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From Math Review to Numerical Methods Proficiency: Hybrid TBL and Lecture Approaches in a Materials Course

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Abstract

Equipping students with the skills necessary for independent research is a crucial goal of graduate coursework, particularly in materials science and engineering. These courses are structured not only to advance technical mastery but also to foster critical thinking, collaborative problem-solving, and adaptability to emerging research challenges. This paper describes the ongoing restructuring and continuous improvement efforts for a one-semester, three-credit graduate course required for materials science PhD students. Initially, the course focused on a comprehensive review of math, enabling students to revisit and strengthen foundational engineering concepts through manual calculations and analytical methods. While some students appreciated this review, feedback revealed that the curriculum lacked sufficient rigor for graduate-level study and did not adequately prepare students for advanced research applications.

Recognizing this gap, the course transitioned to emphasize numerical methods—reflecting the reality that most authentic engineering problems cannot be solved analytically and require computational solutions. The integration of contemporary numerical approaches posed its own instructional challenges, particularly in ensuring students felt confident applying these new techniques to open-ended research problems. Alongside content evolution, the course structure was modified to incorporate experimental learning through team-based learning (TBL). TBL is well-documented for improving academic performance and fostering deeper understanding by engaging students in collaborative tasks and requiring pre-class preparation. Initial attempts to implement TBL exclusively were met with resistance, as faculty noted recurring difficulties students faced without some lecture structure. In response, a hybrid model was developed, blending targeted lectures with team-based activities to balance active engagement and direct instruction. This paper presents the process of curricular modification, synthesizes faculty reflections on instructional effectiveness, discusses key challenges encountered, and offers best practices for implementing a hybrid TBL and lecture approach in graduate-level materials science and engineering numerical methods courses.

Introduction and Background

Computational competencies such as programming and the use of modeling and simulation tools have become a core form of quantitative literacy expected of graduate and professional specialists in mathematics, engineering, and materials science [1], [2]. Quantitative and numerical methods support the development of accurate, objective, and reproducible models, enabling researchers to interrogate complex systems and communicate results with rigor and transparency. Materials science research routinely generates large volumes of numerical data from experiments, high-throughput characterization, and simulation workflows; leveraging this information effectively requires fluency in both mathematical theory and computational implementation. Many contemporary materials science projects rely heavily on computational approaches to understand and predict behavior across length scales from atomic-level interactions to macroscopic properties through density functional theory, molecular dynamics, phase-field models, finite element simulations, and data-driven surrogates [3], [4], [5]. Thus, advanced statistical methods and data analysis techniques are essential for identifying patterns, trends, and anomalies in materials data and for drawing meaningful, evidence-based conclusions that can guide design and discovery [6], [7], [8]. These approaches demand strong foundations in linear algebra, differential equations, numerical analysis, and programming, along with the ability to interpret and validate computational results in the context of physical principles [9], [10]. In response, many Materials Science and Engineering (MSE) programs continue to offer dedicated numerical methods or numerical analysis courses, while others are moving toward integrating numerical problem solving into multiple courses (e.g., transport, mechanics, thermodynamics, and laboratory courses) so that students encounter and apply these tools repeatedly and in varied contexts [11], [12].

At the same time, the pedagogy of graduate-level STEM education has undergone significant scrutiny and evolution. National and disciplinary reports have called for modernization of engineering and science education to better align with rapidly changing research landscapes, interdisciplinary collaboration, and diverse career pathways beyond academia [13], [14]. Critics argue that traditional, instructor-centered models are insufficient for preparing graduate students to tackle open-ended, data-intensive problems and to work effectively in collaborative, cross-functional teams [15]. Instead, there is a growing emphasis on student-centered, evidence-based teaching practices that promote active engagement, metacognition, and transferable skills such as communication, leadership, and ethical reasoning [16], [17], [18]. Within this broader context, graduate curricula are increasingly expected not only to deepen technical expertise but also to cultivate the habits of mind necessary for independent, self-directed research in complex domains such as computational materials science.

Team-Based Learning (TBL) has emerged as a structured active-learning framework that aligns well with these goals. In a TBL course, students are responsible for learning foundational material before class, after which in-class time is devoted to readiness assurance tests, targeted clarification, and challenging application exercises completed in permanent teams, with the instructor acting primarily as a facilitator [19]. TBL has been shown to improve problem-solving skills, conceptual understanding, and student engagement in engineering and other STEM disciplines, in part because it requires individual accountability, peer-to-peer explanation, and repeated practice with complex, real-world tasks [20], [21], [22], [23]. Studies report positive outcomes such as improved performance on higher-order assessments, greater perceived relevance of course material, and enhanced teamwork and communication skills [24]. At the graduate level, TBL and related active-learning approaches have also been used within pedagogy-focused courses to train future faculty in evidence-based teaching, curriculum design, and the effective use of educational technology, underscoring the role of structured, collaborative learning environments in preparing graduate students for both research and instructional responsibilities [25], [26]. In numerical methods education specifically, long-term design projects and open-ended computational challenges have been used to reinforce mathematical concepts, promote authentic modeling experiences, and help students transfer numerical techniques to their own research problems [27].

Despite this growing body of work on active learning, TBL, and computational instruction, there are relatively few studies that examine hybrid models, especially at the graduate level, that deliberately blend TBL with targeted lectures in computationally intensive materials science courses [28]. Pure TBL implementations can place substantial responsibility on students to extract and organize complex technical content independently, which may be challenging when they are simultaneously acquiring new mathematical formalisms, programming skills, and domain-specific models. Conversely, purely lecture-based formats risk reducing numerical methods to procedural exercises, with limited opportunity for collaborative problem solving or for connecting algorithms to open-ended research questions. This paper addresses that gap by presenting a curriculum and course design study of a required graduate-level numerical methods course for materials science PhD students that has undergone multiple iterations: from an initial math review model to a fully TBL-oriented structure, and ultimately to a hybrid TBL–lecture format. The work is framed as a curriculum and implementation course redesign. The goals of the manuscript are to (1) articulate the rationale for shifting from a traditional math review toward a numerical-methods-focused curriculum aligned with contemporary materials research; (2) examine how a hybrid TBL plus lecture structure can better prepare graduate students for independent computational research in materials science; and (3) propose practical guidelines and best practices for balancing collaborative, team-based activities with instructor-led conceptual framing in graduate-level numerical methods coursework.

Course Context and Initial Structure

The course serves as a core requirement for first-year PhD students enrolled in the hard materials track within the MSE program. It is a three-credit graduate course that meets twice a week for 80-minute sessions and is intended to provide a mathematical foundation for key concepts in materials science and engineering. Historically, the class emphasized material transport processes, focusing primarily on diffusion and related phenomena. However, the official course description articulates a broader objective, which details providing a mathematical foundation for key concepts in MSE and introducing mathematical techniques commonly applied in materials research. Over time, misalignment became evident between the course's practice-oriented focus on transport and the program's stated learning outcomes, which emphasized MSE research–oriented application problems. To ensure coherence with the broader curriculum and to better equip students for advanced research, the course underwent a structured redesign to reestablish its foundation in mathematical principles relevant to materials science. The full timeline of the graduate numerical methods course from a math review can be found in Figure 1. These progressive modifications transformed the course from a traditional mathematics refresher into an applied numerical methods experience emphasizing computational literacy through both independent and collaborative learning. Table 1 summarizes the changes made across iterations.

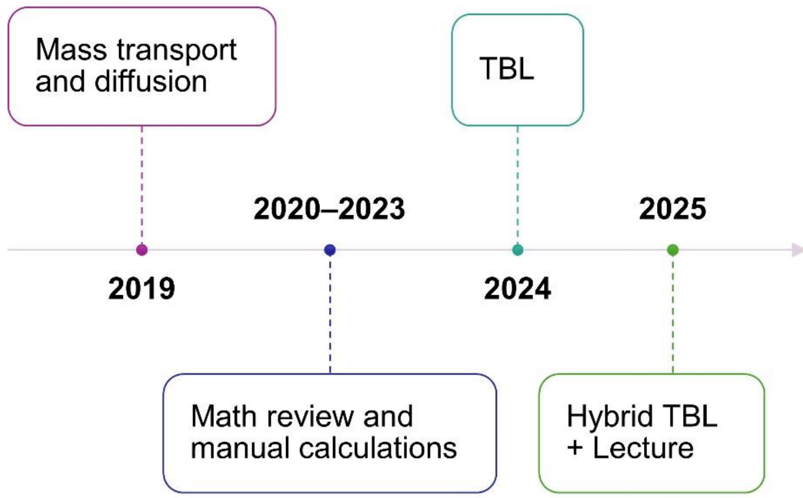

Figure 1. Evolution of the graduate numerical methods course from a math review format to a hybrid team-based and lecture-based computational methods course, highlighting major structural and pedagogical changes across offerings

Table 1: Summary of changes across course iterations.

Phase	Focus	Instructional Mode	Key Change
1	Math Review	Lecture-based	Manual analytic problem solving
2	Numerical methods	Full TBL	Readiness tests + FAT-based collaboration
3	Hybrid integration	TBL + targeted lectures	Reintroduced conceptual mini lectures

Phase 1: Math Review Focus

Following discussions with several senior faculty members and feedback from past instructors, the first phase of the redesign centered on reinforcing core mathematical concepts essential for analyzing materials behavior. The course retained a traditional lecture-based format, emphasizing manual problem solving to promote conceptual fluency and mathematical rigor. Students revisited foundational topics such as Fourier series, ordinary and partial differential equations, special functions, matrix algebra, and vector calculus. Through weekly problem sets and in-class derivations, the course encouraged students to strengthen their analytical reasoning and recall of techniques often encountered in undergraduate engineering mathematics.

During the three-year period that this math-intensive version was implemented, student feedback consistently expressed appreciation for the opportunity to refresh their mathematical knowledge in an advanced context. Many noted improved confidence in tackling theoretical derivations and analytical problem-solving. Nevertheless, recurring concerns emerged regarding the lack of direct application to research activities and the overall limited rigor expected at the doctoral level. Specifically, both students and faculty observed that while the course effectively revisited mathematical theory, it did not adequately bridge the gap between analytical foundations and real-world materials research, where computational modeling plays a central role.

In response to these findings, the instructional team recognized the need to evolve the course toward integrating numerical methods. Authentic materials science problems, such as simulating diffusion across microstructures or modeling thermal transport with non-linear boundary conditions, are rarely solvable using purely analytical techniques. Consequently, the next phase of course development emphasized computational approaches, introducing topics such as iterative solvers, finite difference methods, interpolation, numerical integration, and optimization techniques. Incorporating these topics would not only enhance the rigor of the course but also increase its relevance to the computational demands of contemporary materials research.

Students would be required to apply these techniques using software tools such as MATLAB or Python to solve open-ended, research-like problems. For example, modeling heat distribution in heterogeneous materials or analyzing the stability of time-dependent systems would provide opportunities for students to translate mathematical theory into simulation-based practice. By applying numerical methods to realistic materials phenomena, students would extend their understanding of both the physical behavior of materials and the computational frameworks that underpin modern engineering research. This shift marked the beginning of a transition from a purely theoretical review toward a more integrated, research-driven learning experience focused on developing the computational literacy required for success in the field.

Phase 2: Full TBL Implementation

In the fourth year of the course's redesign, the instructional team implemented a full TBL structure, applying it to the newly integrated numerical methods content. The revised curriculum has now expanded beyond core mathematical principles to include computational statistics and Monte Carlo simulations, which are topics critical for modeling uncertainty and variability in materials systems [29]. The objective was to foster deeper engagement through structured collaboration and active learning, encouraging students to develop both technical competence and problem-solving confidence.

Students were expected to complete assigned textbook readings before class to ensure adequate preparation for higher-level discussions. Because the course targeted graduate students, the reading requirements were intentionally rigorous and designed to promote self-directed learning. Each class session followed the TBL format, beginning with Individual and Team Readiness Assurance Tests (IRAT and TRAT) to assess comprehension of pre-class materials, followed by team-based challenge problems called Focused Application Task (FAT), which required applying numerical concepts to open-ended engineering scenarios. The consistent rhythm of testing and problem-solving aimed to reinforce knowledge retention and promote accountability within student teams.

Despite these well-intentioned goals, early feedback highlighted several challenges. Students reported that the volume of pre-class reading and the daily sequence of readiness tests left little time for reflection or deeper exploration of computational tools. Many felt that the fast-paced structure was overwhelming and diminished their confidence when attempting complex, open-ended numerical problems. Faculty observations confirmed that while students were highly engaged in the team activities, their conceptual grounding, particularly in connecting mathematical theory with numerical implementation, was weaker than expected.

In response to these observations, a mid-semester adjustment was made following a scheduled university break. The course structure was modified to adopt a modular format, where each major topic would span an entire week rather than a single class session. Under this refined approach, students completed assigned readings and preparatory tasks at home, then spent the first class of the week completing readiness assessments and participating in a guided question-and-answer session. The instructor provided targeted summary notes to reinforce key concepts and clarify common misconceptions identified during the assessments. The second-class period was then devoted entirely to collaborative problem-solving and more exploratory team activities.

This adjustment significantly improved student reception and learning outcomes. Students appreciated the more deliberate pacing and the opportunity to contextualize mathematical ideas before tackling complex computational problems. However, feedback also indicated that the complete removal of short lecture segments left some students craving additional conceptual grounding and explicit demonstrations, especially when learning new numerical methods or software syntax. These insights informed the next iteration of the course, which evolved into a hybrid format combining targeted mini-lectures with TBL-based application sessions.

Phase 3: Hybrid TBL and Lecture Model

By the fifth year of implementation, the course entered a refinement phase that adopted a hybrid teaching model integrating targeted lectures with TBL activities. This structure aimed to preserve the collaborative engagement and accountability of TBL while reintroducing lecture components to strengthen conceptual understanding. The hybrid format provided a balanced approach, allowing students to first develop a clear theoretical framework before applying numerical techniques to authentic research-style problems.

Each instructional week was organized around two 80-minute class sessions. The first session focused on conceptual framing, including step-by-step demonstrations of core numerical techniques and software implementation. Faculty began each module with the IRAT and TRAT, which encouraged students to consolidate their understanding and identify areas requiring clarification. This was followed by a concise lecture segment, designed to contextualize key mathematical concepts and highlight their relevance to materials science research.

The second-class session of each week was fully dedicated to team-based challenge problems. During these sessions, students collaboratively developed and debugged computational codes, shared approaches through peer explanation, and discussed strategies for modeling research-inspired materials phenomena. This format allowed the instructor to act as a facilitator, guiding discussions, clarifying conceptual misconceptions, and modeling good coding practices. A sample weekly schedule illustrating this structure is presented in Table 2.

Table 2: Example weekly schedule of Hybrid TBL and Lecture course structure.

Week	Day	Module	Topic
1	1	Roots	Solving Nonlinear IRAT + TRAT + Lecture
1	2	Roots	Solving Nonlinear FAT
2	1	Roots	Optimization IRAT IRAT + TRAT + Lecture
2	2	Roots	Optimization FAT

The addition of short, targeted lectures proved beneficial for student learning. Students demonstrated greater fluency in translating mathematical equations into numerical algorithms and increased confidence in tackling open-ended problems. The hybrid structure offered continuity between theory and application, which is an outcome that neither a purely lecture-based nor a fully TBL model had previously achieved. A sample time allocation for an 80-minute class session in the hybrid team-based learning format is illustrated in Figure 2.

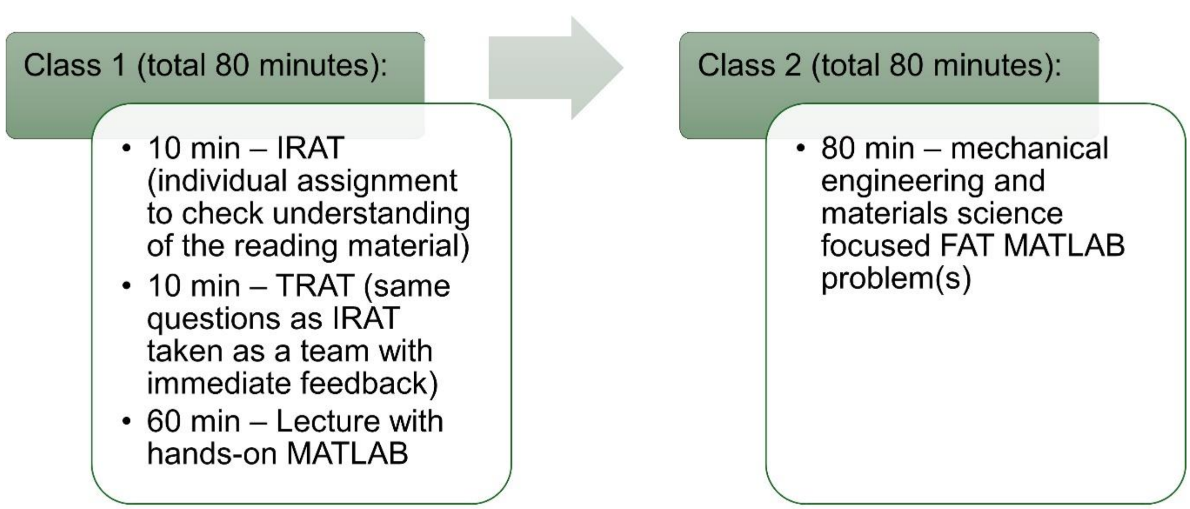

Figure 2. Example time allocation across the two weekly class meetings in the hybrid team-based learning format, showing the distribution of readiness assurance, lecture with hands-on examples, and FATs.

Assessment methods were also revised to better reflect the computational emphasis of the course. Each exam was divided into two parts: a traditional written component assessing analytical reasoning and a computational component evaluating practical application skills. Students first completed the written portion under timed conditions to demonstrate their conceptual mastery and problem formulation. After submitting the written exam, they proceeded to the computational section, where they solved a numerical problem similar in structure to the in-class challenge problems. This dual-format assessment reinforced the course's integrated learning objectives by evaluating both theoretical understanding and computational proficiency.

Results and Observations

Transitioning the course from a mathematics review to one focused on computational methods was a necessary step toward aligning the curriculum with research and professional expectations in materials science and engineering. Although TBL remains an evolving instructional strategy within this course, evidence suggests that students benefit considerably from this pedagogical approach. Assigning preparatory readings has proven particularly effective in motivating students to engage with course materials before class. As a result, students arrive better prepared to participate in discussions, leading to more meaningful in-class interactions focused on theoretical interpretation and application rather than basic comprehension. Consequently, lecture sessions have become more engaging and productive, as students now have specific conceptual questions and can reference textual sources to deepen their understanding.

Table 3: Assessment structure of the course and its alignment with key learning objectives

Assessment Type	Supported Objectives
Pre-class readings	Foundational knowledge and independent study.
IRAT	Individual accountability and foundational conceptual understanding.
TRAT	Teamwork and peer explanation of concepts.
FAT	Critical thinking, computational proficiency, and application to open-ended problems.
Exams	Integrated assessment of theory and computation.

A particularly successful component of the course has been the FATs. Students consistently praise these problems for their rigor and for the critical thinking required to solve them collaboratively. Working in teams has produced additional cognitive and social benefits; students have explicitly reported that peer-to-peer teaching enhances their grasp of the material. Collaboration also enables students to approach problems from multiple perspectives and to contextualize computational solutions within real engineering applications. Furthermore, students report significant improvement in their MATLAB proficiency, with several alumni noting that they have successfully applied these computational techniques in subsequent classes and research projects. A noteworthy outcome is that approximately 90% of students complete their FAT assignments before class ends, demonstrating increased engagement, autonomy, and problem-solving fluency. Table 3 reflects the course assessment structure and alignment.

Limitations and Challenges

1. Balancing direct instruction and team activities.

As class sizes have grown, managing instructional time has become increasingly complex. Because portions of the class meeting are allocated to IRATs and TRATs, some students, particularly those with weaker computational backgrounds, require additional guidance during TBL sessions. Finding a balance between whole-class instruction and group facilitation remains a continuing challenge.

2. Course logistics.

The success of TBL depends heavily on both attendance and punctuality. Even logistical factors, such as classroom location and setup, can influence timeliness and team morale. Policies regarding late arrivals, make-up assessments, and credit for TRAT participation must be clearly communicated from the outset. Additionally, optimal implementation of TBL requires classrooms designed for collaboration: adequate space, movable seating, and access to computational tools. Standard lecture rooms often constrain group dynamics and limit teamwork effectiveness. Another ongoing logistical question involves assessment design. Because the course relies on computational tools such as MATLAB, determining the appropriate balance between written theoretical exams and computational projects continues to be an area for experimentation, especially given evolving concerns about artificial intelligence and academic integrity [30].

3. Addressing diverse computational backgrounds.

One of the most persistent instructional challenges is the heterogeneity of students' computational experience. Incoming PhD students may range from advanced users to complete beginners in MATLAB or numerical analysis. Experience shows that intentionally pairing students with differing skill levels fosters mutual learning and helps distribute expertise so that no single group contains most of the strongest students or dominates class performance. Less experienced students benefit from peer guidance, while advanced students strengthen their conceptual understanding by teaching others.

4. Ensuring equitable contribution in teams.

The interdisciplinary nature of material science draws students from mechanical engineering, materials science, and chemistry, which introduces a wide variation in prior mathematical preparation. For example, some students may be encountering linear algebra or matrix operations for the first time. This variability can make equitable participation challenging, as some team members must simultaneously learn new mathematical concepts while applying them within numerical methods problems. Clear expectations for balanced participation are communicated at the beginning of the course, and a peer evaluation process allows students to assess the contributions of their teammates. These evaluations are reviewed and incorporated into final grade determinations to ensure fairness and accountability.

Best Practices and Recommendations

- Form diverse teams intentionally. Instructors should assign teams rather than allowing self-selection to prevent clustering by ability or background. Balanced teams have proven to be more effective and equitable [31], [32].
- Develop course policies proactively. Clear and transparent policies help manage late arrivals, absences, and assessment participation. A suggested model: late students take the IRAT upon arrival; excused absences result in waived IRATs, but participation in TRAT credit and rescheduled FAT deadlines are granted. Unexcused absences receive no make-up opportunities.
- Based on peer feedback, administering the IRAT online through the university's learning management system before class, with scores hidden from students, may further optimize instructional time. This approach can streamline readiness assurance, particularly in hybrid delivery contexts. To help prevent access to notes or other unauthorized materials during the IRAT, software such as Respondus LockDown Browser may be employed.
- Implement an appeal process. Students should have the opportunity to contest IRAT or TRAT questions if they believe their reasoning was correct. Allowing written appeals within a one-week window ensures fairness while preserving valuable class time.
- Provide usable MATLAB code templates. Supplying structured code at the start enables students to experiment independently, modify input parameters, and visualize the impact of their changes, promoting active learning and computational confidence.
- Start small with FATs. Begin with a single, well-scaffolded problem and gradually increase complexity as students develop proficiency. Overly ambitious initial assignments can overwhelm beginners and hinder group cohesion.
- Select readings and lectures strategically. Since lecture time is limited in a hybrid TBL format, faculty should focus on conceptual mastery and methods application rather than broad coverage.
- Adopt two-part examinations. Combining a written exam assessing theory and MATLAB fundamentals with a computational problem-solving component has proven effective in demonstrating both conceptual and practical proficiency.

Conclusion and Future Work

The hybrid TBL–lecture design is particularly well suited to MSE because students must integrate mathematics, physics, and materials phenomena within computational frameworks. This mirrors authentic research practice, where collaboration, iterative modeling, and physical validation are essential for reproducible simulation results. Accordingly, the redesigned course has enhanced student independence, collaboration, and computational competency in a graduate-level numerical methods course for materials science. Although these observations come from a single institution and instructor, they offer actionable guidance for similar courses seeking to balance analytical rigor with computational authenticity. Future work will focus on securing Institutional Review Board (IRB) approval to formally evaluate student learning outcomes, teamwork dynamics, and long-term skill retention across multiple course offerings.

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Appendix A: Module Sample

Example Module: Solving Nonlinear Equations (Roots)

- **Assignment Sample:**

  Read chapter 1

- **IRAT/TRAT Sample:**

  Which of the following best describes the convergence rate of the bisection method?
  a. Linear convergence
  b. Quadratic convergence
  c. Cubic convergence
  d. Exponential convergence

- **FAT Sample:**

  When water flows through a trapezoidal channel section, the cross-sectional area of the fluid (A) and the wetted perimeter of the fluid (P) are related as

$$P = \frac{A}{y_n} - y_n \cot\theta + \frac{2y_n}{\sin\theta}$$

  Find the value of θ for which $P = 3$m, when $A = 1\text{m}^2$ and $y_n = 0.5$m with $30°$ and $60°$ as the initial approximations for θ and $\varepsilon = 0.001$.

a. Pick an iterative method to solve. Which function did you use? Why?
b. Value of θ?
c. How many iterations did your method take to solve?