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Assessing and Remediating Knowledge Improves Problem-solving Performance in Middle School Math Compared to Remediating Problem-solving Steps

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ABSTRACT

A widespread practice in education is to give students problems to solve, ask them to show their work and, when they make mistakes, show them the correct way to solve the problem to arrive at the right answer. This approach is consistent with the precepts of Classical Test Theory, which operationalizes learning in terms of the number of correct answers given to problems. The present paper challenges this approach by comparing it to an alternative that assesses what subject matter knowledge students have using a methodology called Cognitive Structure Analysis (CSA) and remediating any knowledge gaps. This study follows a previous study (Leddo and Ahmad, 2024) that showed that when high schoolers had their mathematics knowledge assessed and remediated using CSA, they performed 10 percentage points better on a post-test than those whose problem-solving steps were assessed and remediated. The present study extends this to middle school math. Middle schoolers were initially either given problems to solve and feedback in the form of being shown correct step-by-step solutions to the problems or had their concept knowledge assessed using CSA and then provided feedback to remediate any knowledge deficiencies they had. All students were then given a 20-question problem-solving post-test. Results showed that those whose CSA-assessed knowledge was remediated scored 13 percentage points higher on the post-test than those whose step-by-step procedures were remediated. Moreover, those students who had their step-by-step procedures remediated showed no improvement in problem solving performance from pre-test to post-test. Results suggest that assessing and remediating concept knowledge may provide a quick, cheap, and easy way to improve academic performance compared to the traditional assessment and remediation approach of emphasizing correct solutions to problems.

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Introduction

As far back as we can remember, math classes across America (possibly around the world) and across time share one feature in common. Whether for homework assignments or tests, teachers would tell their students " show all work." Teachers would then review students' problem-solving solutions, and if the students made mistakes, the teacher would highlight the incorrect steps and show the students corrected versions. The implication is that by seeing what they did and what they should've done students would improve their problem-solving performance. Indeed, this method is so pervasive that it makes its way into educational software. Many programs ask students to solve problems, and if students enter the wrong answers, they are shown the correct step-by-step solutions. The purpose of the present paper is to extend our previous work (Leddo and Ahmad, 2024) that questions whether this time-honored tradition of correcting problem-solving mistakes is the best way to improve student performance and to explore an alternative approach, i.e., correcting students' knowledge, may be more effective.

In the history of education, assessments have been used as a means of measuring the extent to which students have learned the content that they have been taught. In both classroom settings and standardized testing, this content is operationally defined as the number of correct answers a student gives on test questions in the past various frameworks have been utilized by teachers and educational organizers to test. Students' knowledge is typically categorized by whether students are required to select correct answers from a set of answer choices, or to construct their own answers to problems. While both categories of framework have their benefits, they include drawbacks that affect their accuracy in assessing students' knowledge.

Multiple-choice assessments require students to select, differentiate the correct answer choices from several distracting answer choices. They are widely used in standardized, testing environments and classrooms due to their efficiency when it comes to grading (Chaoui, 2011). However, students often score higher on multiple-choice tests than they do on constructive responsive tests as students can increase their scores through guessing (cf. Elbrink and Waits, 1970; O'Neil and Brown, 1997), which is often cited as a reason why multiple-choice tests should not be used.

Constructive assessments require that students formulate their own answers to questions rather than choose from different answer choices as with multiple choice assessments research when investigating math, problem-solving that students are more likely to use guessing strategies when given multiple-choice test, but are more likely to reason mathematically when given constructive tests (Herman et al., 1994), thus increasing its validity in measuring students actual learning (Frary, 1985).

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These frameworks are based on classical test theory, one of the major pillars of assessment methodology, which assumes that the total number of correctly answered test items indicates the student's level of knowledge (cf., de Ayala, 2009). The challenge with the key assumption of Classical Test Theory, though, is that the assumption that correct answers indicate learning and vice versa may not be entirely true. A medical analogy works well here. Normally, if a person shows outward signs of illness s/he is probably sick (although there could be non-medical reasons why a person can appear sick such as overexertion or lack of sleep). Similarly, a student who makes a lot of mistakes on a test probably has a lack of knowledge (unless, for example, s/he was distracted or sick during the test). However, a person can look healthy and still have an underlying illness. Similarly, a student may get correct answers on a test and have knowledge deficiencies. They could be regurgitating information or formulas they do not truly understand or guessing correctly on multiple-choice exams.

More importantly, the lack of correct answers does not inform the teacher what concepts need to be remediated. A doctor does not stop his/her diagnosis after observing symptoms. Instead, they conduct additional tests to discover the cause of the symptoms so that an appropriate remedy can be applied. Indeed, we would consider it a medical malpractice for a doctor to treat only the symptoms, and not the underlying causes of diseases. Similarly, an incorrect answer to a test question is a symptom that may indicate an underlying knowledge deficiency. We consider it educational malpractice to stop the assessment at that point without diagnosing the underlying knowledge deficiency that is causing that incorrect answer. Unless that cause is identified, how can the appropriate instruction be given?

In previous papers (Leddo et al, 2022; Ahmad and Leddo, 2023; Bekkari and Leddo, 2023; Zhou and Leddo, 2023), we have proposed an alternative method of assessment, one that measures what underlying concepts a student has about the subject matter rather than how well the student performs when solving problems. This method is called Cognitive Structure Analysis or CSA (Leddo et al., 1990). It is based on decades of cognitive psychology research that have illustrated that people possess various knowledge types, each of which is organized and used differently in problem-solving. Since people possess different types of knowledge, our framework integrates several prominent and well-researched formalisms. These include semantic nets, which organize factual information (Quillian, 1966); production rules, which organize concrete procedures (Newell and Simon, 1972); scripts, which are general goal-based problem-solving strategies (Schank and Abelson, 1977; Schank, 1982); and mental models, which explain the causal principle behind concepts (de Kleer and Brown, 1981). Because our framework integrates these four knowledge types, it is called INKS for the INtegrated Knowledge Structure. We note that the National Council of Teachers of Mathematics (2000) has developed a taxonomy of strands necessary for students to be considered mathematically proficient that uses similar terminology:

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conceptual understanding, procedural fluency, strategic competence, and adaptive reasoning. In many ways, the strands of conceptual, procedural and strategic do correspond to our own. The key difference is that the National Council of Teachers of Mathematics frames these strands in terms of desired skills/behavioral outcomes whereas the INKS framework conceptualizes these in terms of the specific knowledge needed to achieve those outcomes.

The INKS framework is based on research by John Leddo (Leddo et al., 1990) which showed that true mastery of a topic or subject requires all four knowledge types. The framework also brings helpful implications for instruction. For example, in John Anderson's ACT-R framework, people initially learn factual/semantic knowledge that is later operationalized into procedures (Anderson, 1982). Research by Leddo takes this one step further showing that expert knowledge is organized around goals and plans (referred to in the literature as "scripts" – Schank and Abelson, 1977; Schank, 1982) and abstracted into causal principles (referred to in the literature as "mental models" – cf., de Kleer and Brown, 1981) that allow people to construct explanations and make predictions/innovations in novel situations.

To identify the root cause of the mistake, the query-based assessment framework, CSA, incorporates principles from the INKS knowledge representation framework. CSA is chosen because previous research describes a strong correlation between user knowledge — as assessed by CSA — and performance practical problem-solving. In one previous research project, we found that using an automated multiple-choice CSA system to access student learning produced measures of knowledge that correlated .88 with student problem-solving performance and measures of change of knowledge as a result of the instruction that correlated .78 with change in performance from pretest to post test. Moreover, at risk students who had their learning needs diagnosed using CSA performed at a mainstream level three grades higher than their own after a 25-hour tutoring program in science (Leddo and Sak, 1994). Leddo et al. (2022) extended these findings. Students were given open ended questions to assess their factual (semantic), strategic (script-based), procedural, and rational (mental model) concept, knowledge of Algebra 1. The total INKS knowledge and individual component knowledge scores were correlated with the total number of correctly solved problems. Results showed correlations of .966 between problem-solving and total knowledge, .819 between problem-solving and strategic knowledge, .866 between problem-solving and factual knowledge, .937 between problem-solving and procedural knowledge and .788 problem-solving and rational knowledge. These findings were extended to pre-calculus (Zhou and Leddo, 2023), biology (Ahmad and Leddo, 2023), and elementary school math (Bekkari and Leddo, 2023). In two other projects, assessments produced using the CSA methodology produced assessments of students. Learning agreed with teachers' assessments, approximately 95% - 97% of the time which was statistically equal to teachers' assessments with each other (Leddo et al., 1998, Liang and Leddo, 2020).

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Our previous work in CSA shows that CSA can be a powerful tool in helping educators assess what students do and do not know. CSA has been presented as an alternative to the classical test theory approach of measuring learning as a function of the number of correct answers students give. However, it could be reasonably argued that the purpose of education is to improve student performance, and, therefore, replacing an assessment system with one that directly measures underlying knowledge but does not raise student performance would be less appropriate. Leddo and Ahmad (2024) addressed that issue directly. In that study, high school and college students were initially assessed in their knowledge of logarithms. Half were assessed using CSA and the other half were assessed by asking them to solve problems and show all work. After each problem, students received remediation on either their knowledge concepts (in the CSA condition) or in their problem solving steps (the "show all work" condition). Results showed that remediating problem solving steps raised student performance from an average of 68% on the pretest to 75% on the post-test, a statistically significant increase. However, those who had their knowledge assessed and remediated scored 85% on the post-test, a statistically-significant, full-letter grade higher performance than those in the "show all work" condition.

The purpose of the present study is to extend the Leddo and Ahmad (2024) findings to a middle school population. The same experimental procedure was replicated using middle school-appropriate math topics and middle school students.

Method

Participants

The participants in this experiment were 27 middle school students from Phoenix, Arizona and Northern Virginia. Participants had varying levels of mathematical knowledge. They were not paid for participation but were giving compensation in the form of service hours (credit for performing service work to help an external organization).

Materials

Two Google Forms were created that covered questions surrounding algebraic problems, a specific mathematical topic. Questions, in the form of short answer responses, were created that tested factual, strategic, procedural, and rational knowledge, i.e., knowledge based on the components of the INKS framework. Participants received feedback in the form of the correct concept knowledge associated with each question. The participants who received their Google Form were called the 'Knowledge Feedback Group' or experimental condition.

The second Google Form, called the 'Problem-Solving Assessment,' tested participants' ability to solve questions based on their knowledge of algebraic questions. They received correct step-by-step solutions after each problem. The participants who received this Google Form were called the 'Performance Feedback Group' or control condition.

The knowledge assessment contained 26 questions with 4 types of questions in each section: fact, procedure, rationale, and strategy.

The first section contained all the fact-based questions that would analyze the participant' ability to provide definitions of various aspects of algebraic questions:

Fact-based questions:

"What is a two sided equation?"

"What is a variable?"

"What is an equation?"

"What is a coefficient?"

"What is the definition of like terms?"

"What is an exponent?"

"What is a value?"

Procedure-based questions:

"What do you do when both sides of the equation have like terms?"

"What do you do when you're done solving the problem?"

"What is the next step after understanding the relationships in a word problem?"

"What is the next step after solving the expressions inside the parentheses in an equation?

"What is the initial step when analyzing a problem that involves multiple variables and relationships?"

"What should you do once you have determined the values for variables in an equation?"

"What should you do after setting up an equation with multiple variables?"

Rationale-based Questions:

"Why do you combine like terms and simplify both sides?"

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> "Why do you isolate the variable term?"
>
> "Why do you solve for the variable?"
>
> "Why do you identify and define the variables?"
>
> "Why do we evaluate exponents?"
>
> "Why do we identify the given relationships?"
>
> "Why do we substitute known values?"
>
> "Why do we isolate the variable of interest?"

Strategy-based questions:

> "What strategies can you use when solving equations with variables on both sides of the equal sign?"
>
> "What strategies can you use when analyzing word problems and making them into equations with variables?"
>
> "What are some strategies you can use when you're using the order of operations?"
>
> "What strategies do we use when finding the value of a variable based on another variable?"

The problem-solving assessment contained 20 questions that mimicked algebraic questions seen in a classroom. The problems were separated into groups based on the instructions being asked. After each group of questions, the participant would receive the strategies and answers for that group. All problems were done by hand.

Each participant was given 1 point for a correct answer and no points for an incorrect answer. No half-credit points were given for any question.

Finally, a 20-question post-test was constructed that problems for participants in both conditions to solve. The post-test questions were based on the subject matter covered in the two initial assessments.

<u>Procedure</u>

Participants were randomly assigned to one for the two groups (the Performance Feedback group and the Knowledge Feedback group). 15 were assigned to the Performance Feedback group and

12 were assigned to the Knowledge Feedback group. The two assignments were administered through Google Forms, which were sent to each participant through email. The Google Forms contained both the initial assignment and the 20-question post-test. Participants were instructed to complete the answer in detail. They were given as much time as needed to complete the task. However, the Participants were given no help throughout the session, nor were they allowed to use external resources.

Results

The pre-test and post-test scores for each group were tabulated. For both groups, the post-test scores were the scores on the final, 20-question test. For that, the mean number of correct answers was 15.87 or 79.35% for the control group and 18.58 or 92.9% for the experimental group. This difference was statistically significant, $t(25) = 2.25$, $p = .03$. Interestingly, the 13.55 percentage point improvement for the middle school samples was comparable to the 10-percentage point improvement in the CSA plus remediation group compared to the control group in the previous Leddo and Ahmad (2024) study with high school students, suggesting assessing and remediating knowledge rather than problems solving steps once again produced a full letter grade improvement in student performance. Notably, no student in the experimental group scored below 16 correct answers or 80%.

As with our previous study, we offer an analysis of the effectiveness of remediating problem-solving steps. In the Leddo and Ahmad (2024) study, remediating problem-solving steps produced a seven-percentage point improvement in performance, which was statistically significant. In the present study, the mean pre-test and post-test scores were an identical 15.87 or 79.35%, suggesting that remediating problem-solving steps produced no improvement in problem solving performance. Since the experimental condition's pre-test assessed knowledge components rather than problem solving performance, a meaningful pre-test/post-test score comparison cannot be made.

Discussion

The goal of the present research was to logically extend our previous research on Cognitive Structure Analysis as an alternative assessment method to measuring the number of correct answers as prescribed by Classical Test Theory. Here, we wanted to see if assessing and remediating middle school students' mathematical knowledge would produce greater student achievement than assessing and remediating student problem-solving performance. Results showed that assessing and remediating knowledge produced greater post-test scores than assessing and remediating steps students used to solve problems. Moreover, results showed no statistically-significant increase in performance after remediation was provided for problem-

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solving steps. These results are consistent with and extend to middle schoolers our previous research on assessing and remediating knowledge as a way to boost student performance.

As such assessing and remediating student knowledge using CSA offers a potential solution to raising student achievement. According to the US Department of Education's National Assessment of Educational Progress (NAEP, 2022), only 36% of US fourth graders scored at or above the proficient level (grade level) in math, while 26% of eighth graders did, and 24% of twelfth graders. Not only do most students perform below grade level in math, based on national standards, but the percentage of students who do perform below grade level increases as they progress through their schooling. In other words, these students fall further and further behind.

If the present research results hold up, CSA offers a quick, cheap and easy way to immediately raise student achievement. This approach can be easily taught to teachers and can be administered through simple media like Google Forms without resorting to rewriting textbooks (and thereby incurring enormous expense).

Admittedly, more research ought to be done. We would want to generalize our approach to other topics in math, other subjects, and other grade levels. However, our previous research in CSA does point to a consistency that how much knowledge a student has as measured by CSA reliably predicts how well they will solve problems in various subjects. We have now extended this research to show that remediating INKS-based knowledge deficiencies assessed by CSA will lead to higher problem-solving performance than simply correcting their problem-solving performance mistakes.

There is another way CSA-based assessment and remediation may boost student achievement. After years of watching students say things like "I don't get it" or "I'm stuck" when learning new material, we began conducting studies to see if students can be taught to assess their own knowledge using CSA. It turns out that students can be taught to reliably assess what they know and what they do not know (Cynkin and Leddo, 2023; Dandemraju, Dandemraju and Leddo, 2024). We have also taken the next logical step in that area to see if students can not only assess their knowledge gaps but also then remediate these gaps. It turns out that students can do so very successfully.

To address this issue, Ravi and Leddo (2024) conducted a study in which high school students learned an advanced topic in chemistry by watching a video. Half the students were told to rewatch the video to fill in any knowledge gaps, while the other half were taught to self-assess their knowledge using CSA and then told to rewatch the video to fill in any assessed knowledge gaps. The group that was taught to self-assess scored 15 points or 1.5 letter grades higher on a post-test than students who simply rewatched the video without self-assessment. Nehra and

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Leddo (2024) replicated the Ravi and Leddo study to the learning of Spanish. They found that high school students performing self-assessment plus remediation scored, on average, 25 percentage points or 2.5 letter grades higher than those re-reading the material without performing a self-assessment. Prakash and Leddo (2025a) extended the Ravi and Leddo (2024) and Nehra and Leddo (2024) findings to another subject area: high school reading comprehension. The results revealed a mean post-test score of 8.3 out of 12 (69.17%) for the control group and 11.2 out of 12 (93.33%) for the experimental group. This difference in averages was statistically significant ($t = 3.75$, $df = 11.07$, $p < .01$). Notably, individual scores further illustrated the disparity: the lowest score in the control group was 41.67%, whereas the lowest in the experimental group was 83.33%. This is the difference between an F letter grade and B letter grade. Following this, another study conducted by Prakash and Leddo (2025b) examined CSA's effectiveness in teaching math, specifically, the topic of Bayes' Theorem, and found a 27-point improvement. Statistical analysis yielded a t-value of 4.38 ($df = 18$, $p = 0.0004$), confirming the significance of the difference. Individual scores also highlighted the disparity. The control group's lowest score was 6/20 (30%), whereas the experimental group's lowest score was 15/20 (75%). Following this, a history assessment revealed that students who utilized CSA for self-assessment and remediation significantly outperformed their peers in the control group (Prakash and Leddo, 2025c). Post-test results demonstrated that the experimental group achieved an average score of 87.5%, whereas the control group scored 65.8%, indicating a substantial difference in comprehension and retention of historical concepts.

These results on high school students were further extended by Leddo, Clark and Clark (2025) in their investigation of middle school math. Leddo, Clark and Clark found that middle school students who self-assessed using CSA and then remediated their knowledge gaps scored 18 percentage points higher on a posttest than those who relearned material without first performing a self-assessment.

Following this, Prakash and Leddo (2025d) conducted a study on middle school students' reading comprehension, specifically through an analysis of To Kill a Mockingbird, a novel that explores complex themes of ethics and social structure. Students in the experimental group were trained to evaluate their own knowledge gaps and use targeted remediation strategies, while those in the control group engaged with the text without structured self-assessment. Results showed that students in the self-assessment group scored 16 points higher on a post-test than those who re-read the material without self-assessment. This was followed up with a study on middle school science (Prakash and Leddo, 2025e), in which students learned about topics in ecology. Results showed that students who used the self-assessment technique plus remediation scored on average 98% on a post-test, while those who simply reread the material without self-assessment scored on average 77.5%.

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Finally, Sathiyamoorthy and Leddo (2025) showed that college students who used CSA to self-assess and then remediate knowledge performed 13 percentage points higher on a college psychology post-test than those who simply reread the material after initially learning it. Taken together, these results suggest that regardless of whether the students self-assess and remediate knowledge or the assessment and remediation is mediated by technology, assessing and remediating knowledge greatly improves student performance compared to traditional methods of assessment. This indicates that student achievement could be increased systemically and cheaply by introducing CSA-based knowledge assessment into educational practices.

References

Ahmad, M. & Leddo, J. (2023). The Effectiveness of Cognitive Structure Analysis in Assessing Students' Knowledge of the Scientific Method. International Journal of Social Science and Economic Research, 8(8), 2397-2410

Anderson, J.R. (1982). Acquisition of cognitive skill. Psychological Review, 89, 369-405.

Bekkari, V., & Leddo, J., (2023). Cognitive Structure Analysis: Assessing Elementary School Students in Math to Determine the Types of Knowledge They Have. International Journal of Social Science and Economic Research, 8(10)

Chaoui, N (2011) "Finding Relationships Between Multiple-Choice Math Tests and Their Stem Equivalent Constructed Responses". CGU Theses & Dissertations. Paper 21.

Cynkin, C. and Leddo, J. (2023). Teaching Students to Self-Assess Using Cognitive Structure Analysis: Helping Students Determine What They Do and Do Not Know. International Journal of Social Science and Economic Research, 8(9), 3009-3020.

Dandemraju, A., Dandemraju, R. and Leddo, J. (2024). Teaching students to self-assess their own chemistry knowledge. International Journal of Social Science and Economic Research, 9(2), 541-549.

de Ayala, R. J. (2009). The theory and practice of item response theory. New York: The Guilford Press

De Kleer, J. and Brown, J.S. (1981). Mental models of physical mechanisms and their acquisition. In J.R. Anderson (Ed.), Cognitive Skills and their acquisition. Hillsdale, NJ: Erlbaum

Elbrink, L., & Waits, B. (Spring, 1970). A Statistical Analysis of Multiple Choice Examinations in Mathematics. The Two-Year College Mathematics Journal, 1(1), 25-29.

Frary, R. (Spring, 1985). Multiple-Choice Versus Free-Response: A Simulation Study. Journal of Educational Measurement, 22, 21-31.

Herman, J. L., Klein, D. C., Heath, T. M., & Wakai, S. T. (1994). A first look: Are claims for alternative assessment holding up? (CSE Tech. Rep. No. 391). Los Angeles: University of California, Center for Research on Evaluation, Standards, and Student Testing

Leddo, Clark and Clark (2025). Using self-assessment and remediation to raise middle school student achievement in math. International Journal of Social Science and Economic Research, 10(3), 1083-1092.

Leddo, J., Cohen, M.S., O'Connor, M.F., Bresnick, T.A., and Marvin, F.F. (1990). Integrated knowledge elicitation and representation framework (Technical Report 90-3). Reston, VA: Decision Science Consortium, Inc..

Leddo, J., Li, S. & Zhang, Y. (2022). Cognitive Structure Analysis: A technique for assessing what students know, not just how they perform. International Journal of Social Science and Economic Research, 7(11), 3716-3726.

Leddo, J. and Sak, S. (1994). Knowledge Assessment: Diagnosing what students really know. Presented at Society for Technology and Teacher Education.

Leddo, J., Zhang, Z. and Pokorny, R. (1998).Automated Performance Assessment Tools. Proceedings of the Interservice/Industry Training Systems and Education Conference. Arlington, VA: National Training Systems Association.

Liang, I. and Leddo, J. (2020). An intelligent tutoring system-style assessment software that diagnoses the underlying causes of students' mathematical mistakes. International Journal of Advanced Educational Research, 5(5), 26-30.

NAEP Mathematics: National Average Scores. (n.d.). Www.nationsreportcard.gov. https://www.nationsreportcard.gov/mathematics/nation/scores/

National Council of Teachers of Mathematics (2000). Principles and Standards for School Mathematics. Reston, VA: NCTM.

Nehra, P., & Leddo, J. (2024). The effects of Cognitive Structure Analysis in self-assessing and remediating knowledge gaps in introductory Spanish. Journal of Educational Psychology, 45(3), 78-89.

Newell, A. and Simon, H.A. (1972). Human problem solving. Englewood Cliffs, NJ: Prentice

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O'Neil, H. F., & Brown, D. S. (1997). Differential Effects of Question Formats in Math Assessment on Metacognition and Affect. Applicated Measurement in Education, 331-351.

Prakash, P. & Leddo, J. (2025a). Using Self-Assessment and Remediation to Raise Student Achievement in Reading Comprehension. International Journal of Social Science and Economic Research, 10(1), 277-286.

Prakash, P. & Leddo, J. (2025b). Using Self-Assessment and Remediation to Raise Student Achievement in Mathematics. International Journal of Social Science and Economic Research, 10(1), 447-456.

Prakash, P. & Leddo, J. (2025c). Using Self-Assessment and Remediation to Raise Student Achievement in History. International Journal of Social Science and Economic Research, 10(3), 650-659.

Prakash, P. & Leddo, J. (2025d). Using Self-Assessment and Remediation to Raise Middle School Student Achievement in Reading Comprehension. International Journal of Social Science and Economic Research, 10(3), 1130-1140.

Prakash, P. & Leddo, J. (2025e). Using Self-Assessment and Remediation to Raise Middle School Student Achievement in Science. International Journal of Social Science and Economic Research, 10(4), 1471-1482.

Quillian, M.R. (1966). Semantic memory. Cambridge, MA: Bolt, Beranek and Newman.

Sathiyamoorthy, S.S. and Leddo, J. (2025). Using Self-Assessment and Remediation to Raise College Student Achievement in Psychology. International Journal of Social Science and Economic Research, 10(5), 1859-1869.

Schank, R.C. (1982). Dynamic Memory: A theory of learning in computers and people. New York: Cambridge University Press.

Schank, R.C. and Abelson, R.P. (1977). Scripts, Plans, Goals, and Understanding. Hillsdale, NJ: Erlbaum.

Zhou, L.N. & Leddo, J. (2023). Cognitive Structure Analysis: Assessing Students' Knowledge of Precalculus. International Journal of Social Science and Economic Research, 8(9), 2826-2836.