to increase with experience, training, and expertise (Schvaneveldt et al., 1985, 2002). High achievers in a chemistry course showed, on average, more coherent knowledge structures than low achievers (Wilson, 1994). Because density and coherence are two properties of the structure of knowledge that relate to performance, they may be important to understanding the role of knowledge and its structure in problem solving.

Eliciting and assessing knowledge structures: Pathfinder Networks. The idea that knowledge is structured or organized and that this may be an important aspect of learning is not a new idea (see Johassen, et al., 1993 for a review on this topic). In this study we use the technique for structural elicitation developed by Schvaneveldt (1990) called *Pathfinder Networks*. We favor the Pathfinder method for eliciting knowledge structures because it works to identify the structure at the concept relation level. Pathfinder identifies the structure of knowledge by differentiating concepts that are directly related, *edges*, compared to concepts that are indirectly related through a shared relation with another concept, *paths*.

The Pathfinder analysis provides a more detailed assessment of the structure of knowledge than, for example, multidimensional scaling (Schvaneveldt, et al., 1985). Multidimensional scaling (MDS) works to describe the latent structure that organizes the spatial relations and structure of a knowledge set (see Carroll & Arabie, 1998, for further

review). MDS estimates the number of dimensions required to represent the spatial relations of a knowledge set. This provides the general ways concepts are related and unrelated to each other, but not the specific connections between concepts. For example, an MDS analysis of a bicycle mechanic's bicycle knowledge structure may show groupings for concepts related to turning, to forward motion, and to gears. Whereas, a Pathfinder analysis could show that the mechanic structures their bicycle knowledge by the functional relations between the bicycle parts; the handlebar is related to the tire by its relation to the stem, to the steer tube, to the fork, to the wheel axle, to the hub, to the spokes, to the rim, to the tube, and finally the tire. This sort of analysis provides more information about the structure of bicycle knowledge than recognizing that some bicycle parts are organized by a "turning" dimension.

Pathfinder analysis provides a graphical representation, a PF-Net, of the specific relations between concepts that structure an individual's knowledge in a particular content domain. PF-Nets are link-weighted representations of the structure of one's knowledge in a domain. The links, or edges, between concepts are "weighted" by the similarity or relatedness between those concepts; each link carries a numerical weight that corresponds to the proximity of these concepts in an individual's memory (Schvaneveldt et al., 1985). Figure 1 shows three examples of the graphical output from PF-Net analyses for knowledge of a bicycle's gears.

A PF-Net can be displayed as either a 2D or 3D spatial graph composed of nodes, edges, and paths (Figure 1). In the following explanation of Pathfinder analysis it is important to distinguish between each of these characteristics of a PF-Net. The graph

nodes are the key concepts within a specific domain. In Figure 1 there are nine nodes that correspond to the different parts of a bicycle's gear system (e.g., derailleur, chain, cable). An edge is the term used to describe a direct link between two concepts. Each edge has a numerical value or *weight* that represents the strength of the relation, the larger the number the stronger the relation. The formula used for deriving the edge weights is discussed in a following section. For example, Participant A in Figure 1 has four edges connecting the derailleur node to barrel adjuster, to cable, to pulley, and to chain each of an equal weight, 2. In comparison the cable node has four edges and three of these edges carry a greater weight, 3, to indicate the stronger inter-node relation. When two nodes are not connected with an edge then they are connected with a path. For example, Participant A's structure in Figure 1 shows that the shift lever is related to the derailleur not directly by an edge, but by a path that travels through the cable node; this is a largely accurate illustration of the causal path that transfers movement in the shift lever to movement in the derailleur.

The first step in eliciting a knowledge structure, whether using a MDS or Pathfinder analysis, is to identify the key concepts that best represent the content of that domain. In our example in Figure 1 the key concepts are the nine bicycle parts that compose the gear system. Once the concepts have been identified it is possible to see how an individual has organized and structured these concepts in memory. To elicit an individual's knowledge structure, the individual rates the relatedness of each unique pair of concepts. This provides the raw relatedness ratings that are the input for the Pathfinder analysis.

A practical limitation in these analyses is the choice of how many concepts should be used to represent a domain's content. In a typical Pathfinder analysis a participant is presented with a list of 10 to 30 concepts and asked to provide similarity or relatedness ratings for all unique concept pairs. There are $n(n - 1)/2$ pairwise ratings for n concepts, so, for example, eliciting the structure of a knowledge set defined by 10 concepts requires 45 similarity ratings, 15 concepts requires 105 ratings, and 30 concepts requires 435 ratings. Doing 435 ratings can take longer than an hour and makes fatigue a concern for eliciting an accurate representation of an individual's knowledge structure.

Pathfinder analysis uses the similarity ratings to determine the edge weights, and to construct the link-weighted graphic representation of the knowledge structure (Figure 1). Pathfinder first creates a base graph that has all nodes connected to all other nodes by an edge. That is, it is the graphical representation of the unaltered similarity ratings made by the individual. The Pathfinder algorithm, stated below, then removes edges when a path is a better representation of the inter-node relation. The aim of the analysis is to determine what and how many edges the individual uses to structure his or her knowledge.

The Pathfinder algorithm determines if a path is a better representation of the inter-node relation by comparing all-possible path lengths to the edge length. If a path length is shorter than the edge length, the edge is dropped and the path is maintained as the better representation of the inter-node relation. The length of a path is a function of the individual's ratings, and two parameters defined by the researcher, r and q (Schvaneveldt, 1990). These two metrics determine the maximum number of edges in a

path, q , and the function for determining the length of the edges when being summed as a path, r . The q -metric can range from 2 to $n-1$, where n is the number of nodes in the graph. Setting the q -metric to $n-1$ allows for a greater variety of paths to be considered in comparison to the edge, increasing the algorithm's ability to represent relations with paths and to remove edges. The r refers to Minkowski's r -metric and can be set from 1 to infinity. If the rating data is ordinal, as is most often the case, the r -metric must be set to infinity.

The Pathfinder algorithm uses the following equation to compute path lengths, where the edge lengths (i.e. the inter-concept similarity ratings) are w_1, w_2, \dots, w_k :

$$W(P) = \left(\sum_{i=1}^k w_i^r \right)^{1/r}$$

When r is set to 1, unaltered edge lengths are used to determine the path's length. For example, consider a schema composed of concepts A, B, and C with the following edge lengths: the AC edge has a length of 4, the AB edge has a length of 1, and the BC edge has a length of 2. In this example the AC edge will be removed in the final graph because its length is greater than the ABC path, a length of 3. The relationship between concept A and concept C is more succinctly represented by their connection through concept B. As r increases from 1, the length of each edge and the subsequent path is reduced; when r is set to infinity, path lengths are maximally reduced. Setting the r parameter to infinity and the q parameter to $n-1$ produces a graph with the fewest possible edges given the individual's similarity ratings (see Schvaneveldt, 1990, for an in depth discussion of the Pathfinder algorithm and these parameters). In practice the q parameter is almost always

set to $n - 1$ and the r parameter to infinity.

The advantage in eliciting and assessing the structure of knowledge with a link-weighted representation, such as a PF-Net, is the detail it provides about the structuring of knowledge. Pathfinder provides the structure of knowledge as it is organized by the specific links that an individual makes between concepts and the strength of these links. This level of detail is essential for the purposes of this study because it allows three characteristics of a knowledge structure to be quantified and used in further analyses, such as regression modeling of problem-solving behavior. These three characteristics of a knowledge structure, *density*, *coherence*, and *similarity* to an expert's structure, were mentioned above as they relate to performance. Now we turn to a more technical description of these characteristics and their derivation.

Knowledge structure, its density, coherence, and expert similarity. This study was driven by a desire to gain a better understanding of adult mental capacity by examining experience-related problem solving (i.e., the type of everyday problems where knowledge is pertinent). One important step is, therefore, a thorough examination and assessment of problem-related knowledge. Pathfinder analysis provides three characteristics of a knowledge structure that may be important to the utility of knowledge for problem solving: Similarity of the structure between two graphs (typically the similarity between student and expert graphs), the density of the structure, and the coherence of the structure.

Similarity (C). The structural similarity of two graphs is computed by comparing each concept's neighborhood to its neighborhood in the other structure (Goldsmith &

Davenport, 1990). A complete description of the theory and computation of the structural similarity between knowledge structures can be found in Goldsmith and Davenport (1990, p. 83-87) and more succinctly in Goldsmith and colleges (1991, p. 96). A neighborhood is defined as the set of nodes that share an edge with a node. A node neighborhood identifies the concepts that are most strongly connected with the node or concept. Comparing node neighborhoods provides an assessment of how similarly two people have organized their domain knowledge. The first step in the *C* analysis is to compute a correlation that will quantify the similarity of the node neighborhoods in the two graphs.

To illustrate this step consider Figure 1. In the graph for Participant A the sprocket cluster node has a small neighborhood consisting of only one other node, chain. In comparison, the Professional Mechanics' neighborhood for the sprocket cluster node includes the nodes chain and derailleur. Therefore, the two neighborhoods will have a high, but not perfect correlation that quantifies their similarity. However, Participant B's neighborhood for the sprocket cluster node is very dissimilar to the other graphs in Figure 1. Participant B's sprocket cluster neighborhood includes the shift lever, barrel adjuster, limit screw, and the pulleys nodes. Participant B's sprocket cluster node neighborhood is, therefore, quite different from the Professional Mechanics' neighborhood for that node.

Once node neighborhood comparisons are done for each node, the average of these correlations is then used to quantify the similarity of the two graphs. This measurement of knowledge structure similarity, referred to as *C*, ranges from 0 to 1, where 0 means there is no commonality between the graphs and 1 indicates identical

graphs. In Figure 1, Participant A's graph is more similar, $C = .62$, to the Professional Mechanics graph than Participant B's graph, $C = .14$. The similarity between a student's and an expert's knowledge structure quantifies the extent to which the student has acquired a structure to knowledge that mirrors the expert's structure. If the structuring of knowledge is important in determining its utility, C may be one of the best assessments of learning and potential to solve related problems.

Density. The density of structural knowledge refers to the number of edges in a network, which is argued to capture the complexity of the knowledge structure in terms of the number of interrelations among the nodes. A knowledge structure's density is assessed as the number of edges divided by the total number of possible edges in the knowledge set, $n-1$, where n is the number of nodes in the graph. In this sense the simplest graph has each node connected to no more than two other nodes, while the most complex or dense graph relates every node with every other node. The specific importance of structural complexity is somewhat unclear. Increasing structural complexity has been negatively related to problem solving performance, and may indicate some basic misunderstanding of the concept interrelations. However, having too simplistic a structure may also indicate a misunderstanding of the interrelations within a domain. Despite this ambiguity, density provides information about the structure of knowledge without the need of an expert referent knowledge structure.

Coherence. Coherence assesses the consistency of ratings between concepts (Appendix A provides a programming script for computing coherence in R). It captures how consistent an individual is in their use of inter-concept relations for structuring his or

her knowledge. Concepts that are rated as highly similar should have a similar pattern of relations within the knowledge structure. To the extent that similar concepts have similar patterns of relations within the network, the coherence value will increase up to a maximum of 1. Coherence scores less than .20 indicate severe inconsistencies in the cognitive network and are most often found when the task is not taken seriously or there is little to no understanding of how the concepts relate to each other (Schvaneveldt et al., 2002). Higher coherence characterizes expert knowledge structures, reflecting a complete and clear understanding of how the concepts relate to each other.

Neither density nor coherence captures as much structural information as similarity or *C*. However, the former assessments do provide information about the structure of knowledge without the need of an expert comparison. To date, there is little research examining the relation between these knowledge structure characteristics, learning, and problem solving. This study includes these assessments of a knowledge structure to further explore their relation to learning and problem solving.

Summary of General Cognitive Abilities and Knowledge in Problem Solving

The extended Gf/Gc theory of human cognitive abilities is a theory that identifies cognitive abilities that are involved in solving the types of problems seen in IQ tests. The model identifies three classes of abilities, vulnerable, expertise, and sensory-perception cognitive abilities, which aid in finding the solutions to problems. This review has focused on describing how vulnerable and expertise abilities are employed to solve different types of problems. An emphasis in this review is the disparity in our understanding of expertise compared to vulnerable abilities.

Vulnerable abilities, Gf, SAR, and Gs, are rather well defined and studied, and it seems clear how these abilities are employed in solving at least certain types of problems, specifically novel problems. When the problem is novel and previous experience and knowledge is not relevant, vulnerable abilities may serve to organize environmental information into knowledge of the problem. It is, however, this knowledge component of problem solving that is less well understood. Knowledge content is important for solving problems and, consequently, a variety of content tests, such as mechanical, have been developed to predict and explain problem solving in these particular domains. While content knowledge is surely important, we argue that it is how this content is organized and structured that determines the utility of knowledge to solve particular problems. The purpose of this review is to describe how the contribution of expertise abilities in problem solving goes beyond knowledge content and needs to include how this knowledge is structured.

Learning from a particular experience and developing skill at solving related problems is a complex process that is likely to tap personal characteristics beyond general reasoning and knowledge. Two characteristics that we feel are particularly relevant to predicting differences in learning and problem-solving skill are effort and mechanical self-efficacy. Mechanical self-efficacy describes an individual's belief in his or her ability to act meaningfully and effectively with physical principles and mechanical systems and has been shown to have a moderate positive association with performance on the Bennett Mechanical Comprehension Test (Grand, 2008). The learning and problem-solving tasks that were used in this study were mechanical in nature, and one's mechanical self-

efficacy may be an important predictor of these outcomes. Learning and problem solving rarely occur without an individual exerting some effort to learn from an experience (e.g., Salomon, 1984; Chase, Chin, Oppezzo, & Schwartz, 2009) or to engage in problem solving (e.g., Darabi, Nelson, & Palanki). Therefore, it is important to include assessments of differences in learning effort and problem-solving effort when researching predictors of differences in learning and problem-solving skill.

The purpose of this study was to build a better understanding of how adults solve experience and knowledge related problems, and subsequently to add to the understanding of adult intelligence. An important indicator of one's intelligence is skill at solving the variety of problems that arise while performing his or her personal and professional responsibilities. The current theories of adult intelligence do not generalize to this type of everyday problem solving because of their focus on the more fluid aspects of intelligence. We argue that the way knowledge is organized is an important determinant in who can and cannot solve a problem. If this is the case, a next step in understanding adult intelligence is to explore the relation between general cognitive abilities and the acquisition and application of knowledge, particularly its structure. In this study we test five primary hypotheses that, if supported, provide evidence that general reasoning is associated with problem solving because it facilitates the acquisition of an expert-like knowledge structure that facilitates the identification of problem causes and solutions.

- *Hypothesis 1 (H1; learning)*. The acquisition of procedural knowledge is a function of learning effort, prior knowledge, general reasoning, and mechanical self-efficacy.

- *Hypothesis 2 (H2; learning)*. The structure of knowledge is a function of prior knowledge, general reasoning, learning effort, and mechanical self-efficacy.
- *Hypothesis 3 (H3; problem solving)*. Skill at identifying the causes of gear problems is a function of the knowledge structure, procedural knowledge, general reasoning, mechanical self-efficacy, and problem solving effort.
- *Hypothesis 4 (H4; problem solving)*. Skill at describing procedures to fix gear problems is a function of procedural knowledge, the structure of knowledge, general reasoning, mechanical self-efficacy, and problem solving effort.
- *Hypothesis 5 (H5; problem solving)*. Overall knowledge is a stronger predictor of problem-solving skill than general reasoning.

In H1 and H2 we seek a better understanding of the individual differences that are related to the differences in knowledge acquired from a training experience. In H3 and H4 we seek to explore the relation of general reasoning to solving experience related problems when differences in knowledge are accounted for. In H5 we hope to expel any doubts that knowledge is an important factor in determining skill at solving problems. As long as problem-solving skill is an indicator of intelligence, then support of these hypotheses is evidence that the structure of knowledge is an important aspect of intelligence.

Method

Participants

Participants ($N = 174$, 111 female) were recruited from the Psychology Department's subject pool at a large public university located in Southern California. Participants responded to an advertisement on the Department's subject pool website and

received course credit for their participation. The sample was predominantly college freshmen and sophomores, with a mean age of 19 years old ($SD = 1.6$ years). Participants represented a range of disciplinary majors (20% Biology, 20% Business, 17% Psychology, 10% Sociology, 33% other). The sample was ethnically diverse, with 41% Asian, 34% Hispanic, 8% Filipino, 7% Other or Mixed, 5% European American, 3% African American, and 3% Middle Eastern, which reflects the diversity of the region.

Professional bicycle mechanics ($N = 3$) were recruited to develop an expert knowledge criterion. A bicycle shop in Southern California was solicited for volunteers to participate in this study. Interested mechanics were given a short description of the study, and told that their responses would be used as a criterion for assessing bicycle knowledge. Their participation was voluntary and there was no monetary incentive to participate in this study. Mechanic participation was limited to questions about their professional mechanic experience and the elicitation of their bicycle gear structural knowledge. All mechanics were male, their age ranged from 24 to 31 years old, and professional bicycle mechanic experience ranged from 1 to 5 years.

Measures

The measures and video used in this study are described below. All measures are available in the appendices, and the URL address to the training video is available upon request.

English language proficiency. Fluency with English was assessed as the self-reported proportion of the participant's life that English was the primary form of communication and by responses to two self-report Likert questions (1 = *Very difficult to*

4 = *Very easy*): “How difficult do you find it to understand spoken English?,” and “How difficult do you find it to write answers in English?”

General reasoning. The 16-item version of the *International Cognitive Ability Resource* (ICAR-16; Condon & Revelle, 2014; Appendix B) was used to assess general reasoning. The ICAR-16 has four types of reasoning problems: four matrix-reasoning items, four quantitative reasoning items, four verbal reasoning items, and four three-dimensional rotation problems. The items were presented in increasing difficulty, and participants were allowed 30 minutes to finish. All participants completed the ICAR-16 within 25 minutes. The proportion of correct responses was used as an indicator of general reasoning.

Prior bicycle knowledge. The extent of participants’ understanding of a bicycle was assessed with an open-ended measure asking for the names of bicycle parts, such as the brakes and handlebars (Appendix C). Participants were instructed to write out as many bicycle parts as they could. The total number of parts correctly listed was summed and used as an indicator of bicycle knowledge. Components that can be added to a bicycle but are not essential to a working bicycle (e.g., bells, baskets, reflectors, etc.) were not counted toward the prior knowledge score.

Mechanical self-efficacy. Mechanical self-efficacy was assessed using an 8-item self-report measure (Grand, 2008; Appendix D). Participants are asked to indicate their confidence on a 5-point scale (1 = *Not at all confident*, 5 = *Completely confident*) at completing 8 mechanical tasks. For example, “Figure out how a mechanical item works (e.g., a flashlight, simple engine, etc.) by observing how its internal components operate

(gears, belts, switches, etc.).” This scale demonstrated high reliability ($\alpha = .85$). The average scale score was used as an indicator of mechanical self-efficacy.

Learning to set up the gears of a bicycle (the training task). Participants completed a self-guided training session in which they read the following instructions and individually watched a 12-minute video.

“We are interested in how different ways of presenting mechanical information influences learning and performance. You have been randomly assigned to one of three learning conditions: Written directions, video directions, or in-person directions. Throughout the learning process please do your best to fully engage and master the material. This is a challenging but achievable part of bicycle maintenance. When the training period has finished you may have the opportunity to use your newly learned skill in another part of this study. Additionally, you will be learning how to fix one of the most common problems on geared bicycles.”

Although participants were told they would be randomly assigned to one of three learning conditions, all participants were assigned to the same video condition and watched the same training video. The 12-minute training video was created specifically for use in this study. Figure 2 shows the major parts of the video and their duration. In the video, a mechanic demonstrates common bicycle gear problems and a procedure for setting up and adjusting the gears. The video was accompanied with an audio commentary defining the various parts, explaining the common problems, and describing the steps the mechanic carries out while setting up the gears. The video begins with an overview of what a geared bicycle is, how the gears are operated, and shows examples of 4 common

problems with a bicycle's gears. The mechanic then identifies and explains the function of the different parts involved with changing gears: shift levers, cables, cable housing, cable stops, barrel adjuster, derailleur, high and low limit screws, the chain, derailleur pulley, the sprocket cluster, and crankset. Figure 3 provides screenshots of the video to illustrate how the gear parts were identified during the video. After identifying the primary components, the mechanic carries out a common procedure for setting up the gears. Specifically, the mechanic (1) detaches the cable from the derailleur at the cable-fixing bolt, (2) sets the high limit screw, (3) sets the low limit screw, (4) reattaches the cable to the derailleur at the cable-fixing bolt, (5) adjusts the cable tension, and (6) checks for smooth shifting across the sprocket cluster. The visual orientation to this procedure, in the way of an outline, is also illustrated in Figure 3. As the mechanic completed each of the six steps the outline slide in Figure 3 was displayed with the upcoming step highlighted. The video concludes with a short review of the bicycle gear parts and how they are integrated into the drive system of a bicycle.

Procedural knowledge. Knowledge of the procedural sequence used by the mechanic in the video to set up the gears was assessed in two ways. The first assessment was composed of 8 multiple-choice items that asked what was done before or after a particular step (Appendix E). The proportion of correct responses was used as an indicator of procedural knowledge. In the second assessment, participants were presented with a randomized list of the eight procedural steps and asked to order the steps as they should be carried out (Appendix F). The rank order of each step was compared to the correct order and 1 point was subtracted for each position away from the correct position.

A score of zero indicates that all steps were placed in the correct order. A score of -1 indicates that 1 step was out of order by one position. The two assessments of procedural knowledge were *z*-scored and their average was used as the indicator of procedural knowledge.

The structure of knowledge. Participants' understanding of the interrelations of the bicycle's gear parts and how this information was structured as knowledge was assessed with two measures. In the first measure, *definition knowledge*, participants defined each of the nine bicycle gear parts covered in the training video by the parts' functional relations. In the second measure, *relatedness ratings*, participants rated the relatedness of each bicycle gear part to each of the 8 other parts (Appendix G and H respectively). PF-Net analysis was then used with the participant's ratings to derive the structure of their knowledge and assess its characteristics. Both of these measures assess the way in which an individual has structured their knowledge. In defining the parts by their functional interrelation the individual is describing the interrelations between parts that are argued to structure this knowledge. It is in essence a written description of what parts the participant believes to be directly related and how these relations allow for a gear change. The relatedness ratings then provide a means of quantifying different aspects of this structure (e.g., similarity to an expert knowledge structure). Definition knowledge and similarity to an expert knowledge structure, *C*, were standardized and averaged to provide an indication of the participants' organization of bicycle gear knowledge relative to that of expert bicycle mechanics.

Definition knowledge. Participants were asked to define each of the nine essential components in the rear drive train of a bicycle: Derailleur, shift lever, cable, barrel adjuster, cable-fixing bolt, limit screw, pulleys, chain, and sprocket cluster. The instructions directed participants to “describe what each component is, and what its function is in allowing a cyclist to change gears.” The name of each component and space to type a definition was provided. All nine components were presented simultaneously and in a random order. Participants were required to spend no less than 6 minutes reporting their answers. The definitions were scored by two raters on a 4-point scale and the average of their judgments was used. The 4-point scale was as follows: 1 = *Incorrect, no understanding of the component indicated*; 2 = *Incorrect, but indicates some idea of what/where the component*; 3 = *Correct, has a functional description, but incomplete or has inaccuracies*; 4 = *Correct, accurate descriptions of the components functionality*. Inter-rater reliability between the two judges of definition accuracy demonstrated high consistency, $r = .96$. The average score of the nine definitions was used as an indicator of the participant’s understanding of the components’ functional interrelations.

Relatedness ratings (RR). Participants were asked to rate the relatedness of each gear part to all other parts covered in the training video on a 5-point scale (1 = *unrelated*, 2 = *moderately related*, 3 = *largely related*, 4 = *extremely related*, 5 = *synonym*). For example, how related is the derailleur to the chain, to the sprocket cluster, to the cable, and so on until they have rated the relatedness of the derailleur to all of the other parts. Then participants rated the relatedness of the chain to the sprocket cluster, to the cable,

and the remaining parts. All 36 unique pairwise ratings were randomized and presented simultaneously.

These RR were scored using PF-Net Analysis (Schvaneveldt, 1990), with participants' RR compared to the aggregated RR by the three professional bicycle mechanics. Pathfinder scores evaluated the participants' data by its similarity to RR of experts, the coherence of the ratings, and the density of the knowledge structure. The similarity measure assesses the similarity between two sets of RR and ranges from 0, no similarity, to 1, identical (see Goldsmith & Davenport, 1990, for further discussion). Participants with high similarity values are considered to have a better organization of their knowledge than participants with low similarity values (Goldsmith et al., 1991). The coherence measure assesses the extent to which a set of ratings is consistent. In this sense, consistency is defined as the extent that the similarity between concepts is related to the similarity between their patterns of relations with the other concepts. For example, high coherence occurs when two extremely similar concepts also have very similar relations with the other concepts in the knowledge network. Coherences scores are a type of correlation and can range from -1 to 1, with 1 representing perfect consistency (see Schvaneveldt, 1990, for computational details). The complexity of a knowledge structure is assessed as its density. A knowledge structure's density is the proportion of edges present compared to the total number of possible edges. Experts tend to have less complexity in the structure of their knowledge, which suggests that knowledge structures that are very complex may be more difficult to use and hinder performance.

Solving bicycle gear problems. Skill at solving common problems with a bicycle's gears was assessed with open-ended short answer questions (Appendix I). Each question stated a problem and asked the participant what the cause of the problem was and what should be done to correct the problem, *cause identification* and *procedural solution* respectively. Responses are structured to assess understanding of the underlying cause of the problem, Part A, separate from understanding of the procedure to fix the problem, Part B. Participants were required to spend at least 2 minutes per problem before they could work on the next problem.

Two judges rated both parts of the responses on a 4-point scale, and their average rating was used for the score of each question (1 = *Incorrect, answer demonstrates no understanding of the problem*; 2 = *Incorrect, but some understanding of the problem is demonstrated*; 3 = *Correct, but misses some details of a complete solution*; 4 = *Correct, answer demonstrates complete understanding of the problem*). The participants' average score for Part A were used as an indicator of skill at identifying the cause of problems, and the participants' average score for Part B were used as an indicator of skill at fixing gear problems. Overall bicycle gear problem solving skill was assessed as the average of the scores on Part A and Part B. The ratings demonstrated acceptable consistency between the judges ($ICC_{cause} = .82$ [.80, .84], $ICC_{solution} = .69$ [.66, .71], $ICC_{overall} = .76$ [.75, .78]).

Effort. Participants reported their effort put into the study on two Likert scale questions (1 = *The least effort possible*, 5 = *The most effort possible*). Participants were

asked how much effort they put into learning, and how much effort they put into solving the problems.

Design and Procedure

The relations between general reasoning, the structure of domain specific knowledge, and domain specific problem solving were observed in a between-subjects design. Figure 4 illustrates the following procedure that was used for data collection. College undergraduates participated individually for approximately two hours, during which they completed questionnaires and watched a training video on desktop computers in a Psychology Department computer laboratory. Participants were seated at one of 13 computers and were given a written consent form. After providing informed consent participants began the study by responding to the questionnaires presented on the computer monitor. The questionnaires were presented in the following order: *Demographic Information, ICAR-16, Bicycle Component Knowledge, Mechanical Self-Efficacy, and Training Instructions*. After the training instructions participants put on headphones and watched the training video on their computer screen. A researcher monitored the participants to insure that the video was watched from beginning to end in full-screen mode without pausing, fast forwarding, or replaying the video.

Knowledge of the training task was then assessed with four questionnaires. First, participants free recalled the definitions of the key bicycle gear parts covered in the video. Second, multiple-choice questions about the procedure presented in the video were answered. Third, a randomized list of the key procedural steps was placed in the correct procedural order. Fourth, participants rated the pairwise relatedness of the nine bicycle

gear parts covered in the video. The final part of the study asked participants to provide written solutions to nine common bicycle gear problems and to report their effort as a participant in the study. The study concluded with a debriefing statement, the participant's questions were answered, and they were thanked for their participation.

Results

This study was designed to predict differences in knowledge after a short training period and skill at solving problems related to the training material. Subsequently, three sets of variables were assessed: pre-existing individual differences that were expected to relate to learning and performance in this domain (i.e., general reasoning, prior knowledge, mechanical self-efficacy, English proficiency), knowledge variables that assess learning after the training period (i.e., procedural knowledge, the structure of knowledge), and variables that assess skill at solving bicycle gear problems (i.e., identifying the causes of the problems, describing procedures to fix the problems). The following sections will provide descriptive results of the pre-existing characteristic variables, the knowledge variables, and the problem-solving variables, before moving to the analyses of the primary hypotheses of this study.

To test for any gender differences that may have arisen due to the mechanical nature of the learning experience and problem solving, we compared the means for men and women on a number of the study variables. We computed independent sample two tailed *t*-tests for gender differences in general reasoning, prior bicycle knowledge, mechanical self-efficacy, procedural knowledge multiple-choice, procedural knowledge rank order, structural knowledge definitions, structural knowledge similarity, overall

bicycle gear knowledge, problem cause identification, problem procedural solution, and overall problem-solving skill. Only the assessments of knowledge structure acquired from the training video had significant mean differences. There was a marginally significant difference between men, $M = .38$, and women, $M = .34$, on their similarity to the expert knowledge structure, $t(164) = 1.94$, $p = .06$, Cohen's $d = -0.31$. There was a significant difference between men, $M = 2.73$, and women, $M = 2.50$, on their definition knowledge, $t(172) = 2.10$, $p = .04$, Cohen's $d = -0.33$. These gender differences are small, observed in only two of the study variables, and the relation of gender to mechanical learning and problem solving was not the focus of this study. Therefore, the data was not analyzed separately for men and women and further gender differences were not examined.

Descriptive Analyses

Assessments of pre-existing individual differences. To determine what individual differences are related to learning from training and later applying the learned knowledge to solve problems, four pre-existing individual differences were assessed: general reasoning, prior bicycle knowledge, mechanical self-efficacy, and English proficiency. The descriptive statistics for each of these variables are presented in Table 1, and the correlation matrix for these variables is presented in Table 2.

The assessment of general reasoning was normally distributed around a mean of 41% correct ($SD = 20\%$). The scores ranged from 0 to 87, indicating that the assessment of general reasoning was appropriate for assessing the range of reasoning skills in this sample. The assessment of prior bicycle knowledge indicated that most participants were

relatively unfamiliar with the parts that compose a bicycle. The median number of parts reported was 6 ($SD = 2.51$), and the distribution was kurtotic with positive skew ($skew = 1.4$, $kurtosis = 4.5$). Most participants, 60%, reported the median number of bicycle parts or fewer. The assessment of mechanical self-efficacy was normally distributed around a mean of 2.72 ($SD = 0.61$), with scores ranging from 1 to 4.5, representing most of the 1 to 5 Likert scale range. This indicates that the average participant was slightly less than confident in his or her general mechanical skill, and no participants were “completely confident” in their general mechanical skill.

The University from which the sample was collected encourages international exchange programs and has a number of students for whom English is a second language. Because both learning and performance in this study required English proficiency, language was an important consideration. The majority of the sample reported that English has been the primary form of communication during their life ($median = 94\%$ of life, $SD = 24\%$, $range = 5\%$ to 100% , $skew = -1.47$, $kurtosis = 1.24$). The assessment of English proficiency had positive skewness around a median of 1 ($SD = 0.64$, $range = 1$ to 3.5 , $skew = 1.2$, $kurtosis = 0.84$), indicating that most of the sample found writing and understanding English very easy. An aggregate variable of these four measures showed no significant relations to either the learning outcomes or the problem-solving outcomes. The estimated correlation coefficients ranged from $-.07$ to $.03$, $p-values > .10$.

Assessments of knowledge acquired from training. After watching the training video, learning was assessed as knowledge of the procedure for adjusting a bicycle’s gears and knowledge of the interrelations among the parts that compose a bicycle’s gears.

Participants completed two assessments of procedural knowledge and two assessments of their knowledge structure that were combined to create the respective composite variables used in the analyses. The descriptive statistics for each of these variables are presented in Table 1, and the correlation matrix of these variables is presented in Table 2.

Participants' scores on the procedural knowledge multiple-choice assessment were normally distributed around a mean of 47% ($SD = 23\%$, $range = 0\%$ to 100%). Most participants were able to answer 4 of the 8 questions correctly, and there was good overall variance. The responses to the procedural knowledge rank order assessment were normally distributed around a mean of 14 rank order positions off from perfect ranking ($SD = 4.86$, $range = -2$ to -28). These two assessments of procedural knowledge had a strong positive correlation, $r(171) = .42$ [$.29, .54$], $p < .0001$. Higher scores on the multiple-choice assessment were related to better performance on the rank ordering assessment. The content overlap combined with a strong correlation between these two variables provided the justification for creating a procedural knowledge composite variable.

The sample's definition knowledge was normally distributed around a mean of 2.6 ($SD = 0.70$, $range = 1.06$ to 4). Most participants were somewhat accurate in their functional definitions of the bicycle gear parts, while some showed no understanding of the parts and others had a very accurate understanding of the parts' functions.

Participants' similarity to the relatedness ratings of expert mechanics was normally distributed around a mean of .35 ($SD = .13$, $range = .09$ to $.69$). Eight participants' relatedness ratings were not used because there was no variation in the

ratings (i.e., all fours or all ones). No participant had a perfect match with the experts' ratings, but the mean indicates that most participants had acquired an organization to their bicycle gear knowledge that was moderately similar to the experts' structure. The similarity and definitions knowledge measures had a very strong positive relation, $r(164) = .63$ [.52, .71], $p < .0001$). The strong relation between these variables and their emphasis on knowledge of the functional inter-concept relations provided the justification for their aggregation into a composite variable. The procedural knowledge composite and the structure of knowledge composite had a strong positive relation, $r(164) = .58$ [.47, .67], $p < .0001$. Participants who learned the procedure for adjusting bicycle gears tended to also have organized their knowledge similar to the professional bicycle mechanics.

The assessment of RR coherence provided evidence that on average a 12-minute training video was not enough training to organize knowledge into a structure that would allow one to make consistent RR. The sample's distribution of coherence scores was normally distributed around a mean of .17 ($SD = 0.34$, $range = -.62$ to $.82$). The range of coherence scores, with many below zero, was a concern for the use of this measure in further analyses. Schvaneveldt and colleagues (2002) suggested that coherence scores below .20 indicated poor learning engagement, misunderstanding of the RR task, or misunderstanding of the RR content. In this sample, 47% of participants had coherence scores below .20, and 29% had scores below zero. Coherence scores exhibited a similar pattern of correlations with the study variables as the other assessments of knowledge structure, similarity and definitions knowledge. For example, coherence had a moderate positive relation with overall problem-solving skill, $r(164) = .30$ [.16, .43], $p < .0001$.

Coherence also had a significant positive relation with general reasoning, $r(164) = .18$ [.03, .32], $p = .02$. Table 3 presents the correlations of coherence with the other study variables. The presence of a significant number of coherence scores below zero raises concerns about the appropriateness of this measure as an assessment of the structure of knowledge in this sample. The training task in this study may have been insufficient for participants to develop the aspects of knowledge that are assessed by coherence. Coherence scores are not included in the test of our hypotheses, despite initial plans to the contrary.

The PF-Net analysis of the structural characteristics of knowledge provides an assessment of the complexity of a knowledge structure as its density (i.e., the proportion of edges in the structure to total possible edges). The analysis of this structural characteristic of knowledge was purely exploratory and is included to improve the understanding of this structural characteristic of knowledge. In this sample the assessment of the density of the knowledge structures had a positive skew around a mean of .44 ($SD = .13$, $range = .22$ to $.94$, $skew = 0.83$, $kurtosis = 0.52$). The average participant's knowledge structure had 16 of the 36 possible edges (i.e., direct links between gear parts), compared to the average mechanic who had 15 edges ($M = .41$, $SD = .07$), and the aggregated knowledge structure of the mechanics with 11 edges, $density = .24$. The minimal difference between the complexity of the average mechanic and the average participant makes it unclear if density is a useful metric for assessing learning. However, having a more complex knowledge structure was associated with poorer overall problem solving skill, $r(164) = -.25$ [-.39, -.10], $p\text{-value} < .01$. Density was also

moderately related to general reasoning skill, $r(164) = -.27 [-.40, -.12]$, $p\text{-value} < .001$. This suggests that skill at reasoning may facilitate the acquisition of less complex knowledge structures. Table 3 presents the correlations of density with the other study variables.

Assessments of skill at solving bicycle gear problems. Participants were tested on their skill at identifying the causes of gear problems and their skill at coming up with procedures to fix the problems. The descriptive statistics for each of these variables are presented in Table 1, and the correlation matrix for these variables is presented in Table 2.

Skill at identifying the causes of the problems was distributed around a mean of 1.75 with positive skewness ($SD = 0.57$, $range = 1$ to 3.39 , $skew = 0.62$, $kurtosis = -0.37$). After training, the average participant was able to loosely describe the problems' causes, but the explanations tended to contain some inaccuracies or vagueness about these causes. More participants were unable to describe the causes than were able to provide accurate identifications of the causes, as indicated by the positive skew of the distribution. However, 31% of the sample had an average cause identification score above two and was able to identify the causes of most of the problems.

The distribution of skill at describing procedural solutions for the gear problems had a positive skew around a mean of 1.7 ($SD = 0.5$, $range = 1$ to 3.44 , $skew = 0.77$, $kurtosis = 0.31$). The average participant did not describe feasible solutions to the problems, but did indicate some understanding of the problems and how to solve them. Compared to problem cause, only 21% of the sample averaged a problem solution score

above two, indicating that they had described feasible solutions to most or all of the problems. Participants' skill at identifying the causes of problems was strongly correlated with skill at describing procedural solutions to the problems, $r(172) = .84$ [.78, .88], $p < .0001$. A participant that was able to describe the causes was more likely to also be able to describe solutions to the gear problems.

The distribution of overall problem-solving skill, the aggregate of skill at identifying causes and developing solutions, had positive skew around a mean of 1.72 ($SD = 0.51$, $range = 1$ to 3.39 , $skew = 0.66$, $kurtosis = -0.03$). Thus, after watching a 12-minute training video, the average participant was relatively unskilled at solving problems with bicycle gears, but did demonstrate some understanding of how to fix gear problems. Despite the difficulty of the learning and problem-solving tasks, 28% of the sample had an average overall problem-solving score above two and was able to describe how to fix some of the gear problems.

Effort at learning and solving the gear problems. Participants' self-reports of their effort to learn were normally distributed around a mean of 3.39 ($SD = 0.90$, $range = 1$ to 5 , $skew = -0.31$, $kurtosis = 0.29$). The average participant reported putting *some effort* into learning from the video, and more participants reported putting *a lot of effort* into learning than *very little effort*. Similarly, self-reported effort into solving the problems was normally distributed around a mean of 3.27 ($SD = 0.86$, $range = 1$ to 5 , $skew = -0.12$, $kurtosis = 0.25$). The average participant reported putting *some effort* into solving the gear problems, and more participants reported putting *a lot of effort* into solving the problems than *very little effort*. Learning effort and problem solving effort

had a strong positive correlation, $r(170) = .64 [.55, .72]$, $p < .0001$. A participant who put a lot of effort into learning was likely to put a lot of effort into solving the problems. The non-perfect relation and the substantive difference of these variables indicated that each was providing unique information and that further analyses could benefit from their use as independent variables rather than as an aggregated variable.

What Predicts Mechanical Learning and Problem-Solving?

This study was designed to assess individual characteristics that were likely to be related to the acquisition of knowledge, and then to assess the importance of these characteristics and the acquired knowledge in solving related problems. Following are the primary study hypotheses, also presented at the end of the introduction chapter, organized by the outcome and its position in the study's procedure. In each hypothesis the relative strength of each predictor is hypothesized to follow the order in which each variable is presented in the hypothesis.

- *Hypothesis 1 (H1; learning)*. The acquisition of procedural knowledge is a function of learning effort, prior knowledge, general reasoning, and mechanical self-efficacy.
- *Hypothesis 2 (H2; learning)*. The structure of knowledge is a function of prior knowledge, general reasoning, learning effort, and mechanical self-efficacy.
- *Hypothesis 3 (H3; problem solving)*. Skill at identifying the causes of gear problems is a function of the knowledge structure, procedural knowledge, general reasoning, mechanical self-efficacy, and problem solving effort.

- *Hypothesis 4 (H4; problem solving)*. Skill at describing procedures to fix gear problems is a function of procedural knowledge, the structure of knowledge, general reasoning, mechanical self-efficacy, and problem solving effort.
- *Hypothesis 5 (H5; problem solving)*. Overall knowledge is a stronger predictor of problem-solving skill than general reasoning.

The above hypotheses were tested using linear multiple regression analyses. To ease interpretation, all of the variables were standardized before analysis and the estimated standardized regression coefficients are reported. To understand the relative strength of each predictor compared to the other predictors in the model, all predictors were entered into the regression models simultaneously. This served the purpose of allowing each predictor to account for only the outcome variance that was unique to its relation with the outcome, rather than accounting for outcome variance that overlaps with other predictors. Additionally, because the standardized regression coefficients are reported, the relative strength of the predictors within each model can be assessed. The variance inflation factors (VIF) of each regression model were checked to assess concerns of multicollinearity. In all of the reported regression models VIF values were below two, indicating that multicollinearity was not a concern in the interpretation of these regression results.

What predicts learning and the acquisition of knowledge? Participants' learning after training was assessed in two ways, in terms of the procedural knowledge they had of fixing bicycle gears and the structure of their knowledge, which reflects their understanding of the functional relations between the parts that compose a bicycle's

gears. These variables were examined independently, as described in H1 and H2, and as an aggregate variable used to index overall learning, H5.

H1 stated that learning effort, prior knowledge, general reasoning, and mechanical self-efficacy would predict the extent of procedural knowledge acquired after training, when controlling for the effects of the other variables in the regression model. H1 was supported for all predictors except mechanical self-efficacy, which reached only marginal significance (see Table 4). Learning effort did have the strongest relation to procedural knowledge, indicating that personal effort is an important aspect of the learning process. Prior knowledge and general reasoning were also significantly related to procedural knowledge. Prior knowledge of bicycle parts had a slightly stronger relation with procedural knowledge than did general reasoning, but both were important in predicting the extent of procedural knowledge that a participant acquired from the training video. This regression model accounted for 33% of the variance in procedural knowledge scores. The remaining two thirds of unexplained variance suggest that learning mechanical procedures is a function of more than effort, reasoning, and prior knowledge.

H2 stated that prior knowledge, general reasoning, learning effort, and mechanical self-efficacy would predict the structure of acquired knowledge, when controlling for the effects of the other variables in the regression model. H2 was supported for all predictors except mechanical self-efficacy, $p\text{-value} = .31$ (see Table 4). The strongest predictor of the structure of knowledge was the prior knowledge that participants had of bicycle parts, that is the number of bicycle parts they could name before watching the training video. Learning effort and general reasoning had almost identical relations to the structure of

acquired knowledge. This result is in contrast to their relations with procedural knowledge in H1 where learning effort was a notably stronger predictor of learning. This regression model accounted for 37% of the variation in how knowledge of bicycle gears was structured. The presence of a substantial amount of unexplained outcome variances indicates that the structuring of knowledge is a function of more than prior knowledge, general reasoning, and learning effort.

In the interest of understanding the acquisition of overall bicycle gear knowledge, the aggregate of procedural and knowledge structure was regressed on general reasoning, prior knowledge, learning effort, and mechanical self-efficacy (see Table 4). The results of this analysis concur with the results of H1 and H2. Prior knowledge and learning effort had nearly identical relations to overall gear knowledge. General reasoning was a significant predictor of overall knowledge, but its relation was weaker than that of prior knowledge and learning effort. These results provide evidence that effort and prior knowledge may be more important than general reasoning in acquiring knowledge about a bicycle's gears. This regression model accounted for 43% of the variation in overall gear knowledge scores.

What predicts who can solve bicycle gear problems after training? After participants watched the training video on fixing bicycle gear problems their skill at identifying the cause of gear problems and describing a procedure to fix those problems was assessed. Our interest was in determining what predicts an individual's skill at solving bicycle gear problems, specifically in comparing the role of knowledge to general reasoning in problem solving skill. In the following tests of H3, H4, and H5 we also

include mechanical self-efficacy and effort put into solving problems in the regression models. Self-efficacy describes one's feelings of competency to perform, so it was expected that mechanical self-efficacy would predict an individual's skill at solving mechanical problems. Furthermore, solving problems is expected to require effort, so it was expected that self-reported problem-solving effort would be associated with the assessments of mechanical problem-solving skill.

H3 stated that skill at identifying the causes of gear problems would be predicted by the structure of knowledge, procedural knowledge, general reasoning, mechanical self-efficacy, and problem-solving effort. This hypothesis was in part supported (see Table 5). The structure of knowledge and procedural knowledge did have significant positive associations with skill at identifying the cause of the problem. The structure of knowledge had the strongest relation with this skill; the estimated standardized regression coefficient was double that of procedural knowledge. It was expected that extent of procedural knowledge and the structure of knowledge would be stronger predictors of skill at identifying problem causes than general reasoning, but general reasoning was expected to have a significant, if smaller, relation to this skill. General reasoning was not a significant predictor of skill at identifying the cause of gear problems. This provides evidence that knowledge structure is more important in figuring out why gears are malfunctioning than general reasoning. Also, counter to the prediction, neither mechanical self-efficacy nor problem-solving effort was a significant predictor of problem cause identification skill. This result suggests that knowledge structure has a stronger role in the process of identifying the cause of gear problems than general

reasoning, mechanical self-efficacy, or problem-solving effort. This regression model accounted for 51% of the observed variation in problem cause identification scores, 49% of which is accounted for by procedural knowledge and knowledge structure. A follow up Hierarchical regression analysis tested for a significant improvement in explained outcome variance when general reasoning, mechanical self-efficacy, and problem-solving effort were added to a model containing knowledge structure and procedural knowledge. There was not a significant improvement in explained outcome variance, $F(3, 159) = 2.04, p = .11$, which indicates that general reasoning, mechanical self-efficacy, and problem-solving effort did not help explain differences in problem cause identification.

General reasoning was a significant predictor of the structure of knowledge acquired, H2, but not of skill at identifying the cause of the gear problems, H3. The comparison of these results indicated that the structure of knowledge might mediate the relation between general reasoning and problem cause identification. Using Hierarchical regression we tested and supported a hypothesis that the relation between general reasoning and problem cause identification is mediated by knowledge structure. In step one we regressed problem cause identification on general reasoning; predicted problem cause score ($R^2 = .14, df = 163$) = general reasoning ($\beta = .37, p < .0001$) + error. In step two we added knowledge structure to the regression model; predicted problem cause score ($R^2 = .45, df = 162$) = general reasoning ($\beta = .14, p = .03$) + knowledge structure ($\beta = .61, p < .0001$) + error. The decrease in the magnitude and significance of the estimated coefficient for general reasoning when knowledge structure was included in the model is evidence for partial mediation, $F(1, 162) = 93.15, p < .0001$. This result supports the

assertion that general reasoning is related to problem cause identification skill because of its relation the structure of knowledge.

H4 states that skill at describing procedures to fix gear problems would be predicted by procedural knowledge, the structure of knowledge, general reasoning, mechanical self-efficacy, and problem-solving effort. This hypothesis was supported in part (see Table 5). The structure of knowledge and procedural knowledge were significantly related to skill at describing procedural solutions to gear problems. Counter to our prediction, procedural knowledge was not a stronger predictor of skill at describing procedural solutions than how knowledge was structured. As predicted, general reasoning was a significant but weaker predictor; the estimated standardized regression coefficient was half the size of the coefficient for procedural knowledge. Similar to the H3 results, neither mechanical self-efficacy nor problem-solving effort was a significant predictor of skill at describing procedural solutions for gear problems. This regression model accounted for 52% of the variation in procedural solution scores.

In the interest of examining overall skill at solving gear problems the aggregate of problem cause identification scores and the procedural solution scores was regressed on procedural knowledge, the structure of knowledge, general reasoning, mechanical self-efficacy, and problem-solving effort. Reflecting the results of H3 and H4, how knowledge was structured was the strongest predictor of overall gear problem-solving skill. This result provides evidence that knowledge of the interrelations between the parts of a mechanical system is critical to problem solving in that system (e.g., a bicycle's gear system). Procedural knowledge was the second strongest predictor of overall bicycle gear

problem-solving skill. Reflecting the results of H4, general reasoning was a significant, but much weaker predictor; the standardized regression coefficient was again half the size of the coefficient for procedural knowledge. Similar to results of the tests of H3 and H4, neither mechanical self-efficacy nor problem-solving effort was a significant predictor of overall gear problem-solving skill. This regression model accounted for 55% of the observed variation in gear problem-solving scores.

H5 states that overall bicycle gear knowledge, the aggregate of knowledge structure and procedural knowledge, is a better predictor of gear problem-solving skill than general reasoning. This hypothesis was supported in an analysis that regressed bicycle gear problem-solving scores on overall gear knowledge and general reasoning; predicted problem-solving score ($R^2 = .52, df = 163$) = $knowledge (\beta = .63, p < .0001) + reasoning (\beta = .17, p < .01) + error$. The results from this regression model provide very strong evidence that overall knowledge about a specific mechanical system (e.g., a bicycle) is critical in mechanical problem solving.

Summary of Findings

This study strived to improve understanding of the relation between general reasoning, knowledge acquisition, knowledge organization, and problem solving. The research specifically focused on identifying and characterizing individual differences that predict success in acquiring knowledge and solving mechanical problems. Hypotheses about knowledge acquisition were based on the theoretical assertion that an individual's knowledge is a function of the effort put forth in learning, the prior knowledge the individual has to build from, and the individual's skill at reasoning. Characteristics of the

learning situation, such as presence of a teacher, instructional material, peer collaborator, may also be important, and these were held constant in this study so as to focus on the other elements. All the participants learned from the same video at the same pace. Individual differences among the other variables were observed, but not manipulated or constrained. The results, examined in tests of H1 and H2, support the theoretical assertion that the extent of knowledge acquisition after training is a function of effort put forth, prior knowledge that supports learning, and an individual's skill at general reasoning. While general reasoning was a significant predictor of acquired knowledge, the evidence suggests that effort and prior knowledge are better predictors of who will succeed in the process of acquiring knowledge.

The second aim of this study was to gain a better understanding of the individual differences involved in the process of solving mechanical problems. Tests of H3, H4, and H5 were based on the theoretical assertion that problem-specific knowledge, rather than general reasoning, facilitates or restricts an individual's skill in solving a specific problem. We argue that general reasoning is used in problem solving to acquire problem-specific knowledge, but it is the content and organization of this knowledge that determines problem-solving skill. The results from the tests of H3, H4, and H5 support this theoretical assertion. In the test of H3, reasoning was not a significant predictor of problem solving when two measures of specific knowledge, the structure of knowledge and procedural knowledge, were taken into account. In the test of H4, reasoning was the weakest of the significant predictors, its estimated coefficient half the size of the coefficients estimated for the structure of knowledge or procedural knowledge. In the test

of H5, the estimated standardized regression coefficient for overall bicycle gear knowledge was more than 3 times that of general reasoning.

Discussion

Seventy-two years ago Cattell (1943) first put forward the proposition that an adult's capacity to solve problems is part the fluid capacity for the education of relations and part the crystallized discriminatory habits an individual establishes from experience in a particular field. Today we work to continue this research and further the understanding of crystallized intelligence by incorporating findings from expertise-knowledge research, specifically the findings relating to the structure of expert knowledge. We found that participants with higher general reasoning were more likely to structure their knowledge of bike gears similarly to professional mechanics after a short training video. We found support for Cattell's proposition that while crystallized intelligence was the result of investing fluid intelligence, once in place fluid aspects were no longer necessary for the successful use of crystallized intelligence (Cattell, 1943). The relation between general reasoning, a fluid aspect, and bicycle gear problem solving skill became much weaker when overall bicycle gear knowledge, a crystallized aspect, was included as a predictor of problem-solving skill. These results and the results of the more detailed examinations to be discussed next, demonstrate the need to engage in a dialog between those who research general cognitive abilities and those who research knowledge and expertise.

The design of this study was based on the assertion that to examine the relation between knowledge and experience related problem solving, such as malfunctioning

bicycle gears, it is necessary to examine the individual differences that predict acquiring knowledge about the problem, and the differences in knowledge that relate to problem-solving skill in that domain. Proceeding from the work of Cattell (1943, 1963) and others (e.g., Carroll, 1993; Horn & Blankson, 2005; Schneider & McGrew, 2012; Schweizer & Koch, 2002), we expected that differences in general reasoning would predict how an individual structured his or her knowledge of bicycle gears after a training video, and that it would be the way the knowledge was structured that would explain differences in problem-solving skill more than general reasoning. Five hypotheses were tested that, if supported, would provide evidence in favor of this view of the development of problem-solving skill. The following sections discuss each hypothesis in turn and how the results from testing these hypotheses further our understanding of domain specific problem-solving skill and may lead to a better understanding of intelligence.

Acquiring knowledge from an experience. H1 stated that the acquisition of procedural knowledge in a specific area of bicycle mechanics would be predicted by individual differences in Learning effort, prior knowledge, general reasoning, and mechanical self-efficacy. H2 stated that individual differences in prior knowledge, general reasoning, learning effort, and mechanical self-efficacy would predict how closely an individual would structure knowledge in relation to the structure of professional bicycle mechanics.

The results supported H1 and the proposition that differences in the extent of procedural knowledge acquired from a training experience are related to effort, prior knowledge, and general reasoning. Learning effort was the best predictor of how much of

the bicycle gear adjustment procedure was learned from the training video. Learning effort provides an index of how willing an individual was to invest his or her resources to learn about bicycles and the bicycle gear system. Because procedural knowledge is a set of sequentially fixed relations rather than the more complex set of relations that structure knowledge, we expected effort to be more important for predicting differences in procedural knowledge than general reasoning. This position was supported; memorizing a set of sequential steps to solve a problem seem to relied more on the extent to which a person was motivated to engage in the learning process in an effortful manner. General reasoning and prior knowledge of bicycle parts were nearly equivalent in their utility for predicting the extent of procedural knowledge an individual would acquire from the training video. While learning effort was the best predictor of learning this procedure, general reasoning and prior knowledge were also important individual differences for predicting the extent and understanding of the procedure for fixing bicycle gears. This result highlights the possibility that prior related knowledge may provide a framework or structure that aids in acquiring further domain knowledge, while general reasoning facilitates learning the relation from one step to another in the procedure. Taken together, these results provide good support for H1, that is, individual differences in learning a procedure can be predicted from effort put into learning, differences in general reasoning, and prior knowledge in the problem domain.

The results supported the assertion made in H2 that structuring knowledge from a training experience to be similar to an expert structure is a function of prior knowledge, general reasoning, and learning effort. The similarity between an individual's knowledge

structure and an expert's was best predicted by the individual's prior knowledge. Structural similarity was predicted, to a lesser extent, by learning effort and general reasoning. Learning effort and general reasoning were nearly equivalent in their utility for predicting the similarity of an individual's knowledge structure after the training video. These results suggest that the prior related knowledge provides a benefit when an individual is learning about the relations between a number of different parts and using this information to organizing his or her knowledge of a mechanical system (e.g., bicycle gears). Also, as predicted, general reasoning had a stronger relation with acquiring an expert-like structure than it did with the extent of acquired procedural knowledge. This difference in the predictive utility of general reasoning for the structure of knowledge compared to procedural knowledge supports the idea that general reasoning is more involved in learning when it requires understanding a set of relations that are more complex than a fixed sequence of steps. This type of complex relational understanding is represented in the way the experts structure their knowledge, and is likely to be an important aspect of their problem-solving skill. These results provide good support for H2 and the proposition that structuring experiential information into an expert-like knowledge structure utilizes an individual's prior knowledge, his or her general reasoning, and the amount of effort he or she is will to exert into learning from a training experience.

Our interest in this study was to build a better understanding of how two types of knowledge are acquired from a training experience, procedural knowledge and expert-like knowledge structure. By combining these two types of knowledge and performing an

analysis similar to that of H1 and H2 we provide results that speak to knowledge acquisition more generally. The best predictors of how much knowledge an individual acquired from the training video were learning effort and prior knowledge. General reasoning was a weaker though still highly significant predictor of overall bike gear knowledge after the training experience. Mirroring the results from the test of H1 and H2, these results provide evidence that general reasoning is important in explaining differences in learning, but that there is more to learning than this general cognitive ability. It is perhaps more important to understand an individual's motivation to learn and the knowledge base he or she is starting from when predicting the knowledge he or she will acquire from a learning experience.

Future directions in knowledge acquisition research. The first two hypotheses, H1 and H2, were supported, but the predictors included in these analyses did not account for all of the variation that was observed in procedural knowledge and similarity to an expert knowledge structure. This unexplained variation indicates a need to consider other individual differences that are involved in learning from a training experience. In particular, we propose that a more complete explanation of the differences in procedural knowledge and knowledge structure may come from including assessments of other general cognitive abilities and more focused assessments of the knowledge base an individual had before the training experience.

In this study we assessed a single general cognitive ability, general reasoning. In the extended theory of fluid and crystallized intelligence (Horn & Blankson, 2005) general reasoning has the clearest link to skill at learning the relations that structure

knowledge. The results of H2 indicate that general reasoning was associated with learning the inter-concept relations that structured knowledge more similarly to experts. We argue that general reasoning is helping individuals recognize the relations that are maintained by the parts of the problem. For example, movement in the shift lever affects the derailleur through the cable and this set of relations does not change, that is, it is maintained. Working memory may influence the number of relations that an individual can comprehend at any given time. Increases in working memory may allow an individual to compare and contrast more relations, which could in turn provide a better conceptualization of the overall system of inter-relations and recognition of the pattern of causal relations that determine the systems functionality. The sensory nature of the relations within a system may also tap different sensory and perceptual abilities. For example, in this study participants were asked to learn about a mechanical system, the gears on a bicycle. The training material in this study had a substantial amount of visual spatial information because of the importance of this type of information for understanding the gear system. It is, therefore, likely that individual differences in visual and spatial abilities may predict the amount of relational information that an individual can acquire from this type of training experience. In future work it will be important to include assessments of other general cognitive abilities, such as working memory and visual spatial perception, to understand if and to what extent these individual differences predict what an individual learns from a training experience.

Prior knowledge was the best predictor of acquiring an expert-like knowledge structure after the training video. However, the number of bicycle parts that an individual

can remember and name only indicates their familiarity with a bicycle. We propose that two additional characteristics of participants' knowledge base before training may help to explain why previous experience is such a good predictor of who will have an expert-like knowledge structure after training. In explaining the relation between prior knowledge and post-training knowledge structure we asserted that the prior knowledge is indicative of having a structure for this type of knowledge already in place. However, this is a conjecture and in need of empirical support. Second, our assessment of prior knowledge left a fundamental question unaddressed. Why does familiarity with a topic, such as bicycles, help an individual structure their knowledge of the problem? We believe that experience and familiarity with bicycles may be providing individuals with a better understanding of the physical and mechanical principles that govern the gear system and other mechanical systems. An understanding of these principles may facilitate learning and organizing the relations between the gear parts, and it may be this sort of understanding of general principles that experts use when troubleshooting a mechanical system. In future research it will be important to develop a better understanding of how the knowledge base, specifically the understanding of related general principles, is involved in learning and structuring information about a novel but related problem.

Solving problems related to recent experience. In the test of hypotheses H3 and H4 we worked to build a better understanding of the characteristics of knowledge that are important in predicting who can and cannot solve a specific set of problems related to a recent experience. In H3 we examine the individual differences that predicted skill at identifying the causes of gear problems. In H4 we examine the individual differences that

predict skill at describing procedural solutions to the gear problems. In each of these hypotheses about these two aspects of problem-solving skill we used the same set of individual differences as predictors: similarity to the expert knowledge structure, extent of procedural knowledge, general reasoning, mechanical self-efficacy, and effort put into solving the problems. In H3 we predicted that having an expert-like knowledge structure would be the best predictor of an individual's skill at identifying the causes of the gear problems. Whereas in H4 we predicted that the extent of an individual's procedural knowledge would be the best predictor of skill at describing procedural solutions. In our fifth and final hypothesis, H5, we hoped to test and quantify the relative utility of general reasoning compared to overall bicycle gear knowledge for predicting an individual's gear problem-solving skill.

The results from the test of H3 supported the view that having an expert-like knowledge structure is the best predictor of problem cause identification skill. General reasoning had a weak non-significant relation, $p\text{-value} = .12$, with this aspect of problem-solving skill. It is important to note the difference between the relation of general reasoning in the results from H2 where general reasoning did predict an expert-like structure to an individual's knowledge, and H3 where general reasoning did not predict this aspect of problem-solving skill. The relation between general reasoning and skill at identifying the causes of gear problems is at least partially mediated by the relation of general reasoning to the structure of knowledge. The results from H2 and H3 are strikingly similar to Cattell's position that fluid intelligence is utilized in acquiring crystallized

intelligence, but once the crystallized skill is acquired fluid intelligence is not necessary for the successful application of crystallized intelligence (Cattell, 1943).

The results from the test of H4 did not support the perspective that procedural knowledge was the best predictor of skill at describing procedural solutions to the gear problems. Recall that procedural knowledge is knowledge of the sequential step that if carried out will solve a problem, whereas knowledge structure pertains to the way in which the content of knowledge is organized. Knowledge structure and procedural knowledge were almost equally strong predictors of skill at explaining a procedure to solve the gear problems. Additionally, unlike the H3 results, general reasoning was a significant, if much weaker, predictor of skill at describing procedural solutions. It is unclear if our hypothesis was wrong and the structure of knowledge is an important predictor of procedural problem-solving skill even when an individual has mastered a procedural sequence to solve a problem, or if aspects of the study design affected the utility of procedural knowledge for describing procedural solutions to the gear problems. For example, the brevity of the training video may have made it difficult to fully master a somewhat lengthy and complex procedure. In such a situation it is possible, and perhaps likely, that an individual may use a combination of their general reasoning and knowledge structure to deduce procedural solutions. However, this explanation is speculation. A clearer understanding of the relation between procedural knowledge and skill at describing procedures to fix problems may be obtained in a study design that ensures mastery of the procedural knowledge. The results from the test of H4 does support the idea that the extent of an individual's procedural knowledge is important for

predicting their skill at describing procedural solutions beyond knowing how they have structured their knowledge.

In this set of hypothesis, H3 and H4, we were interested in determining the predictive utility of several individual differences for predicting performance on two aspects of bicycle gear problem-solving skill. However, skill at solving problems related to previous experience and knowledge may be better quantified as the composite of problem cause identification skill and procedural solution skill. Therefore, we performed a similar analysis as was used to test H3 and H4 with overall problem-solving skill as the outcome. The results of this analysis are similar to the results of H3 and H4. In particular an expert-like knowledge structure was the strongest predictor of overall problem-solving skill in this domain, and general reasoning was a much weaker predictor of this skill. Much as in our interpretation of the H3 results, we argue that the results from this analysis support Cattell's view of the relation between fluid and crystallized intelligence. Fluid intelligence aids in acquiring crystallized intelligence, but once a crystallized skill is acquired fluid intelligence is not required for the successful application of crystallized intelligence. Both expert-like knowledge structure and procedural knowledge were strong predictors of overall problem-solving skill. While general reasoning did help predict an individual's problem-solving skill, either type of knowledge was a better predictor an individual's skill in solving bicycle gear problems.

The results from the test of or last hypothesis, H5, provided evidence that domain specific knowledge, the aggregate of knowledge structure and procedural knowledge, is more important than general reasoning for predicting an individual's bicycle gear

problem-solving skill after a training experience. The predictive power of overall bicycle gear knowledge was nearly four times stronger than that of general reasoning for predicting bicycle gear problem-solving skill. This result further emphasizes the need to include domain-specific knowledge, the content and structure of this knowledge, in our theories and study of adult mental capacity and intelligence. Skill at solving problems is an indicator of adult mental capacity, and the content and structure of knowledge is a strong predictor of an individual's skill at solving problems that are related to a recent experience. We are hopeful that the results of this study will generalize to other mechanical domains and to knowledge and experience related problem-solving skill more generally.

In summary, the results of the tests of H3, H4, and H5 accounted for a substantial percentage (over 50%) of variation in skill at identifying the causes of the mechanical problems used in this study, skill at describing procedural solutions to these problems, and overall skill at solving these problems. These results provide strong evidence that knowledge, and to a lesser degree general reasoning, are important factors in one's skill at solving problems where knowledge from previous experiences is pertinent. However, the proportion of unexplained outcome variation is evidence that mechanical problem-solving skill, and potentially problem-solving skill in other domains, is a function of more than knowledge and reasoning. We had expected mechanical self-efficacy and effort put into solving the problems to further explain differences in problem-solving skill. However, when the effects of knowledge and general reasoning were statistically

controlled, effort and mechanical self-efficacy were not significantly related to problem-solving skill.

Future directions in problem-solving research. Future research into the individual differences that predict problems-solving skill in a particular domain can build from our results by exploring the importance of other general cognitive abilities and the role of abstract principles in organizing and structuring experiential information into knowledge. General reasoning has the clearest theoretical link to relational learning, and this is the type of learning that is argued to structure an individual's knowledge about a problem or specific set of problems. Working memory is another general cognitive ability, and it is unclear to what extent an individual's working memory is utilized in problem solving when they are knowledgeable about the problem's content. When a problem is characterized by an extensive or complex knowledge structure with numerous concepts and interrelations, working memory may determine the number of relations an individual can consider when troubleshooting the problem.

The structure of knowledge is an important predictor of skill at solving problems related to that knowledge, but it is unclear what is being used to structure this knowledge. We suggest that it may be the individual's understanding of the related abstract or general principles. Abstract principles, such as the transfer of mechanical energy, describe a general category of causal relations that may determine the way an individual needs to organize their knowledge of a particular problem. An expert has extensive practice with the general principles of their field, and it may be this understanding that allows them to organize the information from a problem into beneficially structured knowledge.

However, both the role of working memory in problem solving when knowledge structure is accounted for, and the role of general principles in structuring knowledge are empirical questions and topics for future research.

A Better Understanding of Problem Solving and Subsequently Intelligence

One outcome of a successful education is to acquire knowledge that will facilitate domain specific problem solving, such as troubleshooting malfunctioning mechanics.

While it is clear that knowledge is important in solving problems, it is somewhat unclear what characteristics of knowledge make it better or worse for problem solving and how different characteristics of knowledge are acquired. Cattell's theory (1943, 1963) that intelligence is part fluid intelligence, roughly described as the capacity to learn, and part crystallized intelligence, roughly described as knowledge, is one theory that has been used to explain differences in problem-solving behavior. The extended fluid and crystallized theory of cognitive abilities (Horn & Blankson, 2005) provides insight into one avenue for acquiring knowledge, the investment of fluid abilities, as well as better understanding of the fluid-like general cognitive abilities that are employed in problem solving. This theory explains the utility of knowledge for problem solving primarily by general content, such as general cultural knowledge or general mechanical knowledge. This broader more general view of crystallized intelligence has left a somewhat nebulous understanding of the role of crystallized intelligence in problem solving behavior. A primary impetus of this study was to expand the understanding of the utility of the crystallized aspects of intelligence by considering the characteristics of a specific set of knowledge, bicycle gear knowledge, and how these characteristics relate to skill at

solving related problems. Furthermore, we hoped to gain a better understanding of the role of general reasoning, a fluid ability, in predicting the characteristics of an individual's knowledge related to a recent training experience. To accomplish these aims we utilized the results and methods of research into expert knowledge. Much of the research in this area is devoted to understanding and characterizing differences in a specific set of knowledge, such as fighter pilot combat maneuvers (Schvaneveldt et al, 2002) or the spacecraft life support systems (Burkolter, et al., 2010).

Knowledge can be categorized as declarative, procedural, or structural (Jonassen, et al., 1993). Each type of knowledge is characteristically different from the other types and is useful for solving different types of problems. In the introduction of this study an example is provided where the content was the same, bicycles gears, but depending on the type of knowledge, different problems could be solved. Declarative knowledge is characterized as discrete facts, such as Santa Fe is the capitol of New Mexico or bicycle chains come in three widths. Declarative knowledge of bicycle parts is essential for the supply clerk who needs to purchase a replacement part. Procedural knowledge is characterized by a rigid sequence of steps to obtain a particular outcome or solve a specific problem. Bicycle mechanics often use procedural knowledge when performing routine tune-ups to ensure that every tune-up checks for and fixes the same problems. Structural knowledge is characterized by an understanding of the inter-concept relations that are maintained within a system. For bicycle mechanics the structure of their knowledge characterizes their understanding of how the bicycle parts are functionally interrelated to transfer pedal motion to wheel motion, handlebar motion to front wheel

directional changes, shift lever motion to derailleur motion, and so on. In this study we set out to explore these differences in knowledge as they relate to problem solving, and to see if Cattell's perspective on the interrelation between fluid and crystallized aspects of intelligence holds true for the relation of general reasoning to these characteristics of knowledge.

The results from this study demonstrate that, yes, differences in knowledge about a recent experience, and specifically the structure of that knowledge, were predicted by general reasoning, and the characteristics this knowledge was a better predictor of problem-solving skill than general reasoning. The theoretical premises set forward by Cattell about the relation between fluid and crystallized intelligence did hold true for the structural and procedural characteristics of knowledge related to this video training experience. In the results from the test of H1 and H2, general reasoning predicted both the extent of procedural knowledge acquired from a recent experience and the way that individuals' structured their understanding of the concept interrelations that were represented in that experience. Much as is predicted by Cattell's investment theory, the investment of general reasoning to learn from this video-training experience had a positive association with these procedural and structural characteristics of knowledge about the recent experience. Cattell's second premise within this theory of intelligence was that once in place crystallized intelligence could be successfully used for problem solving independent of fluid intelligence. The results from our test of H3 and H4 demonstrated that, yes, the structural and procedural characteristics of knowledge about a recent experience were predictive of related problem-solving skill independent of general

reasoning. The procedural and structural characteristics of the experience-related knowledge were much better predictors of one's skill at both identifying the causes of gear problems and describing procedures to fix the problems than general reasoning. The importance and independence of problem specific knowledge in predicting problem-solving skill was most pronounced for skill at identifying the causes of the gear problems. Having an expert-like knowledge structure was a strong predictor of an individual's skill at identifying the causes of gear problems, while general reasoning was not significantly related to this skill. We believe that taken together the results from this study support the proposition that a better understanding of problem solving, and subsequently intelligence, can be obtained by joining the research traditions examining cognitive abilities with those of expertise-knowledge research.

The idea that intelligence is part fluid intelligence, roughly described as the capacity to learn, and part crystallized intelligence, roughly described as knowledge, marked an important change in understanding intelligence and subsequently problem solving behavior. In the 72 years since Cattell put forward this proposition we have moved from a rough understanding of fluid intelligence, to a more precise and well supported understanding of this aspect of intelligence. We can now identify a diverse set of general cognitive abilities (e.g., working memory, general reasoning, processing speed) that provides a more detailed understanding of the fluid aspects of intelligence and differences in the capacity to comprehend and manipulate experiential information. Similar advancements in the understanding of the crystallized aspect of intelligence have not been as pronounced in this research tradition. However, the expertise knowledge

research tradition has made large steps forward in understanding the nature and characteristics of knowledge as they relate to expertise and solving a spectrum of domains-specific problems. The understanding of the more crystallized aspects of intelligence no longer needs to remain at the nebulous general cultural or general mechanical knowledge level. The results from this study support the position that both procedural and structural aspects of knowledge advance our understanding of problem solving behavior and the crystallized aspects of intelligence.

Limitations

As with most studies this study has its limitations. We began this study to gain a better understanding of how people solve problems that are related to their previous experience and knowledge, such as solving bike gear problems after watching a training video. A central part of this study was to assess differences in how knowledge about this recent experience, learning to adjust bicycle gears, was structured and the relation of structural differences to skill at solving bicycle gear problems. Furthermore, we sought to gain a better understanding of how general reasoning is related to different characteristics of this experience-related knowledge and skill at solving bicycle gear problems. We argue that to understand problem-solving skill it is necessary to examine how knowledge is acquired from an experience, the structural and procedural characteristics of this knowledge, and how these characteristics of knowledge are related to solving related problems.

To test our hypotheses about acquiring knowledge from an experience and later solving problems related to this experience we used an observational between-subjects

design. We assessed several individual differences among our participants, including general reasoning and knowledge of bicycle parts, and then asked participants to learn the procedure for adjusting bicycle gears by watching an instructional video. The extent of their knowledge of the gear adjustment procedure and how they structured their knowledge of the gear system's parts was assessed after the video and before participants tried to solve several problems with a bicycle's gears. This study design has several limitations that are important to consider when interpreting the results. In the following sections we will discuss several of the limitation in the learning experience, the assessments of experience-related knowledge, and the assessments of problem-solving skill as they relate to our results.

The training experience was short, not interactive, and minimal reason was given for why an individual may want to master the training material. This learning experience may place limits on acquiring knowledge, restricting the extent that expert-like knowledge structures could be acquired. For instance, only 16 participants acquired a knowledge structure that was highly similar, $C > .50$, to the professional mechanics' structure. It is unclear how this range restriction may limit our understanding of the higher end of structural similarity in relation to problem solving. However, this training experience allowed us to assess how individual differences in effort to learn from the experience were related to differences in the acquired knowledge. This training experiences is also the type of experience where an individual may rely more heavily on general cognitive abilities, such as general reasoning, to learn from an experience.

Limitations in the assessments of knowledge. Acquiring knowledge from an experience builds from the previous experiences and knowledge of an individual (Bodner, 1986; Piaget, 1972). It is, therefore, important to control for previous knowledge and experiences that may help in acquiring knowledge from a new experience. The control for previous knowledge in this study, the number of bicycle parts an individual could name, was an assessment of knowledge content and does not control for how this knowledge was structured. Neither did we assess the extent of differences in other mechanical experiences or knowledge that may have aided in organizing the new information about a bicycle's gears. Experience with other mechanical systems, such as cars, may provide a better understanding of the general mechanical principles, such as transfer of energy, that underlie the relations between the parts of the bicycle gear system. Having a good understanding of the general principles that govern the causal relations of a system may be beneficial for organizing experiential information into an expert-like knowledge structure. Assessing these other differences in an individual's knowledge base before a learning experience may help to explain differences in the knowledge acquired from the experience.

A key purpose of this study was to explore the relation between the way that knowledge is structured and skill at solving related problems. To assess the way that knowledge was structured, participants' relatedness ratings of the nine gear system parts, 36 ratings per participant, were analyzed with the PF-Net algorithm. Analyzing the relatedness ratings with the PF-Net algorithm provided three characteristics of the knowledge structure: how dense the structure was, the level of coherence in the structure,

and the similarity to the structure of experienced bicycle mechanics. Our primary interest was in the relation between structural similarity and problem solving. The measure of structural similarity performed much as we expected given the minimal training received by participants. The average participant had a structure to their knowledge that was moderately similar to the structure of the mechanics' knowledge, and increases in similarity were associated with increases in problem-solving skill. However, the assessment of structural coherence did raise concerns that led us to exclude it from the test of our hypotheses.

The assessment of structural coherence demonstrated an unexpectedly wide range that extended below zero. Coherence assesses the consistency of a knowledge structure on a correlation scale. High coherence, a score of 1, indicates the individual was consistent in the way he or she rated concepts that were strongly related. The coherence assessment is based on the assumption that if two concepts are very related they should have a similar pattern of relations to the other concepts. Almost half of the participants had coherence scores below .20, which could be explained by the relatively minimal training period. The real concern with this assessment of the knowledge structure was that about 20% of the participants had coherence scores below zero. For these participants, an increase in the strength of an inter-concept relation rating was associated with a decrease in the similarity of the concepts' patterns of relations to other concepts. It is unclear if the number of participants with sub-zero coherence in their knowledge structure was due to the brevity of the training period, lack of effort when completing the relatedness ratings, or another aspect of the knowledge structure assessment procedure.

One potential improvement to the procedure for eliciting structural knowledge is the Target approach (Tossell, Schvaneveldt, & Branaghan, 2010). Rather than a list of pairwise ratings, the individual uses a graphical interface that allows them to move concepts closer or farther from a bull's-eye concept depending on how related they believe the two to be. An individual organizes the concepts within the target's concentric rings, and each ring represents a different degree of relatedness. A target is presented for each concept featuring it as the bull's-eye concept. The relatedness ratings are collected for that concept then the next target is presented. This method has the advantage of allowing an individual to see how they have related all the concepts to the bull's-eye concept. Tossell and colleagues (2010) found that the Target method was preferred by experts and was a more efficient method for collecting pairwise ratings. There were also some indications that the Target method provided data of a higher quality and was a more engaging task. A graphical representation of an individual's relatedness ratings like this may aid in eliciting a knowledge structure that is a more accurate representation of the individual's true structure.

Limitation in assessing problem-solving skill. It is our hope that the results from our test of H3, H4, and H5 will generalize to a wide scope of experience-related problems. However, differences in problem content, such as legal versus mechanical, may influence the characteristics of knowledge that are most important to problem-solving skill in that domain. We predict individuals with an expert-like structure to their knowledge in any particular domain will also display a higher proficiency in solving problems within that domain. However, this study focused on a specific mechanical

domain, bicycle gears, and did not test the broader prediction that the way knowledge is structured predicts its utility in solving related problems, regardless of substantive domain differences. To gain a better understanding of the relation of knowledge to solving experience-related problems it is necessary to extend this study design to consider other substantive areas. It will also be necessary to build a better understanding of the type of information that experts use to organize experiential information as a knowledge structure and if this information differs depending on the substantive domain.

The problems-solving skills assessed in this study were specific to the types of problems confronted by bicycle mechanics in the performance of their professional responsibilities. However, our participants simulated solving mechanical problems by describing what they thought the cause was and what steps should be carried out to fix the problem. These individuals did not actually participate in solving these problems on a bicycle. This makes the bicycle gear problems more abstract, and restricts the way an individual can learn about the problem. There was not a physical bike to examine, reference, or learn from. The increase in the abstract nature of the problems may change the way individuals used their general reasoning and knowledge when solving these problems. It is also, however, possible that the skill to solve these abstract types of problems is what underlies the flexibility that expert mechanics demonstrate in the problems they can solve.

Conclusions

The results from this study provide a better understanding of how problems are solved when they are related to prior experience and knowledge. When an individual is

solving a novel problem, such as those seen on IQ test, the knowledge acquired from previous experiences is most often of minimal aid in identifying the solutions. The IQ test problems are purposefully designed to assess differences in specific cognitive abilities. The research tradition that has worked to identify and describe human cognitive abilities has in large relied on IQ test problems for their evidence about the nature and role of cognitive abilities in problem solving. It has been argued that the primary piece missing from our understanding of adult intelligence, and subsequently problem solving, is knowledge (Ackerman, 2000; Horn & Blankson, 2005; Baltes, Dittmann-Kohll, & Dixon, 1984). In this study we worked to expand the understanding of the role of knowledge in problem solving, and to introduce the perspective that the crystallized aspects of intelligence are at least in part determined by the structure of an individual's knowledge in a domain. We provided evidence in support of this position by observing individuals as they acquire knowledge from an experience and then work to solve problems related to that experience.

Was general reasoning predictive of knowledge acquired from the training video, and did it have a stronger relation to knowledge structure than procedural knowledge? Yes, while general reasoning was not the strongest predictor in the results from the test of H1 and H2, it did predict of the extent of procedural knowledge acquired and the way individuals structured their knowledge of bicycle gears. Furthermore, general reasoning was estimated to have a stronger association with acquiring a knowledge structure similar to experienced mechanics than with the extent of procedural knowledge acquired. This supports the view that the utility of general reasoning in solving novel problems is in

organizing experiential information into knowledge that is structured like more experience individuals. That is to say, general reasoning describes an individual's ability to organize experiential information into knowledge that is structured by the causal relations that are maintained in the problem and environment.

Was the structure of knowledge a better predictor of problem-solving skill than general reasoning? Yes, when the effects of knowledge structure and procedural knowledge were accounted for, general reasoning did not predict differences in skill at identifying the cause of the gear problems. In identifying the cause of the gear problems, the structure of an individual's knowledge was a stronger predictor of identifying the correct cause than procedural knowledge. And the structure of knowledge was the strongest predictor of overall gear problem-solving skill. The results of our test of H3 and H4 provide evidence that the way knowledge is structured is an important characteristic of knowledge in determining its utility for solving related problems. What is learned from an experience is more than knowledge content. Knowledge content is organized, and the nature of this structure is important for understanding differences in an individual's proficiency at solving the variety of experience-related problems that they confront while performing their personal and professional responsibilities.

The theory of fluid and crystallized intelligence marked a turning point in the understanding of intelligence and problem solving. With this theory Cattell (1943) asserted that knowledge was an important and unique determinant in one's capacity to resolve the problems they confront and to deal effectively with the environment. However, the vigor that has gone into exploring the fluid aspects of intelligence is less

pronounced in the exploration of the crystallized-expertise aspects of intelligence. "...Gc [the store of knowledge] and TSR [long-term storage and retrieval] measures tap only surface-like indicators of expertise abilities. They do not indicate the depth of knowledge, the ability to deal with many aspects of a problem, the reasoning, and the speed in considering possibilities that characterize high-level expertise performances. Gc and TSR do not measure the feats of reasoning and memory that characterize the most sublime expressions of adult intelligence" (Horn & Blankson, 2005, p. 93). To understand how people confront and resolve their daily problems, and to explain how people deal effectively with their environment we must integrate the two research traditions of intelligence and expertise. It is our hope that the results from this study can be used to further motivate engagement in a dialog that integrates expertise and intelligence.

References

- Ackerman, P. L. (2000). Domain-specific knowledge as the “dark matter” of adult intelligence: Gf/Gc, personality and interest correlates. *The Journals of Gerontology, Series B, Psychological Sciences and Social Sciences*, *55*, 69–84. doi:10.1093/geronb/55.2.P69
- Acton, W. H., Johnson, P. J., & Goldsmith, T. E. (1994). Structural knowledge assessment: Comparison of referent structures. *Journal of Educational Psychology*, *86*, 303–311. doi:10.1037//0022-0663.86.2.303
- Baltes, P. B., Dittmann-Kohli, F., & Dixon, R. A. (1984). New perspectives on the development of intelligence in adulthood: Toward a dual-process conception and a model of selective optimization and compensation. In P. B. Baltes & O. G. Brim (Eds.), *Life-span development and behavior Vol. 6* (pp. 34–77). Orlando, FL: Academic Press.
- Bodner, G. (1986). Constructivism: A theory of knowledge. *Journal of Chemical Education*, *63*, 873–878. doi:10.1021/ed063p873
- Burkolter, D., Meyer, B., Kluge, A., & Sauer, J. (2010). Assessment of structural knowledge as a training outcome in process control environments. *Human Factors*, *52*, 119–138. doi:10.1177/0018720810367646
- Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. New York, NY: Cambridge University Press.
- Carroll, J. D., & Arabie, P. (1998). Multidimensional scaling. In M. H. Birnbaum (Ed.), *Measurement, judgment, and decision making* (pp. 179–250). San Diego, CA: Academic Press.
- Cattell, R. B. (1943). The measurement of adult intelligence. *Psychological Bulletin*, *40*, 153–193. doi:10.1037/h0059973
- Cattell, R. B. (1963). Theory of fluid and crystallized intelligence: A critical experiment. *Journal of Educational Psychology*, *54*, 1–22. doi:10.1037/h0046743
- Chase, C. C., Chin, D. B., Opezzo, M. A., & Schwartz, D. L. (2009). Teachable agents and the protégé effect: Increasing the effort towards learning. *Journal of Science Education and Technology*, *18*, 334–352. doi:10.1007/s10956-009-9180-4

- Condon, D. M., & Revelle, W. (2014). The international cognitive ability resource: Development and initial validation of a public-domain measure. *Intelligence*, *43*, 52–64. doi:10.1016/j.intell.2014.01.004
- Cooke, N. J., & Schvaneveldt, R. W. (1988). Effects of computer programming experience on network representations of abstract programming concepts. *International Journal of Man-Machine Studies*, *29*, 407–427. doi:10.1016/S0020-7373(88)80003-8
- Cornelius, S. W., & Caspi, A. (1987). Everyday problem solving in adulthood and old age. *Psychology and Aging*, *2*, 144–153. doi:10.1037/0882-7974.2.2.144
- Darabi, A. A., Nelson, D. W., & Palanki, S. (2007). Acquisition of troubleshooting skills in a computer simulation: Worked example vs. conventional problem solving instructional strategies. *Computers in Human Behavior*, *23*, 1809–1819. doi:10.1016/j.chb.2005.11.001
- Davis, M. A., Curtis, M. B., & Tschetter, J. D. (2003). Evaluating cognitive training outcomes: Validity and utility of structural knowledge assessment. *Journal of Business and Psychology*, *18*, 191–206. doi:10.1023/A:1027397031207
- Day, E. A., Arthur, W., & Gettman, D. (2001). Knowledge structures and the acquisition of a complex skill. *Journal of Applied Psychology*, *86*, 1022–1033. doi:10.1037//0021-9010.86.5.1022
- Diehl, M., Willis, S. L., & Schaie, K. W. (1995). Everyday problem solving in older adults: Observational assessment and cognitive correlates. *Psychology and Aging*, *10*, 478–491. doi:10.1037/0882-7974.10.3.478
- Gillan, D. J., Breedin, S. D., & Cooke, N. J. (1992). Network and multidimensional representations of the declarative knowledge of human-computer interface design experts. *International Journal of Man-Machine Studies*, *36*, 587–615. doi:10.1016/0020-7373(92)90098-6
- Goldsmith, T. E., & Davenport, D. M. (1990). Assessing structural similarity of graphs. In R. W. Schvaneveldt (Ed.), *Pathfinder associative networks: Studies in knowledge organization* (pp. 75–87). Westport, CT: Ablex Publishing. Retrieved from <http://interlinkinc.net/PFBook.zip>
- Goldsmith, T. E., Johnson, P. J., & Acton, W. H. (1991). Assessing structural knowledge. *Journal of Educational Psychology*, *83*, 88–96. doi:10.1037//0022-0663.83.1.88

- Gonzalvo, P., Cafias, J. J., & Bajo, M. T. (1994). Structural representations in knowledge acquisition. *Journal of Educational Psychology*, *86*, 601–616. doi:10.1037//0022-0663.86.4.601
- Gottfredson, L. S. (1997). Mainstream science on intelligence: An editorial with 52 signatories, history and bibliography. *Intelligence*, *24*, 13–23. doi:10.1016/S0160-2896(97)90011-8
- Grand, J. A. (2008). *Changing gears: Modeling gender differences in performance on tests of mechanical comprehension* (Master's Thesis). Available from ProQuest Dissertations and Theses database. (UMI No. 1463014).
- Horn, J. L., & Blankson, N. (2005). Foundations for better understanding of cognitive abilities. In D. P. Flanagan & P. L. Harrison (Eds.), *Contemporary intellectual assessment: Theories, tests, and issues* (pp. 41–68). New York: Guilford Press.
- Jonassen, D. H., Beissner, K., & Yacci, M. (1993). *Structural knowledge: Techniques for representing, conveying, and acquiring structural knowledge*. Hillsdale, NJ, England: Lawrence Erlbaum Associated, Inc.
- Kivlighan, D. M. (2008). Structural changes in counselor trainee intention use and clients' session evaluation. *Psychotherapy Research: Journal of the Society for Psychotherapy Research*, *18*, 560–72. doi:10.1080/10503300802010830
- Piaget, J. (1972). Developmental epistemology. In *Psychology and epistemology: Towards a theory of knowledge* (pp. 1–10). New York, NY: Viking press.
- Raven, J. (2000). The Raven's progressive matrices: Change and stability over culture and time. *Cognitive Psychology*, *41*, 1–48. doi:10.1006/cogp.1999.0735
- Rowe, A. L., Cooke, N. J., Hall, E. P., & Halgren, T. L. (1996). Toward an on-line knowledge assessment methodology: Building on the relationship between knowing and doing. *Journal of Experimental Psychology: Applied*, *2*, 31–47. doi:10.1037/1076-898X.2.1.31
- Salomon, G. (1984). Television is “easy” and print is “tough”: The differential investment of mental effort in learning as a function of perceptions and attributions. *Journal of Educational Psychology*, *76*, 647–658. doi:10.1037/0022-0663.76.4.647
- Schneider, W. J., & McGrew, K. S. (2012). The Cattell-Horn-Carroll Model of Intelligence. In D. P. Flanagan & P. L. Harrison (Eds.), *Contemporary intellectual assessment: Theories, tests, and issues* (3rd ed., pp. 99–144). New York, NY: Guilford Press.

- Schvaneveldt, R. W. (1990). *Pathfinder associative networks: Studies in knowledge organizations*. (R. W. Schvaneveldt, Ed.). Westport, CT: Ablex Publishing.
Retrieved from <http://interlinkinc.net/PFBook.zip>
- Schvaneveldt, R. W., Durso, F. T., Goldsmith, T. E., Breen, T. J., Cooke, N. J., Tucker, R. G., & De Maio, J. C. (1985). Measuring the structure of expertise. *International Journal of Man-Machine Studies*, 23, 699–728. doi:10.1016/S0020-7373(85)80064-X
- Schvaneveldt, R. W., Tucker, R., Castillo, A., & Bennett, W. J. (2002). *Knowledge acquisition in distributed mission training*. Retrieved from <http://www.dtic.mil/dtic/tr/fulltext/u2/a412238.pdf>
- Smith, E. E., Shoben, E. J., & Rips, L. J. (1974). Structure and process in semantic memory: A featural model for semantic decisions. *Psychological Review*, 81, 214–241.
- Wasserman, J. D. (2012). A history of intelligence assessment: The unfinished tapestry. In D. P. Flanagan & P. L. Harrison (Eds.), *Contemporary intellectual assessment: Theories, tests, and issues* (3rd ed., pp. 3–55). New York, NY: Guilford Press.
- Wilson, J. M. (1994). Network representations of knowledge about chemical equilibrium: Variations with achievement. *Journal of Research in Science Teaching*, 31(10), 1133–1147. doi:10.1002/tea.366031100

Table 1

Descriptive statistics of study variables

Variable	N	Mean	SD	Median	Min.	Max.	Skew	Kurtosis	SE
Age	174	19.36	1.60	19.00	18.00	30.00	2.97	14.46	0.121
English Percentage	173	82.30	24.27	94.44	5.26	100.00	-1.47	1.24	1.845
Ease Spoken English	173	1.43	0.64	1.00	1.00	4.00	1.31	1.09	0.049
Ease Writing English	173	1.53	0.70	1.00	1.00	4.00	1.25	1.24	0.053
General Reasoning	174	40.90	19.92	37.00	0.00	87.00	0.06	-0.59	1.510
Prior Bicycle Knowledge	174	6.38	2.51	6.00	0.00	19.00	1.40	4.50	0.190
Mechanical Self-Efficacy	174	2.72	0.61	2.73	1.00	4.50	0.26	0.22	0.046
Procedural Knowledge MC	174	47.22	23.43	50.00	0.00	100.00	0.01	-0.68	1.776
Procedural Knowledge Rank	173	-14.40	4.86	14.00	-28.00	-2.00	0.01	-0.13	0.369

Continued

Table 1 continued

Descriptive statistics of study variables

Variable	N	Mean	SD	Median	Min.	Max.	Skew	Kurtosis	SE
Knowledge Structure Definitions	174	2.58	0.70	2.56	1.06	4.00	-0.09	-0.76	0.053
Knowledge Structure Closeness	166	0.35	0.13	0.33	0.09	0.69	0.40	-0.30	0.010
Knowledge Structure Coherence	166	0.17	0.34	0.23	-0.62	0.82	-0.33	-0.78	0.026
Knowledge Structure Density	166	0.44	0.13	0.42	0.22	0.94	0.83	0.52	0.011
Problem Cause Skill	174	1.75	0.57	1.67	1.00	3.39	0.62	-0.37	0.043
Problem Solution Skill	174	1.70	0.50	1.61	1.00	3.44	0.77	0.31	0.038
Overall Problem Solving Skill	174	1.72	0.51	1.64	1.00	3.39	0.66	-0.03	0.039
Learning Effort	173	3.39	0.90	3.00	1.00	5.00	-0.31	0.29	0.068
Problem Solving Effort	173	3.25	0.86	3.00	1.00	5.00	-0.12	0.25	0.065

Note. N = complete data, SD = standard deviation, Min. = minimum value, Max. = maximum value, SE = standard error.

Table 2

Correlation matrix of the primary study variables

1. Effort, learning	1.00																		
2. Effort, solving	.64†	1.00																	
3. Effort aggregate	–	–	1.00																
4. Reasoning				1.00															
5. Prior knowledge	.17	.18	.17	.22*	1.00														
6. MSE	.24*	.20	.25**	.29**	.42†	1.00													
7. Procedural, MC	.41†	.30†	.35†	.28**	.33†	.29†	1.00												
8. Procedural, rank	.29†	.19	.20*	.28**	.31†	.30†	.42†	1.00											
9. Procedural aggregate	.41†	.29**	.32†	.33†	.38†	.35†	–	–	1.00										
10. KS, RR similarity	.26**	.23*	.28**	.31†	.36†	.32†	.40†	.40†	.47†	1.00									
11. KS, definitions	.43†	.36†	.43†	.37†	.47†	.32†	.49†	.47†	.57†	.63†	1.00								
12. KS aggregate	.37†	.32†	.38†	.39†	.45†	.35†	.50†	.47†	.58†	–	–	1.00							
13. Knowledge aggregate	.44†	.34†	.43†	.38†	.46†	.40†	–	–	–	–	–	1.00							
14. Problem, cause	.29†	.30†	.28**	.37†	.45†	.38†	.49†	.46†	.56†	.51†	.70†	.66†	1.00						
15. Problem, solution	.36†	.32†	.30†	.42†	.48†	.28**	.52†	.52†	.61†	.45†	.70†	.64†	.69†	.84†	1.00				
16. Problem aggregate	.34†	.32†	.30†	.41†	.48†	.35†	.52†	.51†	.61†	.50†	.73†	.68†	.70†	–	–	1.00			
	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.			

Note. MSE = mechanical self-efficacy, KS = knowledge structure. Correlations with a *p-value* greater than .05 are not displayed. * = *p-value* < .01, ** = *p-value* < .001, † = *p-value* < .0001. The methods section details the specific composition of the aggregate variables. A dash, –, indicates a redundancy between the variables.

Table 3

Knowledge structure density and coherence correlations

	KS, density	KS, coherence
Effort, learning	-.17	.16
Effort, solving		.16
Effort aggregate	-.18	.18
Reasoning	-.27**	.18
Prior knowledge	-.18	.21*
MSE		.25*
Procedural, MC	-.16	.24*
Procedural, rank		.20*
Procedural aggregate	-.17	.27**
KS, density	1.00	-.20
KS, coherence	-.20	1.00
KS similarity	-.18	.29**
KS, definitions	-.31**	.36†
ICR aggregate	-.28**	.36†
Knowledge aggregate	-.23*	.33**
Problem, cause	-.23*	.28**
Problem, solution	-.25*	.29**
Problem aggregate	-.25*	.30†

Note. MSE = mechanical self-efficacy, KS = knowledge structure. Correlations with a *p-value* greater than .05 are not displayed. * = *p-value* < .01, ** = *p-value* < .001, † = *p-value* < .0001. The methods section details the specific composition of the aggregate variables.

Table 4

Learning outcome regression results

R^2 (<i>df</i>)	Outcome	β_0	β_R	β_C	β_{LE}	β_{MSE}
.33 (167)	Procedural knowledge	0	.20**	.24**	.32†	.12
.37 (160)	Structure of knowledge	0	.25***	.34†	.27†	.08
.43 (160)	Knowledge aggregate	0	.24***	.33†	.34†	.12

Note. β_0 = intercept, β_R = general reasoning, β_C = prior component knowledge, β_{LE} = learning effort, β_{MSE} = mechanical self-efficacy. † = *p*-value < .0001, *** = *p*-value < .001, ** = *p*-value < .01, * = *p*-value < .05.

Table 5

Problem solving outcome regression results

R^2 (df)	Outcome	β_0	β_{SK}	β_{PK}	β_R	β_{MSE}	β_{SE}
.51 (159)	Identifying cause	0	.44†	.22**	.09	.09	.05
.52 (159)	Procedural solution	0	.36†	.34†	.18**	-.03	.06
.55 (159)	Problem solve aggregate	0	.42†	.29†	.14*	.03	.06

Note. β_0 = intercept, β_{SK} = the structure of knowledge, β_{PK} = procedural knowledge, β_R = general reasoning, β_{MSE} = mechanical self-efficacy, β_{SE} = problem-solving effort. † = *p-value* < .0001, *** = *p-value* < .001, ** = *p-value* < .01, * = *p-value* < .05.

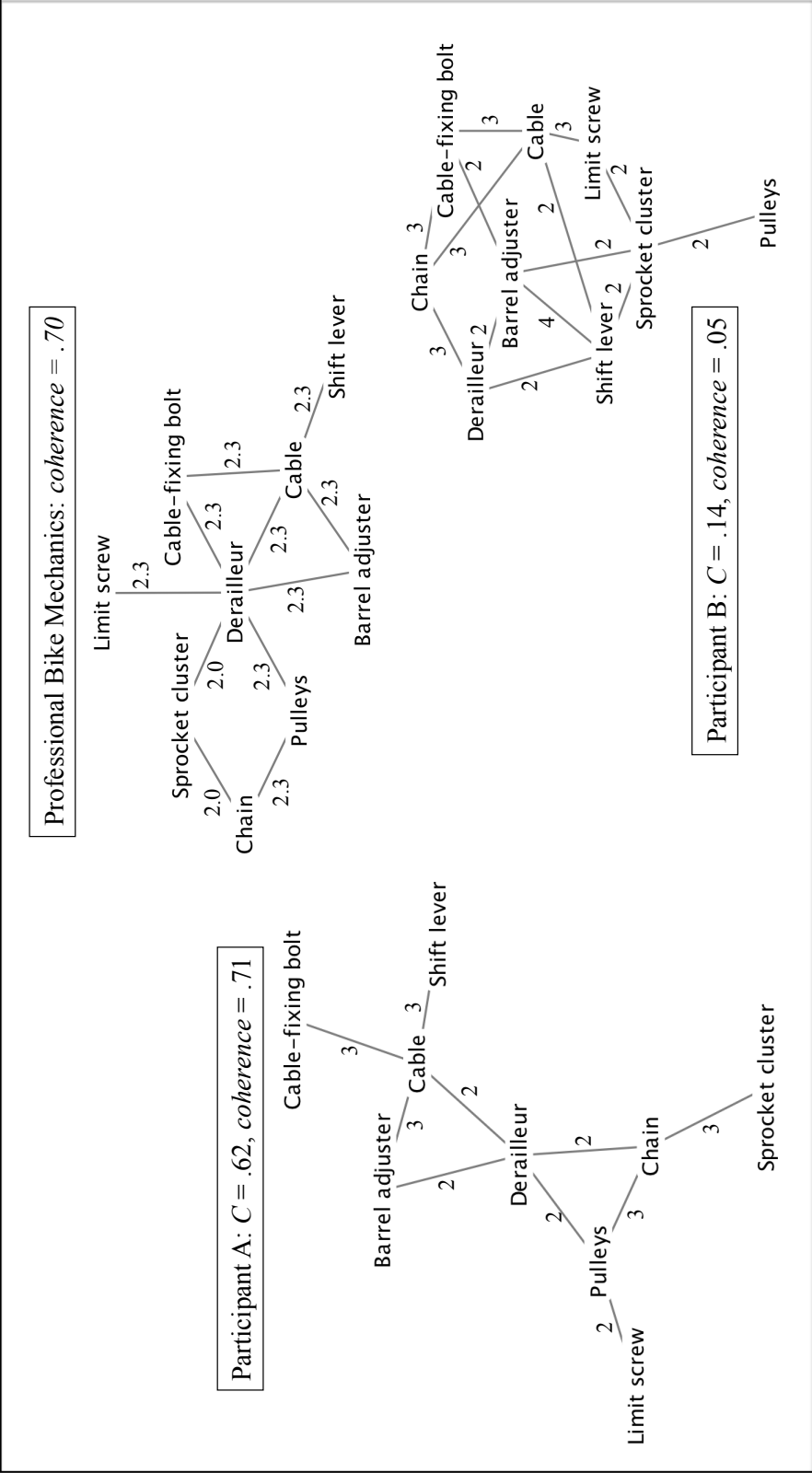


Figure 1. Pathfinder Network graphical display of three knowledge structures. C = the similarity of the structure to the mechanics' aggregate structure. The Professional Bike Mechanics structure is the aggregate structure of three mechanics. The line numbers are the strength of the inter-concept relation, 1 = *Unrelated*, 4 = *Strongly related*.

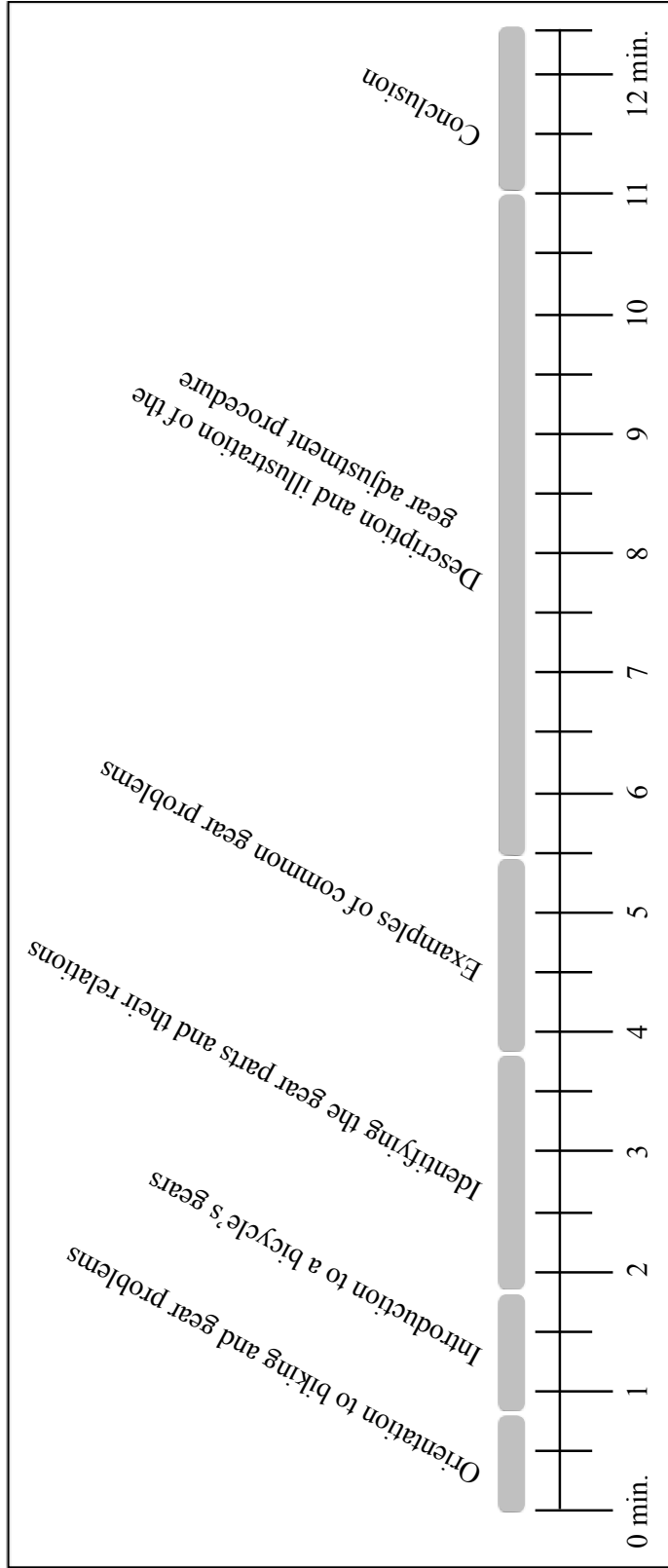
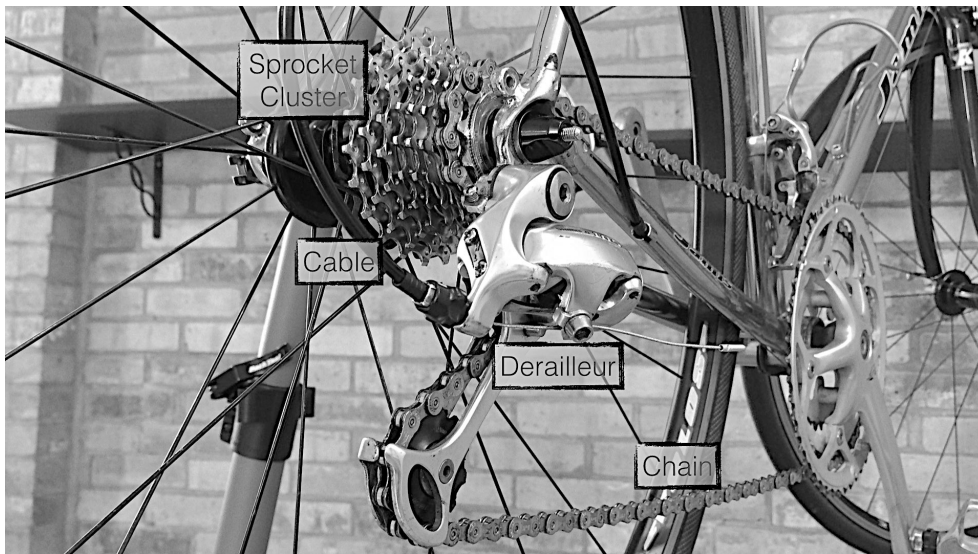


Figure 2. Training video timeline. This figure illustrates the order in which the video training material was presented and the duration of the major sections of the training video.

Bicycle gear overview and part identification (Video time point, 2:15)



Closer view and identification of the gear parts (Video time point, 3:25)

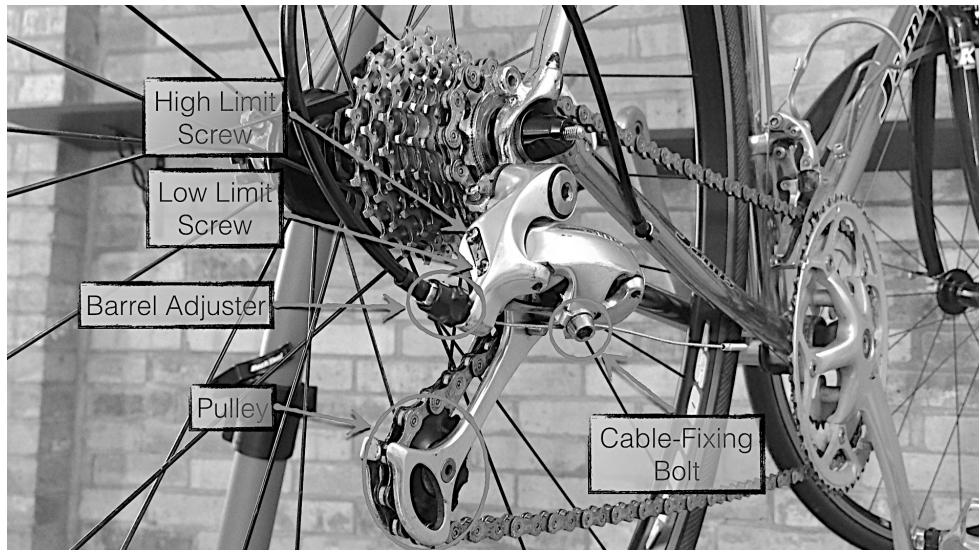


Continued

Figure 3. Training video screenshots. This figure illustrates the visual techniques that were used to highlight the parts of the bicycle's gear system that are being described at that time. Also depicted is the screen which outlines the gear adjustment procedure.

Continued

Closer view and identification of the derailleur parts (Video time point, 3:40)



Introduction screen to the gear adjustment procedure (Video time point, 5:30)

Adjusting the Derailleur

1. Detaching the cable
2. High limit adjustment
3. Low limit adjustment
4. Attach the cable
5. Cable tension adjustment
6. Check for smooth shifting

Figure 3 continued. Training video screenshots. This figure illustrates the visual techniques that were used to highlight the parts of the bicycle's gear system that are being described at that time. Also depicted is the screen which outlines the gear adjustment procedure.

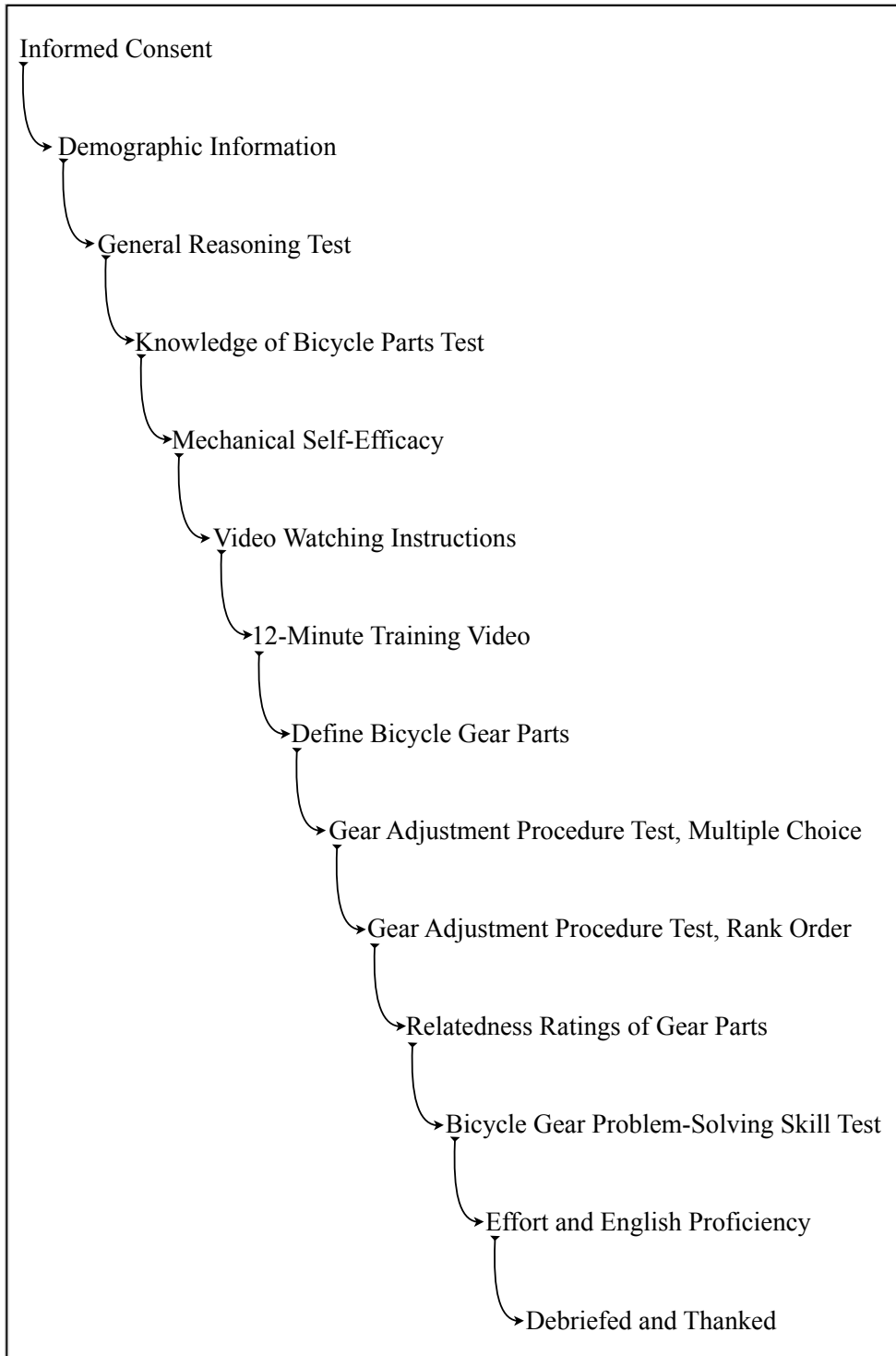


Figure 4. Study procedure. This figure illustrates the sequential procedure used during data collection, starting at Informed Consent and ending at Debriefing.

Appendix A

R programming script for the computation of knowledge structural coherence

Note. The following script provides the same measure of structural coherence as that provided by the Pathfinder Network Analysis software that is freely available at <http://interlinkinc.net>.

To use the below script the data file needs to be organized in the following manner. Row 1 column 1 contains "A" and row 1 column 2 contains "B". The rest of row 1 holds the participant identification number(s). The first two columns of the data frame specify the pairwise relations. For example, row 2 column 1 should contain a "1" and row 2 column 2 a "2"; this identifies row 2 as holding the proximity data for the first and second concept. There should be as many rows as there are unique pairwise relations between concepts, plus the header row with participation identification numbers. Columns 3 to n , where n is the number of participants, should contain the proximity rating data from the study participants.

```
Setwd ("~/Desktop/")
sk <- read.csv ("Proximity_ratings_data.csv")
attach (sk)
library (psych)

makedf <- function (colnames,nrows=1)
{
  tmp <- as.data.frame (matrix (NA,nrows,length (colnames)))
  names (tmp) <- colnames
  return (tmp)
}

position <- c (1: length (sk$A))
sid <- names (sk [3:length (names(sk))])

results <- makedf (c ("NodeA", "NodeB", "Proximity", "Indirect.P", "Indirect.Pz"),
  length (position))
rownumber <- 1

coh.res <- makedf (c ("SID", "Coherence", "Coherence.z"))
coh.res.number <- 1

for (y in sid)
{
  for (x in position)
  {
    indirect.p <- cor (sk [(A==A[x] | B==A[x]) & (B!=B[x] & A!=B[x]), y],
```

```

        sk[(A==B[x] | B==B[x]) & (B!=A[x] & A!=A[x]), y])
    indirect.pz <- fisherz (indirect.p)
    direct.p <- sk[x, y]
    node.a <- A[x]
    node.b <- B[x]
    results [rownumber,] <- c (node.a, node.b, direct.p, indirect.p, indirect.pz)
    rownumber <- rownumber + 1
}
coherence <- cor (results$Proximity, results$Indirect.P, use = "pairwise.complete.obs")
coherence.z <- cor (results$Proximity, results$Indirect.Pz, use =
"pairwise.complete.obs")
subject <- y
coh.res[coh.res.number,] <- c (subject, round (coherence, 3), round (coherence.z, 3))
coh.res.number <- coh.res.number + 1
results <- makedf (c ("NodeA", "NodeB", "Proximity", "Indirect.P", "Indirect.Pz"),
length(position))
}

write.csv (coh.res, file = "Knowledge Structure Coherence.csv")

```

Appendix B

International Cognitive Ability Resource (ICAR-16; Condon & Revelle, 2014)

The ICAR-16 can be acquired at <http://icar-project.com>.

Appendix C

Knowledge of Bicycle Parts

Instructions: Please consider the composition or make-up of a bicycle. How many different parts of a bicycle can you identify?

Appendix D

Mechanical Self-Efficacy (Grand, 2008)

The mechanical self-efficacy scale used in this study can be found in Grand (2008) Appendix C, p. 127.

Grand, J. A. (2008). *Changing gears: Modeling gender differences in performance on tests of mechanical comprehension* (Master's Thesis). Available from ProQuest Dissertations and Theses database. (UMI No. 1463014).

Appendix E

Procedural Knowledge Multiple-Choice

Instructions. Please select the answer for each question that you think is the most correct.

1. The gears on Nate's bike are in desperate need of adjustment. Nate is going to adjust his rear derailleur. What is the first thing he should do?
 - a. **Shift to the smallest rear sprocket.**
 - b. Adjust the low limit screw
 - c. Detach the cable from the derailleur
 - d. Adjust cable tension with the barrel adjuster
2. Sarah just finished adjusting the cable tension so that he has quick and consistent shifts between sprockets 1, 2, and 3. What should she do next?
 - a. Check the high limit screw adjustment
 - b. Make minor cable tension adjustments across the sprocket cluster
 - c. **Adjust the low limit screw**
 - d. Check the cable for rust and corrosion
3. Nate just attached the cable to the derailleur. What is the next step he should do?
 - a. Check the shifting between sprockets 1, 2, and 3
 - b. **Check the high limit screw adjustment**
 - c. Shift into the largest sprocket
 - d. Adjust the low limit screw to align the pulley with the largest sprocket
4. Sarah just finished making minor cable tension adjustments across the entire sprocket cluster. What is the next step she should do?
 - a. **She is done**
 - b. Check the high and low limit screw adjustments
 - c. Inspect derailleur pulley alignment
 - d. Shift into the smallest sprocket
5. Nate just detached the cable from the derailleur. What is the next step he should do?
 - a. Shift into the smallest sprocket
 - b. Adjust the low limit screw
 - c. Check the shifting between sprockets 1, 2, and 3
 - d. **Make adjustments to the high limit screw**
6. Before detaching the cable from the derailleur what should Sarah do?
 - a. **Move the shift lever so that the chain is on the smallest sprocket**
 - b. Check the limit screws
 - c. Make large adjustments in cable tension

- d. Visually check pulley alignment with large and small sprocket
7. What does Nate need to do immediately before he adjusts the low limit screw?
- a. **Pull the cable to make sure the derailleur is fully extended**
 - b. Make cable tension adjustments for the 3 largest sprockets
 - c. Detach the cable from the derailleur
 - d. Check the chain for bent links
8. Sarah is checking the shifting between sprockets 1, 2, and 3. What did she just finish doing?
- a. Attaching the cable to the derailleur
 - b. Adjusting the low limit screw
 - c. **Checking the adjustment of the high limit screw**
 - d. Adjusting the shifting for the largest 3 sprockets

Appendix F

Procedural Knowledge Rank Ordering

Note. When this question was displayed on the computer screen the items were presented in a random order.

Instructions. In what order should the following steps be performed to correctly set up a bicycle's rear derailleur?

- _____ Shift into the smallest sprocket
- _____ Detach the cable from the derailleur
- _____ Adjust the high limit screw
- _____ Attach the cable to the derailleur
- _____ Check for smooth shifting across the entire sprocket cluster
- _____ Check and adjust cable tension between sprockets 1, 2, and 3
- _____ Adjust the low limit screw
- _____ Check and adjust cable tension for the larger sprockets

Appendix G

Definition Knowledge

Note. Participants recorded their part descriptions on a computer. The screen displayed the name of the component to be described followed by a text box to type in.

You have just finished a short tutorial about how to adjust the rear derailleur of a bicycle. We would like to know if you picked up on what some of the key components are in this system.

In the following section please describe

- what each component is and
- what its role is in allowing a cyclist to change gears.

Derailleur

Shift lever

Cable

Barrel adjuster

Cable-fixing bolt

Limit screw

Pulleys

Chain

Sprocket cluster

Appendix H

Relatedness Ratings

Note. Participants completed 36 ratings. The ratings were between the 36 unique pairs in the follow set of bicycle gear components: Barrel adjuster, crankset, derailleur cable, derailleur, limit screw, chain, shift lever, sprocket cluster, and cable-fixing bolt. The contents of Appendix H illustrates the item set up, but does not contain all 36 unique pair-wise rating items. The 36 items were randomized before being presented on the participant's computer screen.

Instructions. Please indicate how related you think the following bicycle components are to each other in the functioning of the bicycles gears.

Derailleur ... Barrel adjuster

1	2	3	4	5
Unrelated	Moderately related	Largely related	Extremely related	Synonym

Derailleur ... Crankset

1	2	3	4	5
Unrelated	Moderately related	Largely related	Extremely related	Synonym

Derailleur ... Cable

1	2	3	4	5
Unrelated	Moderately related	Largely related	Extremely related	Synonym

Derailleur ... Cable-fixing bolt

1	2	3	4	5
Unrelated	Moderately related	Largely related	Extremely related	Synonym

Derailleur ... Limit screw

1	2	3	4	5
Unrelated	Moderately related	Largely related	Extremely related	Synonym

Appendix I

Bicycle Gear Problem Solving

Note. The items on this measure were presented on the computer screen in a random order. An open text box was provided after each part A and part B for participants to type their response.

Instructions: In the following section common problems with the bicycle's derailleur and rear drive train are described.

- Please consider the problem
 - Propose an explanation for the cause of the problem
 - Describe what should be done to fix the problem
1. The chain jumps from sprocket to sprocket during riding.
 - A. What is the most likely cause of the above problem?

 - B. What should be done to fix the above problem?

 2. When shifting into the largest rear sprocket (i.e. lowest and easiest gear) the chain comes off the sprocket cluster into the spokes.
 - A. What is the most likely cause of the above problem?

 - B. What should be done to fix the above problem?

 3. When shifting into the smallest rear sprocket (i.e. highest and hardest gear) the chain comes off of the sprocket cluster.
 - A. What is the most likely cause of the above problem?

 - B. What should be done to fix the above problem?

 4. The shift lever is in the extreme high position and the chain is on the smallest sprocket. When you move the shift lever one click the chain does not move from the smallest sprocket to a larger sprocket (i.e., the gears do not change).
 - A. What is the most likely cause of the above problem?

 - B. What should be done to fix the above problem?

 5. The shift lever is in the extreme low position and the chain is on the largest sprocket. When you move the shift lever one click the chain does not move to a smaller sprocket (i.e., the gears do not change).
 - A. What is the most likely cause of the above problem?

B. What should be done to fix the above problem?

6. Shifting from smaller sprockets to larger sprockets is slow, or the chain does not settle on the larger sprocket after the shift.

A. What is the most likely cause of the above problem?

B. What should be done to fix the above problem?

7. Shifting from larger sprockets to smaller sprockets is slow, or the chain does not settle on the smaller sprocket after the shift.

A. What is the most likely cause of the above problem?

B. What should be done to fix the above problem?

8. You can shift quickly and smoothly to all of the sprockets except for the largest sprocket. When you try to shift to the largest sprocket the chain will not move from the second largest sprocket to the largest sprocket.

A. What is the most likely cause of the above problem?

B. What should be done to fix the above problem?

9. You can shift quickly and smoothly to all of the sprockets except for the smallest sprocket. When you try to shift to the smallest sprocket the chain will not move from the second smallest sprocket to the smallest sprocket.

A. What is the most likely cause of the above problem?

B. What should be done to fix the above problem?