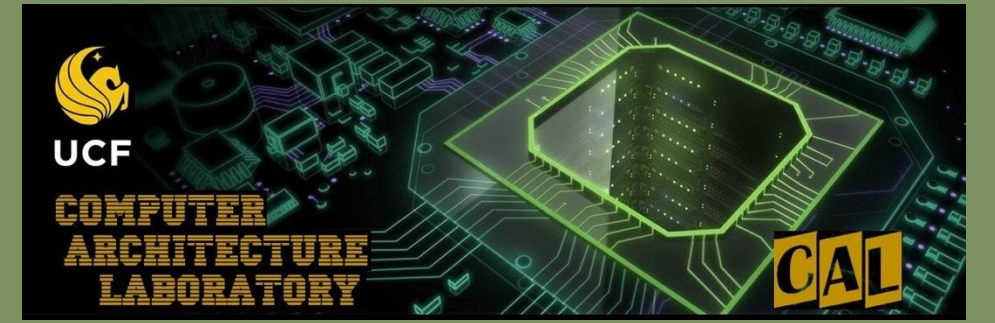




# Agent-Based Model for Optimal Remedial Staffing to Achieve Learning Outcomes within Cost Constraints

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## Abstract

An *Agent-Based Model (ABM)* is developed to assist instructors in **optimizing the allocation of Teaching Assistants (TAs)** in STEM courses, with a focus on improving student outcomes. Parameters including students' understanding of course material, course enrollment, and the amount TA hours, the model estimates student success rates while highlighting effective tutoring strategies tailored to student needs. The ABM quantifies the number of students who are likely to pass a course based on a minimum threshold for comprehension. With the objective of **lowering the D-F-Withdraw (DFW) rate**, a new metric is introduced for identifying how cost effective a selected number of tutors would be at supporting the filling of knowledge gaps within the course and foundational to measuring **thresholds limits** for staffing purposes as shown in Figure 1.

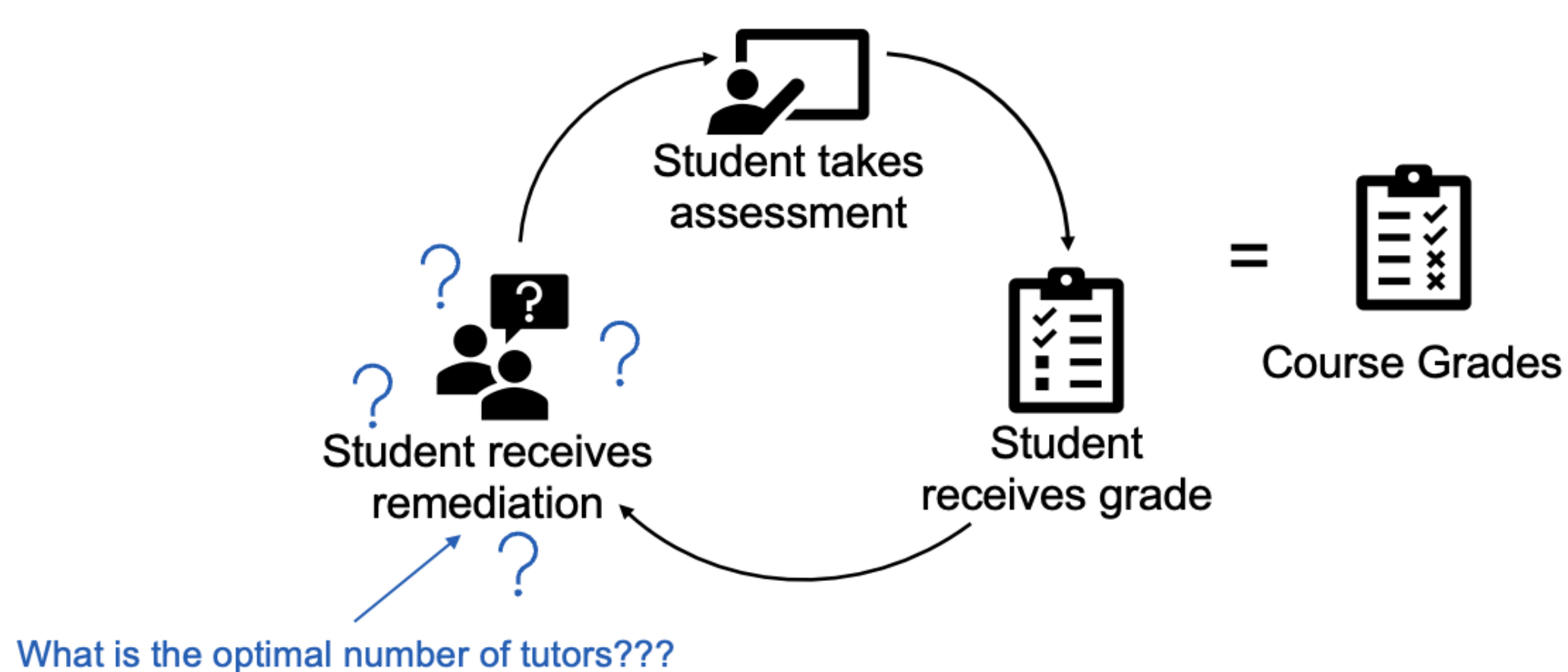


Figure 1: Traditional Remediation-Based Framework.

## Introduction

### Need for Quantifying Optimal TA Staffing

*Automating of identifying optimal TA allocation within higher-ed courses*

### Approximate Cost Constraints

*Identifying approximate financial cost per TAs necessary to support the filling of knowledge gaps presented in Figure 4*

### Agent-Based Model via NetLogo

*Utilization of NetLogo provides a visual and easily append able model to be a general tool for various course configurations shown in Figure 2 and supported with Algorithm 1*

## Research Contributions

**Predictive Modeling:** The study develops an agent-based model (ABM) that successfully estimates the number of students at risk of failing or warning in a required ECE undergraduate course, offering a valuable tool for instructors to anticipate and mitigate student struggles. The estimations are presented in Figure 3 & listed within Table 5.

**Teaching Assistant Effectiveness:** The research demonstrates that increasing the number of teaching assistants can significantly reduce the number of DFW students and identifies an optimal threshold limit on TAs per course configuration (listed in Table 4), providing actionable insights for instructors to enhance support services.

**Cost-Benefit Analysis:** The study introduces a *Relative Cost-Student Support (RCSS)* metric to measure the cost-effectiveness of employing tutors, offering institutions a data-driven approach to allocate resources and invest in tutoring services that provide a clear financial benefit shown in Figure 4.

Table 1: Spring 2022 Semester Gradebook Statistics for Base Model Selection

|                                            | Quiz 1 | Quiz 2 | Quiz 3 | Midterm 1 | Midterm 2 | Final  | Average |
|--------------------------------------------|--------|--------|--------|-----------|-----------|--------|---------|
| Minimum passing grade on quiz              | 17.5   | 17.5   | 17.5   | 70        | 70        | 70     |         |
| # above passing grade                      | 49     | 49     | 46     | 36        | 32        | 22     |         |
| # of students in course                    | 70     | 70     | 70     | 70        | 70        | 70     |         |
| Average # of student's above passing grade | 70     | 70     | 65.714 | 51.429    | 45.714    | 31.429 | 55.7143 |
| # students with passing grades             | 66     |        |        |           |           |        |         |
| The DFW value                              | 4      |        |        |           |           |        |         |
| Average # of tutoring sessions/TA          | 12.25  |        |        |           |           |        |         |

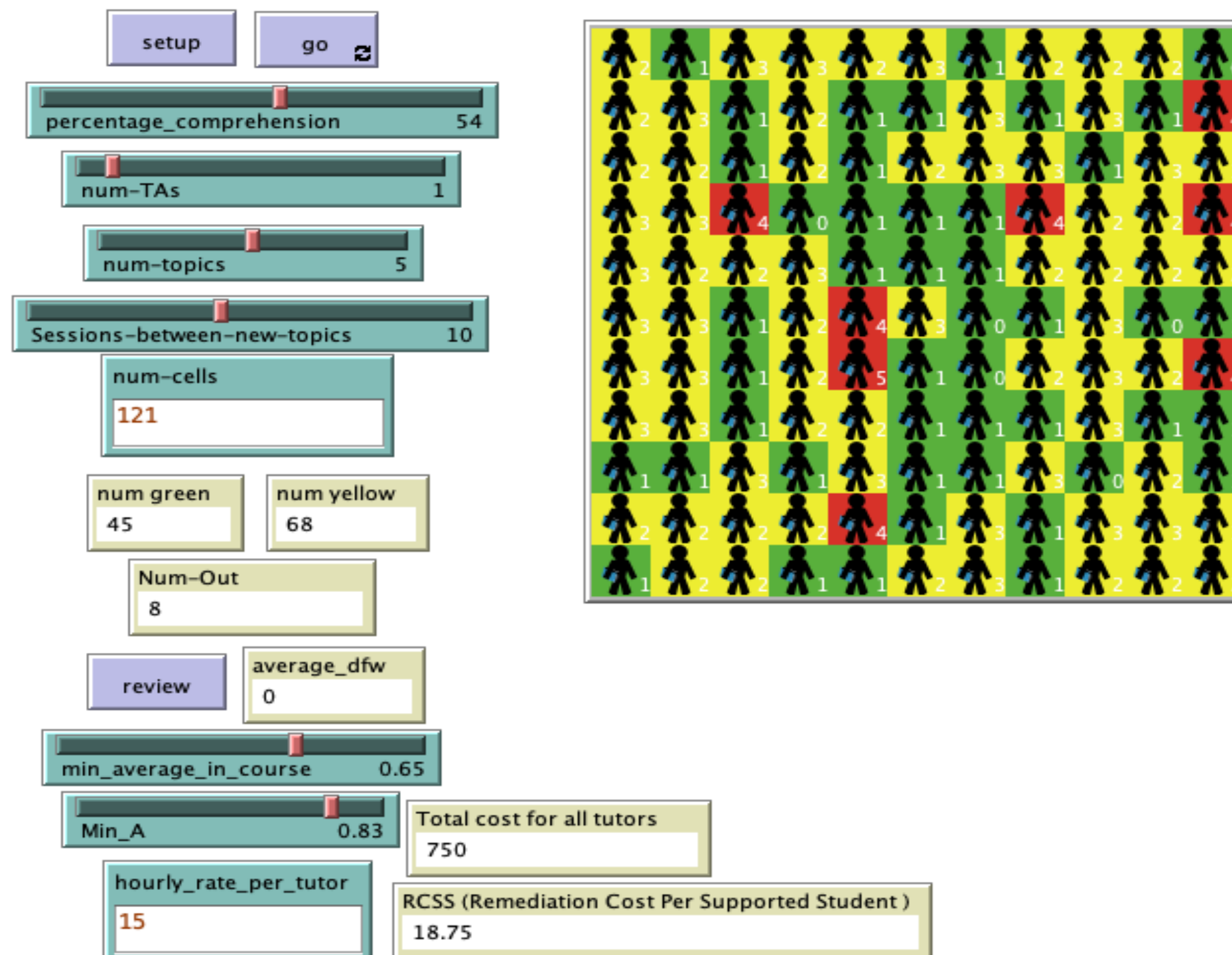


Figure 2: The Base-Model Using NetLogo

Table 2: Input Model Parameters

| Input Variables             | Description                                                            |
|-----------------------------|------------------------------------------------------------------------|
| num-cells                   | Number of students is dynamic to user preference                       |
| percentage_comprehension    | The average satisfactory comprehension on quizzes in the course        |
| num-TAs                     | User specified number of TAs to remediate knowledge gaps               |
| num-topics                  | Number of major topic assessments, such as quizzes                     |
| Sessions-between-new-topics | Number of tutoring/ remediation sessions between major topic in course |
| min_average_in_course       | Minimum percentage value to pass the course                            |
| Min_A                       | Minimum percentage in a course to receive an "A"                       |
| hourly_rate_per_tutor       | Hourly dollar payrate for a teaching assistant (tutor)                 |

Table 3: Output Model Parameters

| Output Variables                              | Description                                                                         |
|-----------------------------------------------|-------------------------------------------------------------------------------------|
| num-green                                     | Number of students that fully comprehended all topics                               |
| num-yellow                                    | Number of students that do not fully comprehend all topics but also pass the course |
| num-out                                       | Number of students that did not get the minimum average required in the course      |
| average_dfw                                   | Average "num_out" value over 100 runs of the simulation                             |
| total_monetary_cost                           | The total cost to pay all the tutors for all the hours worked                       |
| RCSS (Remediation Cost Per Supported Student) | total_monetary_cost over the total number of remediated students                    |

## Experimental Setup

**Course Selection:** The research focuses on a required ECE undergraduate course, which is identified as having high DFW rates, making it an ideal candidate for testing the effectiveness of teaching assistant support.

**Model Parameters:** The ABM considers various parameters such as student population, instructor teaching style, and grading scheme to simulate the learning process and predict student outcomes. Which can be realized in Table 1 and parameters listed in Table 2, & 3

**Simulation and Evaluation:** The model is applied to a four-semester period listed in Table 5, with three out of four semesters' DFW student numbers being successfully predicted within a magnitude of one, allowing for a comprehensive evaluation of its predictive capabilities.

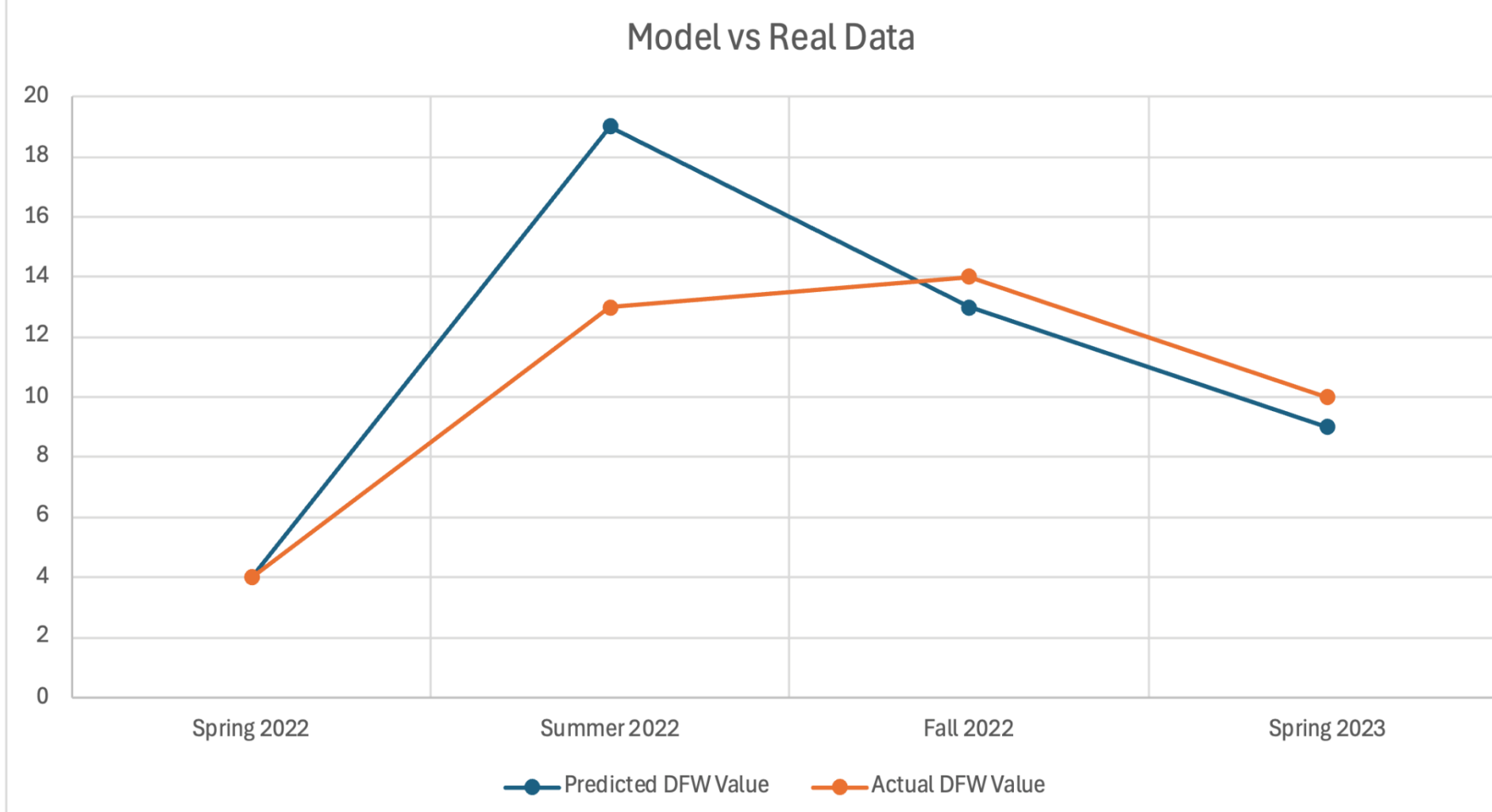


Figure 3: Model Predictions Compared to Real Values

Algorithm 1: Model Flow Pseudo Code for the "go" Procedure

```
1 "go" procedure:
2   Repeat for number of topics there are in the course:
3     Repeat for the number of tutoring sessions:
4       Tutors Remediate students
5       Randomly select and increase (100 - percentage_comprehension) % of patches label value. To Indicate they did not receive the minimum letter grade on the given quiz to demonstrate competency on the topic.
6       Update the cell colors accordingly
7   Count # of red, green, and yellow cells
```

Table 4: Input Parameters to Review Legitimacy of the Model

| Input Parameters            | Spring 2022 | Summer 2022 | Fall 2022 | Spring 2023 |
|-----------------------------|-------------|-------------|-----------|-------------|
| num-cells                   | 70          | 72          | 122       | 121         |
| Percentage_comprehension    | 55          | 40          | 49        | 54          |
| num-TAs                     | 1           | 2           | 3         | 3           |
| num-topics                  | 5           | 5           | 5         | 5           |
| Sessions-between_new_topics | 12          | 4           | 5         | 5           |

Identifying optimal number of tutors for the Spring 2022 semester configuration

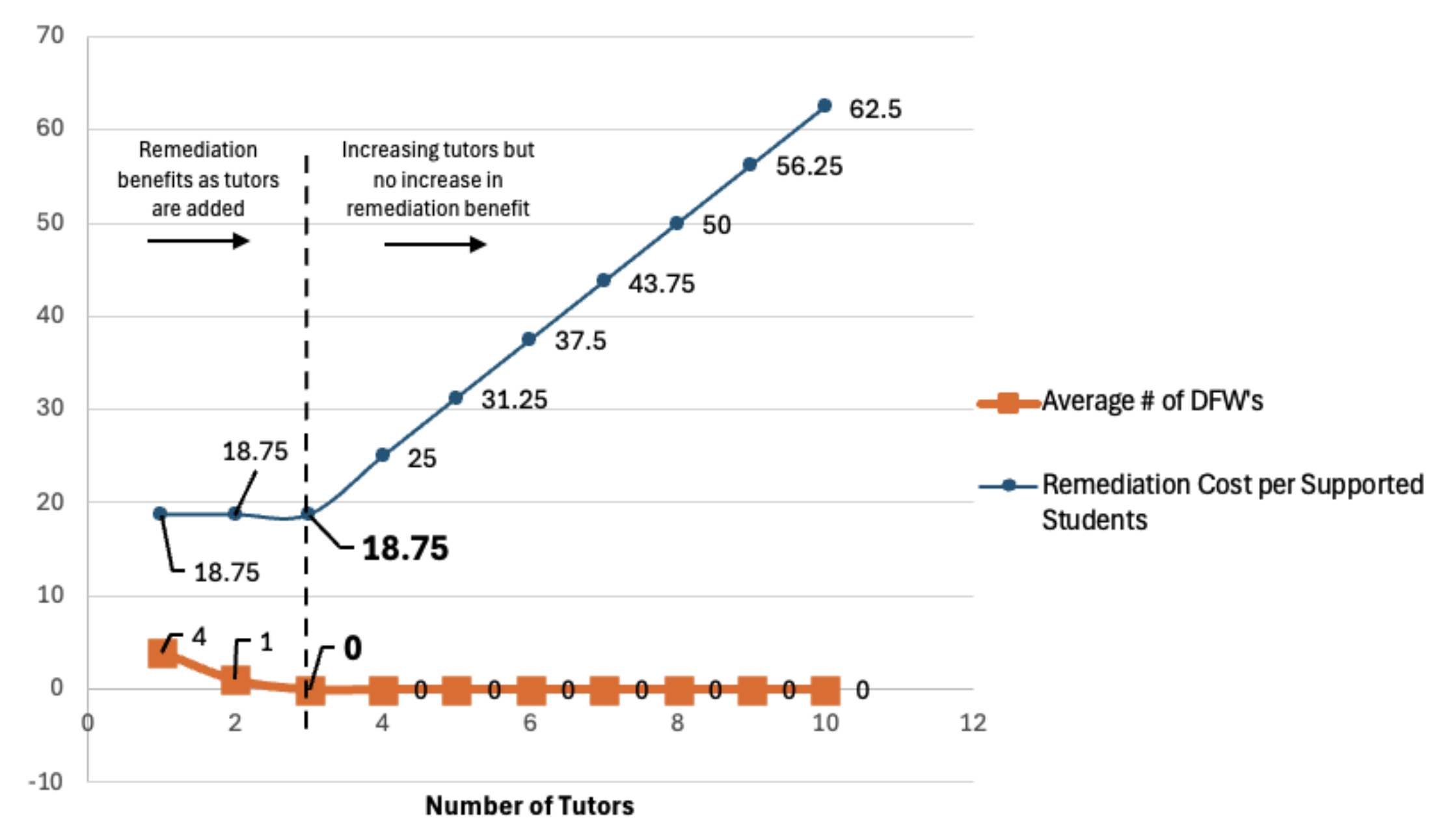


Figure 4: Identifying the Ideal Number of Tutors for the Spring 2022 Semester for the EEL3801 Computer Organization course at large state university in USA

Table 5: Statistical Analysis on the Four Observed Semesters

| Semester    | Confidence Interval at 95% DFW |             | Actual Value |
|-------------|--------------------------------|-------------|--------------|
|             | lower-bound                    | upper-bound |              |
| Spring 2022 | 3.908                          | 4.532       | 4            |
| Summer 2022 | 18.807                         | 19.873      | 13           |
| Fall 2022   | 12.356                         | 13.364      | 14           |
| Spring 2023 | 8.881                          | 9.768       | 10           |

## Conclusions

### Predictive Power

The agent-based model developed in this study demonstrates predictive power in forecasting student outcomes, providing instructors with a valuable tool to anticipate and mitigate student struggles.

### Tutoring Services Effectiveness

The research highlights the effectiveness of tutoring services in reducing DFW rates and improving student outcomes, offering institutions a data-driven approach to allocate resources and invest in support services.

### Future Research Directions

Future work is suggested to explore threshold limits on teaching assistants, cost-effectiveness analysis of different tutoring models, and quantifying student, instructor, and tutor behaviors to further enhance the predictive capabilities of the ABM.

## References

1. R. L. Axtell *et al.*, "Population growth and collapse in a multiagent model of the Kayenta Anasazi in Long House Valley", *Proceedings of the National Academy of Sciences*, vol. 99, no. suppl. 3, pp. 7275–7279, 2002.
2. D. M. Baskow and K. M. Carley, "Agent-based simulation of bot disinformation maneuvers in Twitter", in *2019 Winter simulation conference (WSC)*, 2019, pp. 750–761.
3. Rujimara, J. L. O. Campbell, and R. F. DeMara, "Exploring the Student-to-Faculty Ratio and Degree Attainment in Florida", *Journal of Hispanic Higher Education*, p. 15381927231172583, 2023.
4. DeMara, R. F., N. Khoshavi, S. Pyle, J. Edison, R. Hartshorne, B. Chen, et al., "Redesigning Computer Engineering Gateway Courses using a novel Remediation Hierarchy," in *Proceedings of American Association for Engineering Education National Conference (ASEE-16)*, New Orleans, LA, USA, June 26–29, 2016.
5. Chen, B., R. F. DeMara, S. Salehi and R. Hartshorne, "Elevating Learner Achievement Using Formative Electronic Lab Assessments in the Engineering Laboratory: A Viable Alternative to Weekly Lab Reports," in *IEEE Transactions on Education*, vol. 61, no. 1, pp. 1–10, Feb. 2018, doi: 10.1109/TE.2017.2706667.
6. DeMara, R. F., S. Shekhtsfal, P. J. Wilder, B. Chen, and R. Hartshorne, "BLUESHIFT: Rebalancing Engineering Engagement, Integrity, and Learning Outcomes across an Electronically-Enabled Remediation Hierarchy," *ASCE Computers in Education Journal*, Vol. 10, No. 1, pp. 1–13, January – March 2019.
7. DeMara, R. F., T. Tian, S. Salehi, N. Khoshavi and S. D. Pyle, "Scalable Delivery and Remediation of Engineering Assessments using Computer-Based Assessment," 2019 IEEE Integrated STEM Education Conference (ISEC), Princeton, NJ, USA, 2019, pp. 204–210, doi: 10.1109/ISEC.2019.8882114.
8. Paradiso, J. R., T. Muhs, and B. Chen, "Merging Human and Non-human (System) Data to Describe Students' Adaptive Learning Experience in Postsecondary Gateway Math Courses", in *International Conference on Human-Computer Interaction*, 2023, pp. 325–336.
9. NetLogo user community models, <https://csl.northwestern.edu/netlogo/models/community/Learning%20Equity>, Interaction%20of%20teacher-pupil-environment (accessed Apr. 7, 2024).
10. Shared, <https://shared.rii.org/content/agent-based-modeling-understanding-influence-teacher-student-interactions-learning-and> (accessed Apr. 11, 2024).
11. Amoruso, P., & Garibay, L. O., & DeMara, R. F. (2024, March), Instructor-Facing Graphical User Interface for Micro-Credential Designation and Refinement in STEM Curricula Paper presented at 2024 South East Section Meeting, Marietta, Georgia, 10.18260/1-2-45539.
12. Ghathi, G. and H. Yaghi, "Relationships among experience, teacher efficacy, and attitudes toward the implementation of instructional innovation", *Teaching and Teacher education*, vol. 13, no. 4, pp. 451–458, 1997.
13. Gausen, A., W. Luk, and C. Gao, "Can We Stop Fake News? Using Agent-Based Modeling to Evaluate Countermeasures for Misinformation on Social Media", in *ICWSM Workshops*, 2021.
14. Flaherty, C. "Scaling up student success: Solving higher ed's DFW problem," *Inside Higher Ed* | Higher Education News, Events and Jobs, <https://www.insidehighered.com/news/student-success/academic-life/2024/03/14/scaling-student-success-solving-higher-ed-dfw> (accessed Apr. 12, 2024).

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