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The Reflective Modeling Practitioner: Promoting Self-regulation and Self-confidence in Computational Modeling and Simulation Practices*

JOREEN ARIGYE
School of Engineering Education at Purdue University, Neil Armstrong Hall of Engineering, Room 1300 701 W. Stadium Avenue West Lafayette, IN 47907, USA. E-mail: jarigye@purdue.edu

JOSEPH A. LYON
John Martinson Honors College at Purdue University, Dudley Hall, Suite 1312 363 N. Grant Street West Lafayette, IN 47907, USA. E-mail: lyonj@purdue.edu

ALEJANDRA J. MAGANA**
Department of Computer and Information Technology and School of Engineering Education at Purdue University, Knoy Hall of Technology, 401 Grant St, West Lafayette, IN 4790, USA. E-mail: admagana@purdue.edu

ELSJE PIENAAR
Weldon School of Biomedical Engineering at Purdue University
Martin Jischke Hall of Biomedical Engineering, 206 S Martin Jischke Dr, West Lafayette, IN 47907, USA. E-mail: epienaar@purdue.ed

This study investigated the effects of a team-based modeling intervention that implemented reflective practices to support students' self-regulated learning in the context of modeling assignments. We used a mixed method design to answer the three research questions: (1) What metacognitive strategies do students, organized in teams, implement when solving computational modeling assignments? (2) What are students' levels of performance in solving computational modeling assignments in teams? (3) What are the relationships between teams' level of confidence and their implemented metacognitive strategies and level of performance in the computational modeling assignment? The learning intervention was guided by a reflective modeling practitioner model, bringing together modeling practices with elements of self-regulated learning. The results illustrate students' levels of self-reported confidence in three levels, showing that from the twelve teams studied, seven reported an increase in confidence as the project progressed, three reported a decrease in their confidence, and two reported an initial struggle, but their confidence increased as they completed the assignment. The implications relate to the learning interventions in the team modeling activity that can influence the teams' reported self-confidence, which can impact the skills students acquire and the strategies they use when faced with challenges.

Keywords: computational modeling and simulation, engineering education, self-regulated learning, teamwork

1. Introduction

Computational modeling and simulation are key disciplinary practices for engineering students to develop and apply across disciplines and contexts [1, 2]. Many times, however, these practices can be difficult for engineering students to learn [3] and for engineering faculty to teach [2]. As such, computational modeling skills and practices are often under-taught by instructors and underdeveloped among graduating students.

In recent years, the research around metacognition and self-regulated learning has grown and produced promising results in helping students learn complex subjects and develop stronger STEM identities [4, 5]. The process of regulating one's learning is important not only after the problem is solved but also before and during the problem-solving process [6]. The intent is that students leverage the use of learning strategies to overcome challenges they encounter during the problem-solving process and then reflect on how those strategies worked for them [7]. These strategies build upon each other through repetition and practice as students gain confidence and move from novice-like to expert-like practices [6, 8].

This study investigates the effects of a team-based modeling intervention, where students reported on what they learned, what strategies they used, and how confident they felt as they solved a computational modeling problem. A concurrent nested mixed-methods analysis was used to answer three primary research questions: RQ1: What metacognitive strategies do students, organized in teams, implement when solving computational modeling assignments? RQ2 (Quant): What are students' levels of performance in solving computational modeling assignments in teams? RQ3 (Mixed):

** Corresponding author.

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What are the relationships between teams' level of confidence and their implemented metacognitive strategies and level of performance in the computational modeling assignment?

2. Background

Two bodies of literature contribute to the learning and research design for our intervention. First, we look at models and modeling in engineering education, which gives us multiple design principles for the learning intervention. Next, we look at the literature on metacognition and self-regulated learning to understand the impact and effects of these practices on student learning.

2.1 Models and Modeling in Engineering Education

Learning with and through models in the engineering classroom has been extensively studied [1, 8–11]. This is in large part because modeling is such an important skill to engineering professionals across disciplines [2, 3]. Promoting modeling activities in the classroom allows students to learn vital skills, such as programming and computational thinking, in addition to disciplinary learning [12–15]. Further, models allow students to test their understanding of the world around them through model-based reasoning, moving towards more correct ways of thinking about phenomena [16, 17]. Yet instructors still struggle to incorporate these activities into the classroom because of a lack of room in the curriculum and a lack of previous programming instruction for their students [2].

Model-based reasoning is a form of scientific thinking describing (a) the ways individuals make sense of different forms of external representations in the form of models [18] and (b) how novel scientific representations are created from existing representations [19]. Creating models involves connecting phenomena in the natural world to language, from existing knowledge to new knowledge, and from conception to experiment [20]. As individuals create models, they must engage in cyclical processes of creating, testing, revising, and using externalized scientific models that may reflect their understanding of phenomena [21].

When some of these representations take the form of computational models, individuals can also engage in simulative model-based reasoning [22]. But to effectively afford sophisticated simulation operations through computational models, individuals need to be able to first abstract physical phenomena into some form of a conceptual model, transform that into a mathematical model, followed by a transformation to an algorithmic representation, to then a computational model [14, 23]. These need to be effectively connected and adapted via problem-solving episodes [19].

Multiple frameworks for supporting model-based reasoning and structuring modeling activities in the classroom have been proposed, with significant overlap between them [12, 24, 25]. One such framework involves multiple unique phases of (1) planning the model, (2) building the model, (3) evaluating the model, and (4) reflecting on the model [12]. By structuring modeling interventions in this way, students can build skills such as model-based reasoning and computational thinking [12] and meaningfully engage with the modeling activity [26]. Effectively managing model-based reasoning and computational thinking requires extra metacognitive processes to regulate the complexity of the tasks[8]. Thus, students must plan those models before beginning and evaluate them once they are complete. Additionally, once the assignment is complete, students should reflect on their approach and performance to transfer strategies to future modeling contexts. These are forms of self-regulated learning. By doing so, students will move from novice to expert-like practice [6].

2.2 Self-regulated Learning

Metacognition and self-regulated learning are skills needed to learn how to learn [4, 27]. Applying self-regulation skills during problem-solving processes is one way in which experts separate themselves from novices [6]. Self-regulated learning enables students to apply learning strategies, evaluate their effectiveness, and learn from prior experiences. Students who apply self-regulated learning strategies often have multiple positive educational outcomes, such as achievement outcomes, increased self-efficacy, and persistence in moving forward [4, 28]. Self-regulated learning strategies also support the effective enactment of teamwork processes [29]. Thus, supporting the development of self-regulated learning skills among students can be paramount to student success in future education as well as professional endeavors [30].

Many factors play a role in developing students' self-regulated learning. Such factors include the self-beliefs of the student, the learning context, as well as social factors, including other students or instructors [31, 32]. Thus, understanding how students develop these skills can be a complicated problem. Yet, understanding the different ways that students regulate their learning, as well as with others, may result in instructional guidance conducive to learning or performance improvements over time [33].

One attempt at understanding the self-regulated learners' process is by using Zimmerman's cyclical model of academic self-regulation, which describes the three cyclical phases of forethought, performance control, and self-reflection. Forethought is the process that precedes any effort to act. It includes goal setting, strategic planning, self-efficacy, goal orientation, intrinsic interest, and outcome expectations. Performance control is the process occurring during learning efforts; it includes self-control and self-observation, and self-reflection is the process occurring after learning. It includes self-judgments and self-reactions. All the phases feed into/influence each other, and the cycle is complete when self-reflection processes impact forethought phase processes in future learning attempts.

2.3 The Reflective Modeling Practitioner

For this study, we propose a reflective modeling practitioner as the conceptual framework for our investigation, as shown in Fig. 1. When implementing modeling and simulation practices in the classroom, the goal of instructors should be to help students build the necessary capabilities to transfer their knowledge to new and unique contexts in the future. Self-regulated learning offers the ability to help students in future problem-solving endeavors. Fig. 1 presents a conceptual framework that aligns model-based reasoning processes enacted during the modeling and simulation process defined by Lyon & Magana [12] with the self-regulation and metacognition process proposed by Ertmer & Newby [6] to create reflective modeling practitioners and links them to increased student confidence in their abilities. The reflective modeling practitioner is the conceptual framework that informs the design of our learning intervention.

An alignment between metacognition and self-regulated learning with model-based reasoning while engaging in modeling and simulation has been made previously in the literature [8]. This proposed alignment suggests that integrating metacognitive opportunities and self-regulation into the learning design of modeling and simulation activities may help students move toward becoming expert-like reflective modeling practitioners.

By having students move towards expert-like practice in terms of modeling and simulation alongside self-regulated learning, students should begin to build confidence in their modeling and problem-solving abilities. Increased confidence is intricately linked to expert-like practice and metacognitive practices [6]. Additionally, mastery experiences with a topic also increase one's self-efficacy and self-confidence that one will be able to do it again [34]. Thus, this framework would suggest that experience doing modeling and simulation while integrated with self-regulated learning should build student confidence, which is indicative of expert-like practice.

The modeling and simulation cycle involves planning the model, building the model, evaluating the model, and reflecting on the model [12, 26]. Students must first plan their solutions before they begin coding the model solution. This is natural for some students while difficult for others [8]. Then, students build their model in this framework, often computational, by building the model through the coding process. The students then must have some way to evaluate if their model is operating and whether they have been successful in their modeling activity. Finally, students reflect on the process to understand what they could do the next time differently. This process aligns well with the metacognitive control process suggested by Ertmer & Newby [6], indicative of expert learners. In the planning, metacognitive phase, practitioners think about what the problem at hand asks them to do and their own abilities to solve the problem. In the building, metacognitive phase, practitioners think about what they are doing and why, as well as what will need to be done subsequently. In the evaluating phase, practitioners think about the process by which they came to their solution and the quality of what was produced through that process.

One way to guide learners throughout the integration between self-regulated learning processes and model-based reasoning processes is through reflective prompts [35]. This study used the reflective modeling practitioner framework to identify the learning benefits and challenges students encountered and the confidence they had in their

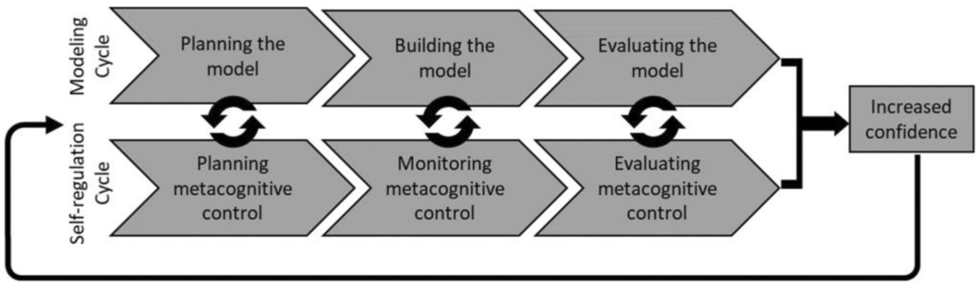

Fig. 1. Alignment of the modeling cycle and the self-regulation process to build reflective modeling practitioners.

learning throughout the process of solving a computational model-based learning activity in teams. Specifically, in this study, students were surveyed throughout the three phases of a modeling and simulation activity.

3. Methods

This intervention study employed a concurrent nested mixed-methods design [36] to answer the three research questions. RQ1 (Qual): What metacognitive strategies did students, organized in teams, implement when solving computational modeling assignments? RQ2 (Quant): What are students' levels of performance in solving computational modeling assignments in teams? RQ3 (Mixed): What are the relationships between teams' level of confidence and their implemented metacognitive strategies and level of performance in the computational modeling assignment? A concurrent nested design was selected because we wanted to identify possible patterns of the reflective practices enacted by the teams of students and the metacognitive strategies, they employed during the modeling assignment. Thus, it was necessary to have a strong emphasis on a qualitative study (RQ1) embedded in a larger quantitative study (RQ2) and then integrate those findings in a further analysis and interpretation stage (RQ3). Thus, the qualitative study was nested within the quantitative study and approached following the process as shown in Fig. 2.

3.1 Context and Participants

The context of the study was a fourth-year undergraduate elective course titled "Mathematical and Computational Analysis of Complex Systems" for biomedical engineering students at a large Midwestern university in the USA. This course was selected because students have to apply their computational knowledge to describe biological systems or solve biological problems by means of computational models. The course topics include an introduction to the analysis of complex system dynamics in biology, medicine, and healthcare. These topics are taught within the context of mathematical and computational models related to diseases (e.g., cancer, HIV/AIDS). The class consisted of 47 undergraduate students majoring in biomedical engineering. According to institutional data, in 2021–2022, 43% of the students pursuing biomedical engineering majors are women, and 57% of the students are men. The majority of the students are White 68%, Asian 13%, International 8%, more than two races 7%, Hispanic or Latino 3% and Black or African American 1%. The students were organized into a total of 12 teams, each with four or five members.

The students had extensive previous preparation in the discipline of biomedical engineering and a foundation including courses in mathematics, statistics, problem-solving, and programming applications for engineers. The learning intervention was based on the course instructor's observations in

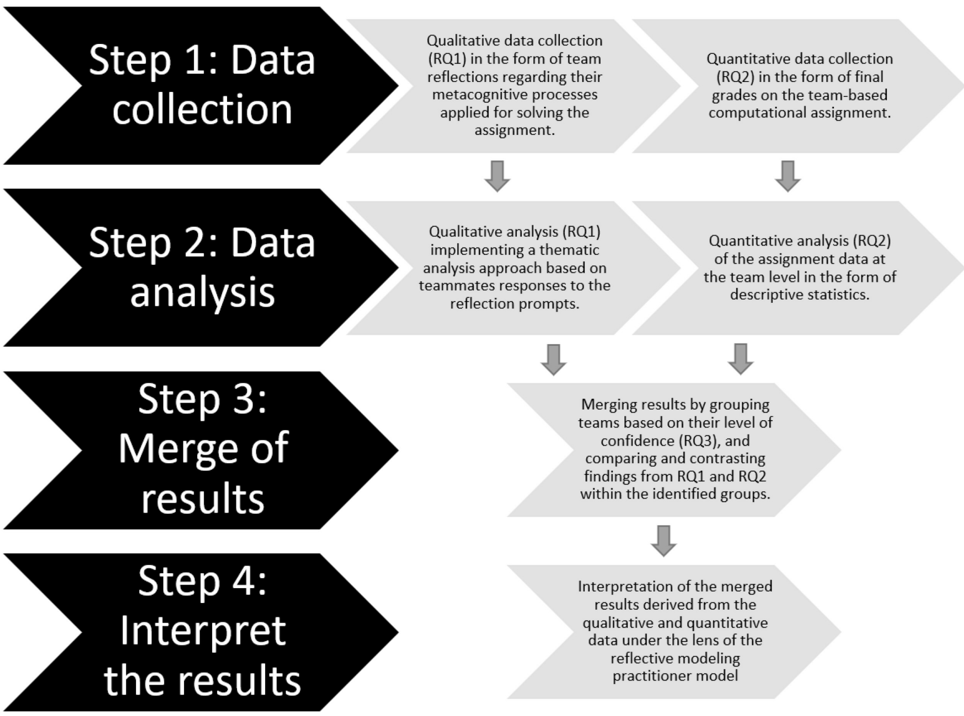

Fig. 2. A visual model of the procedures followed for implementing the concurrent nested mixed-methods design.

previous offerings of the course regarding students' experienced challenges in solving the computational activity posed as the final project. These observations prompted us to characterize the specifics of such challenges as part of the study.

3.2 Learning Design and Data Collection

The intervention implementing the computational modeling practitioner framework consisted of a final project in a course during the fall semester of 2021. This team-based assignment focused on mathematical and computational modeling and analysis of biological systems (refer to Appendix A). We worked with the course instructor to include prompts for students' explanations, decision-making, and reflection processes.

The modified final project prompted students to replicate a model they found in the research literature and modify it to address an additional problem or different set of circumstances. As shown in Appendix A, many explanation questions were added to the assignment to promote the meaning-making of the disciplinary concepts and for students to make their reasoning explicit. As part of the modeling assignment, students were given a list of metacognitive reflection questions to think about their experiences with the modeling problem in terms of interest, confidence, skills learned, and challenges faced. The design of the prompt questions was guided by the various stages of the metacognitive process, including planning, monitoring, and evaluating, as shown in Table 1. Students were instructed to jointly discuss answers to the reflection questions and submit the response that captured all team members' perspectives. The project solutions to the team-based assignments were scored by the instructor for a grade. The reflection prompts were only scored for completion. The data collection method for this study included the team-based responses to the reflection prompts and the grades the teams received in their final project consisting of the solution to the modeling assignment.

3.3 Data Analysis Methods

As shown in Fig. 2, for approaching RQ1 (Qual) regarding the characterization of the metacognitive strategies that team members used when solving computational modeling assignments, students' responses to the reflection prompts were analyzed using an inductive thematic analysis approach. Thematic analysis is a qualitative method of identifying, analyzing, and reporting patterns within qualitative data [37]. We used the inductive approach to capture any emerging themes from each of the questions used to look at the students' metacognitive processes during the modeling intervention. Specifically, data were coded for each reflection question individually to identify themes in the responses. We followed a multi-step process outlined by Braun & Clarke [38], which included (1) familiarizing oneself with the data, (2) generating initial codes and categories, (3) grouping codes and categories into themes, (4) reviewing the themes, (5) naming and defining the themes, and (6) reporting on the themes.

To approach the second research question, RQ2 (Quant), regarding students' performance levels in solving computational modeling assignments in teams, we performed descriptive statistics to summarize teams' performance on the final project regarding measures of central tendency and spread. Finally, to respond to the third research question, RQ3 (Mixed), about the relationships between teams' level of confidence, their implemented metacognitive strategies, and the level of performance in the computational modeling assignment, groups were formed based on the teams' reported level of confidence. For this, each team was then assigned to a group based on their perceived confidence throughout the process: either (1) increased confidence during the assignment, (2) struggled to maintain their confidence during the assignment, or (3) decreased confidence during the assignment. Responses from each of these groups were further analyzed in terms of what they learned, what challenges they faced, and how the team felt about their problem-solving experience.

Table 1. Reflection prompts were used to investigate metacognitive practices during the intervention

Stage of Metacognition	Reflection Questions
Planning metacognitive control	• How interested were you in engaging with this project? • In the beginning, how confident did you feel in your ability to complete this project?
Monitoring metacognitive control	• How did this confidence change as you completed the project? • What skills did you have to develop to accomplish this project? • What strategies did you follow or use to complete this project? • What were the resources or materials you consulted to accomplish this project? • In the context of this project, how did you interact with your professor, TA, or peers?
Evaluating metacognitive control	• What aspects of this project were the most beneficial for your learning? • How effective was your approach to completing this project? • What challenges did you encounter in completing this project? • How did you overcome the challenges or remedy the problems encountered? • What would you do differently in the future when completing similar assignments and projects?

3.4 Ethical and Trustworthiness Considerations

Before initiating any data collection, the investigators obtained ethical approval from the institutional review board under protocol number IRB-2021-1702. According to the Human Research Protection Program (HRPP), the project qualified as exempt because it was conducted in established educational settings with normal education practices. Specifically, it fits the category of research on the effectiveness of regular educational strategies.

To ensure trustworthiness in the analysis, the entire dataset was coded separately by two researchers who had expertise in qualitative research methods and computer science. An initial set of codes was generated, and disagreements were resolved by openly discussing differences in coding and reaching a consensus. The codes were then shared, defined, and synchronized until a final codebook was prepared. From there, one of the researchers analyzed the descriptions of the codes for all the groups' experiences to identify any trends, overlaps, or differences. Participants' quotes were also added to the results to further ensure the trustworthiness of the data. With this setup of experienced researchers and multi-level coding, the coding process and results were deemed satisfactory in terms of their trustworthiness.

4. Results

The results are organized into three subsections regarding the three levels of confidence identified by the students within each team, including (1) increased confidence during the assignment, (2) struggled to maintain their confidence during the assignment, or (3) decreased confidence during the assignment. Refer to Fig. 3 for a summary of the findings. For each of the subsections, we first describe the characteristics of the teams whose experienced confidence was similar. Within these groups of students with similar confidence, we then report on their overall level of performance in the final project and describe the benefits and challenges they encountered. From the 12 teams identified, 7 teams reported an increase in confidence as the project progressed, 3 teams decreased in their confidence, and 2 teams initially struggled, but their confidence increased as they completed the assignment. Specifically, when students were asked to collectively reflect as a team regarding how their initial confidence changed as they completed the project, team 1 answered:

> "Our confidence increased as we completed the project. Initially, we felt confident about certain tasks; however, by the end of the project, we felt confident about all tasks. We gained this confidence when we went over the SIS, SIR, and SIRV models in the class."

Responses like this one above were coded as *teams that increased their confidence*. Team 3 reported:

> "When we reproduced the results of the paper, we ran into some problems, which was a blow to our confidence, but we believed that we could complete this project. Through different methods and seeking help from the professor, helped us improve our confidence."

Responses similar to this one above were coded as *teams that struggled to maintain confidence*. Finally, teams that submitted responses such as the one from team 4 below were coded as teams that decreased their confidence:

> "The confidence changed a lot because, at first, we were confident, and then we couldn't get any similar figure to appear, so we had to go to office hours. After we were able to get a similar line shape, we were feeling more confident, but it wasn't until we completed the reproduced figure that we were fully confident again."

In the following sections, we present our findings organized according to three levels of perceived confidence. For each group, we also describe their respective reflection responses to (a) initial interest and confidence representing the teams' planning metacognitive control, (b) skills acquired and strategies used to solve the assignment representing the teams' monitoring metacognitive control, and (c) the effectiveness of strategies, challenges faced, how challenges were overcome, and reflections on how the team could have done better, as evidence of the teams' evaluating metacognitive control.

4.1 Teams with Increased Confidence

The seven teams that reported an increase in confidence as a result of the project include 1, 2, 5, 7, 8, 11, and 12. The most common skills gained by teams with increased confidence include python coding, modeling, mathematical skills, and reading academic literature. Other than the chosen paper, most teams with increased confidence referenced previous google Collaboratory used in the class to build their models. Most of the teams in this category reported challenges in choosing a good paper, understanding, and replicating the models in that paper. The average performance of these seven teams in the final project was 97.14, with a 1.35 standard deviation. Two representative teams of the group would be teams 1 and 5, explained below.

Team 1 expressed increased confidence as the project progressed; they based their high initial interest on increasing their understanding of the project and were fairly confident from having done similar work prior. They highlighted acquiring python skills, critical thinking, and reasoning skills throughout the project. The team reported a very effective strategy of completing their work by using a divide-and-conquer approach, emphasizing equal team input, and adding team effort to the coding portion. The team faced struggles with understanding the paper, especially using the correct equations and decoding the timescales on the graphs but overcame these struggles by discussing with team members and carefully reading the paper. They think an early start on the project work could have been something they improved on.

Another team of interest, Team 5, also expressed increased confidence as the project progressed; they based their high initial interest in the project on having the chance to create their model and recreate the model from the paper. They were fairly confident at the start because the team possessed good coding skills. Throughout the project work, they acquired python skills, the ability to understand academic papers, especially locating important information, and the epidemiology knowledge that was being taught. The team reported a very effective strategy of completing their work because they assigned tasks based on interest or a skill a member needed to grow in. The team struggled with debugging code, but they reviewed the work and uncovered and solved the problematic areas. In the future, the team would try a more difficult paper since they were successful with this one.

4.1.1 Perceived Learning from Teams Reporting Increased Confidence

There were many skills that students reported learning as they went through the modeling intervention. The top three skills derived from the teams with increased confidence are reported in Table 2.

As observed in Table 2, the top three most reported skills gained by teams exhibiting increased confidence included acquiring coding skills, modeling and simulation skills, and research skills centered on familiarizing with academic literature. Python coding skills were the most frequently reported, followed by mathematical modeling skills and skills in reading academic literature. There was also an overlap between themes regarding perceived acquired skills identified by teams 5 and 8 and team 12.

4.1.2 Perceived Sources of Knowledge from Teams Reporting Increased Confidence

There were many resources that students reported needing as they went through the modeling intervention. The top three resources derived from the teams with increased confidence are reported in Table 3.

Table 2. Top three skills reported by teams with increased confidence

Theme	Teams	Representative Quote
Python skills: Students reported increased knowledge in writing python code	1, 5, 8, 12	"Finally, another skill we had to develop was our coding skills in python to effectively model the equations and produce our desired results."
Modeling and mathematical skills: Students reported gaining modeling skills from the projects needed to analyze, model, and evaluate mathematical equations such as ODEs	2, 7, 12	"The first key skill that we had to develop was being able to break down the various equations present within a paper. This would be the parameters, values of parameters, and the equations themselves to first understand what the paper is trying to model. More importantly, it was critical to understand how these components related to each other and how their parameters impacted one another. Finally, another skill we had to develop was our coding skills in python to effectively model the equations and produce our desired results."
Reading academic literature: Students developed skills around reading academic literature	5, 8	"To complete this project, we had to grow and develop skills in understanding disease dynamics, python coding, and also reading and understanding published papers. In particular, being able to decipher the different papers and locate important information about the model was a skill we all grew throughout the project."

Table 3. Top three perceived sources of knowledge reported by teams with increased confidence

Theme	Teams	Representative Quote
Academic literature: Students reported using related journal articles	2, 5, 8, 11, 12	"Resources consulted to help build the model were the equations used by the paper itself as well as the past Collaboratory notebooks from class that were referenced in order to build the model. Additional references included journal articles about preventative measures for cholera, including the oral vaccines and their efficacy."
Previous course content: Students reported using previously used coursework and assignments	1, 2, 5, 8	"We referred to the knowledge learned in the class and the analysis of different models. We also referred to the coding used in the class to code this project. Other than that, we just referred to the paper we have chosen."
Internet: Students searched the internet	1, 7, 11, 12	"Google, 401 Notes, Previous collaboratories"

Table 4. Top three reported challenges faced by teams with increased confidence

Theme	Teams	Representative Quote
Technical issues: Students reported challenges with the technical part, such as correct equations, model parameters, and units, model errors	1, 2, 11, 12	"The greatest challenge came with keeping the total population consistent as the model was extended to include prevention parameters in Task 7. Specifically, problems were created with adding a vaccinated population which resulted in the total population increasing significantly over time."
Project choice: Students reported challenges with the project they choose	7, 8	"One challenge we encountered came from choosing a topic. Originally, we were going to investigate an article on cholera, but as we looked into the article more, we realized that most of the parameters and methods for modeling were not explained in enough detail to replicate."
Coding issues: Students reported challenges when figuring out the code for the project	5	"We ran into some challenges debugging our code, but these were issues we were able to resolve after everyone looked over the code.

As shown in Table 3, the teams utilized academic literature followed by previous course content such as previous collabs and the internet for research. Teams 2, 5, and 8 had similar patterns for finding information, and teams 11 and 12 also applied similar strategies.

4.1.3 Perceived Challenges from Teams Reporting Increased Confidence

Students faced many challenges as they went through the modeling intervention. The top three challenges derived from the teams with increased confidence are reported in Table 4.

As shown in Table 4, the teams struggled with technical issues related to building the models, followed by difficulties with choosing projects and coding issues. It can be observed that teams with increased confidence struggled with coding yet reported gaining the most skills in python. Teams also struggled with choosing a project; many had project-related technical issues and reported gaining skills in reading and decoding academic literature and mathematical modeling. This was all while utilizing the internet, referring to related academic literature, and consulting previously learned class work.

4.2 Teams with Decreased Confidence

The three teams that reported decreased confidence as the project progressed are 4, 9, and 10. The majority reported acquiring management skills like planning, making iterations during problem-solving, and patience on top of python coding skills. The teams reported referencing past Google Collaboratory examples done in class and consulting the class professor when they met obstacles as the prevalent resources. The prevalent challenges under this category included understanding and replicating the paper and some scheduling issues. The average performance of these three teams in the final project was 96.85 with a 2.55 standard deviation. Two representative teams of this group would be teams 4 and 10, explained below.

Team 4's initial interest was aroused by the ability to reproduce the model from the paper and epidemiology as a topic, and they were initially confident due to experience with prior similar work. They reported acquiring troubleshooting and patience skills. They used the divide-and-conquer strategy, had frequent meetings, and managed the project timelines. They think it was an effective strategy since they finished the work quickly. However, they were challenged with understanding some aspects of the paper, and through seeking help and making more attempts, they succeeded. They think that zooming out of the code and interacting with team members would have been something they could have done better.

Team 10 had an initial interest based on epidemiology as a topic, and the process of creating a model was interesting to them. The team had initial confidence from having done similar work prior, even though they felt uneasy about the project deadlines. They reported acquiring teamwork skills, time management, coding, modeling, planning, and communication skills. They used strategies such as managing and dedicating project time, planning ahead, allocating tasks, and using online meetings for team convenience. They say these strategies were very effective since the project was completed on time, task allocation worked out, and team members still liked each other and had a mutual understanding and respect for each other. They struggled with scheduling since they had to work over thanksgiving break and with replicating the chosen paper because it had some missing parameters. The team overcame these challenges by having all individual team members complete assigned tasks and communicating over GroupMe. In hindsight, they thought they could start their work earlier, have distributed tasks based on interest instead of based on availability, and asked for help earlier.

Table 5. Top three reported skills gained by teams with decreased confidence

Theme	Team	Representative Quote
Python skills: Students reported increased knowledge in writing python code	9, 10	"There are two primary skills we developed while working on this project. The first skill was our ability to read and understand an academic paper on complex system modeling. The second skill was our ability to code and adapt a system into python."
Troubleshooting: Students reported an increased ability to troubleshoot their code	4, 9	"We also developed our problem-solving skills, as the coding part of the reproduced and new models took some time to figure out, especially with errors in the parameters and the different variables we were testing out for our new model."
Reading academic literature: Students developed skills around reading academic literature	9	"The first key skill that we had to develop was being able to break down the various equations present within a paper."

4.2.1 Perceived Learning from Teams Reporting Decreased Confidence

There were many skills that students reported learning as they went through the modeling intervention. The top three skills derived from the teams with decreased confidence are reported in Table 5.

As shown in Table 5, Python coding skills were mentioned the most, followed by code troubleshooting skills and, finally, skills in reading academic literature. Only team 9 reported gaining all these three skills.

4.2.2 Perceived Sources of Knowledge from Teams Reporting on Decreased Confidence

There were many resources that students reported needing as they went through the modeling intervention. The top three resources derived from the teams with decreased confidence are reported in Table 6.

As shown in Table 6, all the teams utilized related academic literature and the internet, and some referred back to previous course content. There was a strong overlap between the three teams' approaches to seeking resources.

4.2.3 Perceived Challenges from Teams Reporting on Decreased Confidence

Students faced many challenges as they went through the modeling intervention. The top three challenges reported by the teams with decreased confidence are reported in Table 7.

According to Table 7, three teams seem to have struggled with different aspects of the project, including technical project issues, python coding

Table 6. Top three reported sources of knowledge by teams with decreased confidence

Theme	Teams	Representative Quote
Academic literature: Students reported using related journal articles	4, 9, 10	"We consulted a lot of literature from online resources and the article itself, especially when making our new results and the assumptions for that model, we had to find vaccine data to back up all of our claims. We also consulted with Dr. Pienaar to get help with getting our reproduced model to work, and what next steps to take in the troubleshooting process."
Internet: Students searched the internet	4, 9, 10	"The resources I used to complete this project were looking at the article and researching malaria on the internet."
Previous course content: Students reported using previously used coursework and assignments	4, 10	"I also looked at the last project to see how everything could be coded and looking to the google Collaboratory's on Brightspace."

Table 7. Top three reported challenges faced by teams with decreased confidence

Theme	Teams	Representative Quote
Technical issues: Students reported challenges with the technical part, such as correct equations, model parameters, and units, model errors	4	"We struggled with finding errors within the model because we followed exactly what the paper said in their tables and equations."
Coding issues: Students reported challenges when figuring out the code for the project	9	"The challenges came with troubleshooting the code and trying to get it to have the exact replicated values. Working on the other tasks went well generally."
Project choice: Students reported challenges with the project they choose	10	"One challenge we encounter came from choosing a topic. Originally, we were going to investigate an article on cholera, but as we looked into the article more, we realized that most of the parameters and methods for modeling were not explained in enough detail to replicate."

issues, choosing a project paper, and reporting time management.

4.3 Teams that Struggled to Maintain Confidence

The two teams that struggled to maintain confidence as the project progressed were teams 3 and 6. The teams reported gaining python coding skills, and some members of team 6 highlighted that they did not gain any skills since 2 of its members did all the coding. The teams reported the chosen paper as the major resource used to complete the project. The teams reported facing scheduling and prioritization challenges on top of the coding and modeling issues. The average performance of these two teams in the final project was 98.65 with a 0.14 standard deviation. Two representative examples of these are teams 3 and 6.

Team 3 was initially interested in the project because there was team consensus when choosing the project paper, and the project presented a platform to apply the class knowledge they had acquired. The team was confident initially, too, because they thought they had good teamwork and had worked on similar work prior. They gained academic reading skills, coding, and debugging skills. They employed strategies such as planning, managing time, establishing timelines, routine progress meetings, and allocating tasks reasonably. They indicated that their strategies were very effective because of their active communication and starting the project early, which helped with managing unexpected issues. They faced scheduling challenges and had an issue with understanding the paper, specifically the graphs. They countered these challenges by finding the time that works for most team members, making more attempts at understanding the paper, and seeking help. Upon reflection, they thought they could have asked additional questions about the project beyond what was required.

Team 6 was uncertain about their confidence as the project progressed because of mathematical modeling and code troubleshooting, even though they were fairly confident from prior experience with similar work. Some reported not having gained any skills since 2 members of the team were dedicated to coding, but others gained coding and time management skills. The team reported a most effective strategy, but they think it could have been better. The strategy was to work individually and meet before the presentation. They also planned and communicated to ensure project success. They struggled with coding, prioritization of tasks, and communication amongst themselves. They think the team could have performed better if they had gotten to know their teammates better before working on the project. They say it felt like working with strangers.

4.3.1 Perceived Learning from Teams Reporting Struggling to Maintain Confidence

There were many skills that students in teams who struggled with confidence reported learning as they went through the modeling intervention. The top three of these are reported in Table 8.

As shown in Table 7, the two teams gained python coding and troubleshooting skills, and in addition, team three identified reading academic literature.

4.3.2 Perceived Sources of Knowledge from Teams Reporting Struggling to Maintain Confidence

There were many resources that students that struggled with confidence reported needing as they went through the modeling intervention. The top three of these are reported in Table 9.

As shown in Table 9, teams 3 and 6 utilized related academic literature as their primary sources of knowledge. Team 3 also used previous course content, and team 6 used the internet as another additional source.

Table 8. Top three reported skills by teams that struggled to maintain confidence

Theme	Teams	Representative Quote
Python skills: Students reported increased knowledge in writing python code	3, 6	"Basic python skills were needed, but it was very similar to the other projects we did."
Troubleshooting: Students reported an increased ability to troubleshoot their code	3, 6	"There were a lot of skills gained through the troubleshooting of the code. We learned the systems dynamics of HIV pathology through trying to see if there were rate constants that could be messing with the code. We learned euler, odeint, and rk4 in python through the several iterations of the code that were made. We also improved our skills in asking for help through office hours and emails."
Reading academic literature: Students developed skills around reading academic literature	3	"To complete this project, we need to have good reading skills and understanding of mathematical models and formulas. For the paper we choose, we need to be able to extract important information and the information we need in this paper. In addition, we also need to have better coding skills and debugging skills."

Table 9. The top three reported resources by teams that struggled to maintain confidence

Theme	Teams	Representative Quote
Academic literature: Students reported using related journal articles	3, 6	"Resources consulted to help build the model were the equations used by the paper itself as well as the past Collaboratory notebooks from class that were referenced in order to build the model. Additional references included journal articles about preventative measures for cholera, including the oral vaccines and their efficacy."
Previous course content: Students reported using previously used coursework and assignments	3	"Other than the academic article, we utilized an old class google colab for the basic structure of our model code. This gave us a general framework that we could build the model around as opposed to starting from complete scratch."
Internet: Students searched the internet	6	"As our paper was centered around Vector Borne Diseases, our group did some additional research online to further understand the relationships between humans and these diseases. Furthermore, we consulted papers online that had similar goals to the paper we chose to better get an idea of what questions we can further examine in our project."

Table 10. The top three reported challenges by teams that struggled to maintain confidence

Theme	Teams	Representative Quote
Project and Time management: Students reported challenges to do with project logistics, such as scheduling meeting times for the group, communication	3, 6	"Finding a time to meet was one of the challenges of completing the project. The paper we selected also had a missing parameter and could've been more detailed in their explanation or references, which delayed our replication of the figure and interpretation."
Coding issues: Students reported challenges when figuring out the code for the project	6	"We ran into some challenges debugging our code, but these were issues we were able to resolve after everyone looked over the code.
Understanding paper: Students reported challenges with understanding and analyzing the paper they chose	3	"Some challenges we encountered in completing this project was choosing a paper and trying to implement the vaccine in only adults age 18+. The first paper we chose did not have enough information to fully solve the ODEs as there was not enough information about the parameter values and the initial conditions."

4.3.3 Perceived Challenges from Teams Reporting Struggling to Maintain Confidence

There were many challenges that students that struggled with confidence faced as they went through the modeling intervention. The top three of these are reported in Table 3.

As indicated in Table 10, teams 3 and 6 experienced time management as their main issue. In addition, team 6 reported challenges with figuring out the Python code, and team 3 reported challenges with difficulties in understanding the paper.

5. Discussion and Implications

Although overall students had a comparable high performance in the final project submission, differences were mainly identified regarding their experienced level of confidence, and their corresponding perceived skills gained, sources of knowledge, and challenges experienced by teams. Fig. 3 presents a visualization summarizing our findings regarding the differences in confidence, skills gained, sources of knowledge, and challenges, allowing us to further elaborate and contrast them. Our results indicate that most teams (7 out of 12) reported increased confidence in their ability to engage in modeling and simulation practices due to the course activities culminating with the learning intervention. Many (10 out of 12) of these teams also reported being highly interested in the subject material and listed being able to choose their project as a highly desirable quality. These were positive design elements as research has identified that interest and confidence in a topic are highly related [39–41]. For instance, Häussler & Hoffmann [40] found that building an interest-based curriculum in physics seemed to positively impact student confidence, especially among female students. Our results seem to qualitatively support this finding; of the teams that reported increased confidence (i.e., 1, 2, 5, 7, 8, 11, 12), six of them (i.e., 2, 5, 7, 8, 11, 12) reported interest in the subject matter. Providing students with opportunities to make choices in their learning process promotes agency in their learning, thus promoting taking responsibility for their learning [42], as well as relevance and involvement [43]. The ability to choose what one can work on seemed to have a net positive effect.

However, choice also seemed to have a downside, as some of the teams that reported a decrease in

Skills Gained	Group	Teams
Python Coding	Increased	1, 5, 8, 12
	Struggling	3, 6
	Decreased	9, 10
Modeling and Mathematics	Increased	2, 7, 12
	Struggling	
	Decreased	
Reading the Literature	Increased	5, 8
	Struggling	3
	Decreased	9
Troubleshooting	Increased	
	Struggling	3, 6
	Decreased	4, 9

Knowledge Sources	Group	Teams
Academic Literature	Increased	2, 5, 8, 11, 12
	Struggling	3, 6
	Decreased	4, 9, 10
Previous Course Content	Increased	1, 2, 5, 8
	Struggling	3
	Decreased	4, 10
Internet	Increased	1, 7, 11, 12
	Struggling	6
	Decreased	4, 9, 10

- Teams with *increased* confidence
- Teams with *struggling* confidence
- Teams with *decreased* confidence

Challenges	Group	Teams
Technical Issues	Increased	1, 2, 11, 12
	Struggling	
	Decreased	4
Project Choice	Increased	7, 8
	Struggling	
	Decreased	10
Coding Issues	Increased	5
	Struggling	6
	Decreased	9
Project and Time Management	Increased	
	Struggling	3, 6
	Decreased	
Understanding the paper	Increased	
	Struggling	3
	Decreased	

Fig. 3. Visualization summarizing skills gained, sources of knowledge, and challenges experienced according to the reported level of confidence by teams.

confidence did so as a result of the choice they had to make early on. Because a project focused on choice must be adequately open on the front end to give students the freedom and creativity of topic choice, it shifted some of the problem scoping from the instructional team to the students as they chose a topic. This may have led to choice overload, where students had too many options (i.e., nearly twenty options), and thus decision quality may be affected, or at a minimum, students are left feeling highly indecisive [44]. Similarly, some teams might have selected a paper or project topic that was overly complex, hence resulting in an overwhelm and inability to achieve a working solution. This left some teams, such as team 4, unable to understand the paper they chose for their modeling project. Teams like team 4 might have felt stuck and unable to proceed, ultimately affecting their confidence. This highlights the need to have guardrails and appropriate check-ins with teams to help them avoid wandering too far off track with their choice while also giving them the benefit of choosing a topic that is of great interest to them. Research studies have suggested many ways to minimize choice overload, including providing filtering mechanisms for students [45]. Perhaps providing students with a set of guidelines or criteria (e.g., a rubric or checklist) to consider for selecting their project would guide students in their choices.

Some of the other teams that had a reported decrease in confidence or struggled to remain confident, such as teams 6, 9, and 10, all discussed wanting to start the project earlier or faster than they did. Additionally, these three teams reported being confident initially due to a variety of factors, such as previous coursework and coding ability. So, what happened that these confident students seemed to lose confidence throughout the process? One reason could potentially be that these students struggled from overconfidence early. Research characterizing the Dunning-Kruger effect [44–46] identified that it is entirely likely that students may overestimate their abilities. As a result, the students started too late on the project and ultimately paid the price in terms of their confidence. Similarly, research has identified that time management is an important skill in academic achievement [49]. Research has identified that time management and self-beliefs have a reciprocal effect on academic inclination in students [50]. One possible way to avoid this pitfall is to have more checkpoints and formative assessments throughout the process so that students start their work earlier and more quickly realize what they do not understand about the subject matter. Another strategy is to embed process management supports within assignments to help a student manage, monitor, and evaluate their processes and progress [51]. Such supports can provide students with ordered and unordered task decompositions [51].

Another finding is that students ultimately saw troubleshooting their code in two different lights. One group saw troubleshooting as a skill learned from the activity, while another saw troubleshooting as a challenge to overcome. While no concrete claim can be made about how this difference in view impacts confidence, it does seem that the students who struggled with their confidence or had decreased confidence in their abilities did seem somewhat likely to have troubleshooting and debugging challenges. One way to potentially change this viewpoint is for coding instructors to not teach debugging as a byproduct of coding issues and mistakes but rather as its unique skill to be learned and mastered in the classroom. That shift in focus changes the hours of troubleshooting from a stalling of the learning process to one of education in itself. Many studies throughout the literature have shown the importance of debugging education and the impact it can have on time spent on debugging code [52, 53].

One more observation is that several teams with decreased or struggling confidence reported issues to do with team formation, team logistics, and overall organization. One reason for this could be that the student's main focus was on learning the technical material in addition to learning a programming language, and hence there is not a lot of effort and support put into team management and coordination. This is not surprising in that traditionally, the skills needed to be an effective team member have often lagged in the engineering classroom [54]. Research has identified that having students work in teams will not necessarily result in developing or enacting teamwork or other leadership skills [55, 56]. Therefore, there is a need to build and assess the teaming capacity intentionally and deliberately to increase students' experience with it, strategies for which have been studied extensively in the engineering education literature [57, 58].

These teams also employed several strategies to distribute the work across their team members. For example, team 5 allocated work based on interest, team 6 allocated work based on competence in a certain task, team 7 allocated work based on availability and close deadlines, and team 8 allocated work equally among its members. These findings align with the broader literature, which has found that individuals will allocate work based on expertise [59] and availability [60]. While there was no apparent pattern of how these different strategies affected reported confidence, it would be productive to learn and support teams with whatever strategy they have deemed best for the project to understand the effects on both learning and self-efficacy.

6. Conclusion, Limitations, and Future Work

The findings of this study provide insights into the complexity of integrating computational modeling assignments at the undergraduate level. Although the findings suggest that students benefited cognitively by the modeling assignment, as evidenced by the level of performance in the project, the results also show the need for students to balance psychosocial factors. Such psychosocial factors include confidence, metacognitive skills like troubleshooting to overcome challenges, time management skills to work on internal deadlines and class deliverables, and teamwork skills to orchestrate the work among the team members. One limitation of this study is the small number of teams represented in the sample; however, this limitation is counterbalanced by the richness of the data inherent to qualitative research and the insights it provides to understanding how students engage in complex tasks such as computational modeling. Another limitation is that by having the unit of analysis at the team level, it can be difficult to trace the data back to individual student learning. Our future work will continue to engage in design-based research to investigate the integration of effective pedagogical approaches to support student learning of computational modeling and simulation practices. For example, in addition to using principles that promote self-regulated learning, we will also integrate principles of cooperative learning to orchestrate the teamwork experience. Furthermore, we will also engage in a deeper analysis of the performance and learning data to better characterize the cognitive processes students employed, and characterize how their artifacts evolved throughout the planning, building, and evaluating stages of the modeling cycle.

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Statements and Declarations

- Availability of data and material
  Data is available on request due to privacy/ethical restrictions.
- Competing interests
  There are no relevant financial or non-financial competing interests to report.
- Research with human subjects
  Data collection procedures for this study were reviewed and approved by the university's Institutional Review Board.
- Authors' contributions
  The authors confirm their contribution to the paper as follows: study conception and design: Magana, Lyon; data collection: Arigye, Lyon, and Pienaar; analysis and interpretation of results: Arigye, Lyon, Magana, and Pienaar; draft manuscript preparation: Arigye, Lyon, Magana, and Pienaar. All authors reviewed the results and approved the final version of the manuscript.

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Joreen Arigye is a third year PhD student pursing Engineering Education at Purdue University. Joreen holds a BS in Software Engineering from Makerere University and an MS in Information Technology from Carnegie Mellon University. She has prior experience in the software engineering and data science industry as well as in the teaching of computer programming and mentoring learners at various academic institutions. Her research interests lie in the learning, teaching, and mentoring of students in computer programming.

Joseph A. Lyon is a continuing lecturer for the College of Engineering at Purdue University teaching engineering design, computer programming, and engineering physics. He received his PhD in Engineering Education from Purdue University.

His research interests are programming education, computational thinking, and mathematical modeling in the engineering classroom.

Alejandra J. Magana is the W.C. Furnas Professor in Enterprise Excellence of Computer and Information Technology and Professor of Engineering Education at Purdue University. She earned a BE in Information Systems and an MS in Technology, both from Tec de Monterrey, and an MS in Educational Technology and a PhD in Engineering Education, both from Purdue University. Her research program investigates how model-based cognition in Science, Technology, Engineering, and Mathematics (STEM) can be better supported by means of expert tools and disciplinary practices such as data science computation, modeling, and simulation. In 2015 Dr. Magana received the National Science Foundation's Faculty Early Career Development (CAREER) Award for investigating modeling and simulation practices in undergraduate engineering education. In 2016, she was conferred the status of Purdue Faculty Scholar for being on an accelerated path toward academic distinction. And in 2022, she was inducted into the Purdue University Teaching Academy, recognizing her excellence in teaching.

Elsje Pienaar is an Assistant Professor in the Weldon School of Biomedical Engineering at Purdue University. She earned her MS and PhD in Chemical and Biomolecular Engineering from the University of Nebraska-Lincoln and did postdoctoral work in Microbiology, Immunology and Chemical engineering at the University of Michigan as well as at Linköping University, Sweden. Dr. Pienaar teaching undergraduate thermodynamics and nonlinear dynamics courses, and a graduate course in multi-scale modeling. Her laboratory uses computational simulations of within-host pathogen, immune and drug dynamics to optimize treatment of infectious diseases. Current projects in the lab include TB, HIV, Non-tuberculous mycobacterial infections and Ebola virus.

Appendix A: Indications for the final project submission

Project description

This project will help you to critically think about the conclusions and analysis included in the paper and then expand on those results to dig a bit deeper on your own. The tasks in this project will guide you through the following:

- Selecting a published paper of interest
- Implementing the model described in the paper
- Reproducing one figure from the paper
- Run a NEW simulation and produce a new result based on your own interests and questions

Task 1: Selecting a paper (5%)

- Please discuss among your group members to select a paper from the ones listed below.

Task 2: Biological background (5%)

- What biological system are they simulating?
- What are the key dynamics/interactions they want to include in their model?

Task 3: Objective (5%)

- What is the biological question the paper wants to answer? OR What is the objective the paper wants to achieve?

Task 4: Model description (15%)

- Identify the equations (you can include the equations in the report if it's feasible, but you do not have to) and briefly outline the variables, parameters and interactions included in the model.
- State if there are boundary or initial conditions used in the model, and briefly describe them.
- What is one assumption that they make in their model construction?
- Discuss the potential implications of this assumption. i.e., what are some ways this assumption could limit the generalizability or accuracy of the results?
- What are the steps that you will follow to implement the model described in the equations? Include a flow chart.

Task 5: Model implementation (20%)

- In the code cell below, please implement the model from your paper. If the paper analyzed multiple versions of a model, you don't have to implement all of them, just be clear about which one your chose.

- Comment your code describing/explaining the steps in your computational solution. Make sure to connect your approach to the biology/health/medical problem where appropriate. E.g., add descriptions of what biological interaction specific parameters represent.
- What were the steps or strategies you followed to check/test that your model implementation is correctly performing the steps you intended?

Task 6: Reproduced results (20%)

- What does the graph show that you reproduced in Task 5?
- What are the authors' conclusions about the graph?
- Do you agree with the authors' conclusions? Please provide an explanation for your answer by interpreting the output and explaining your findings.

Task 7: New results (20%)

- What outstanding question did you have after looking at their results?
- What analysis or modification will you implement to answer this question?
- Implement your new model in the code cell below.
- What does your analysis of the new results show?
- What are your conclusions about the biological system based on your new analysis? Explain your conclusions in detail.
- Discuss why your results make sense in light of the original results. i.e., based on the model updates that you made, why it makes sense to see the differences you do.

Task 8: Summary (5%)

- How can your conclusions be used to design/impact interventions in this system?

Task 9: Project Reflection (5%)

- How interested were you in engaging with this project?
- At the beginning, how confident did you feel on your ability to complete this project?
- How did this confidence change as you completed the project?
- What skills did you have to develop to accomplish this project?
- What strategies did you follow or use to complete this project (e.g., time management, resources, planning)?
- What were the resources or materials you consulted to accomplish this project?
- In the context of this project, how did you interact with your professor, TA, or peers?
- How effective was your approach for completing this project?
- What challenges did you encounter in completing the project?
- How did you overcome the challenges or remedy the problems encountered?
- What would you do differently in the future when completing similar assignments and projects?