# Enhancing Student Learning in Tertiary Education Through Simulation

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Abstract: Simulation-based learning has emerged as a transformative approach to enhancing student learning in tertiary education, bridging the gap between theoretical knowledge and practical application. Our university has employed simulation-based learning in an undergraduate course for nearly a decade, training thousands of students to foster active engagement, critical thinking, and problem-solving skills. The pivot of this approach is a virtual business simulation where students, organized in teams of five, manage a comprehensive business over a twelve-week semester. The simulation has multiple departments ranging from forecasting, finance, operations, transportation, and logistics to give our freshers a holistic overview of how to run a business and the interdependency and connection between departments. Student activities are continuously tracked during the simulation. As instructors, we can download the learner activities after the simulation game. It enables us to develop a predictive model with 90% accuracy in forecasting the students' final scores. This model supports timely, pre-emptive interventions to identify students who might need additional assistance and help them increase their active participation. At the end of the course, each team will give a fifteen-minute presentation to showcase their simulation results, strategic thinking, and data analysis skills using simulation-generated data. This paper provides valuable insights into best practices and future directions for leveraging simulations in tertiary education. It emphasizes the role of simulations in tertiary education, which fosters teamwork, critical thinking, and real-world business acumen. In addition, the simulation also effectively prepares students for professional success in a dynamic and competitive landscape.

# **1 INTRODUCTION**

Our business school welcomes students from diverse academic backgrounds, including those from local polytechnics and G.C.E. "A" level programs. While this diversity enriches the educational atmosphere, it also presents a challenge, as many students begin with limited knowledge of business concepts. We incorporated a cloud-based business simulation into one of our foundational courses to bridge this gap and provide a comprehensive foundation for the business program.

The course integrates business modeling with simulation. The objectives of this simulation are threefold. Firstly, it enables students to grasp a broad spectrum of business concepts, explore the dependency and interconnectivity among various business functions and departments, and understand how to operate a business through hands-on experiential learning. The course emphasizes problem-solving and self-directed learning, equipping students with business modeling, analytical skills, and a resilient mindset to thrive in complex, real-world scenarios.

Since early 2015, we have integrated MonsoonSIM, an innovative and unique pedagogical experiential learning platform, into our business curriculum. The platform immerses students in the complexities of managing a business, covering more than ten interconnected departments, such as retail, wholesale, e-commerce, production, finance, HR, and others. The students learn complex business operations and the fundamentals through an interactive and highly competitive game setting. Since there are more than ten departments with a maximum of five students in a team, each student needs to take charge of more than one department. Good communication skills and collaborative efforts are the byproduct of a successful simulation game. Additionally, the first simulation games act as an ice-

Ma, N. L., Chia, I. S. M. and Choy, M. J. Enhancing Student Learning in Tertiary Education Through Simulation. DOI: 10.5220/0013278300003932 Paper published under CC license (CC BY-NC-ND 4.0) In Proceedings of the 17th International Conference on Computer Supported Education (CSEDU 2025) - Volume 2, pages 705-712 ISBN: 978-989-758-746-7; ISSN: 2184-5026 Proceedings Copyright © 2025 by SCITEPRESS – Science and Technology Publications, Lda. breaker among the team members to get to know each other by having the same common goal of running a company successfully. Over the years, students have consistently given us feedback on the positive impact of the simulation game as an invaluable tool, enhancing their learning and ability to explore the multifaceted business world.

The contribution of this paper is twofold. First, we aim to share our experience designing and implementing a course incorporating simulationbased learning into our business program curriculum. We include a detailed overview of the pedagogical framework, the integration of MonsoonSIM as the simulation tool, and the assessment methodology student performance developed to evaluate effectively. The second objective of this paper is to create a predictive model to forecast the students' final score by leveraging the learner activities during the simulation game in the first week. This model is an early detector to identify at-risk students with low engagement and participation, enabling timely intervention to support their academic journey. With the advancement of technology, students today are leaving enormous amounts of digital traces online, such as login details, online learning platforms, and social media websites. By monitoring student performance through data-driven insights, we aim to optimize learning outcomes, foster personalized learning approaches, and improve overall academic success.

# 2 LITERATURE REVIEW

Granlund et al. (2000) designed a web-based simulation for learning. Using the C3Fire simulation, the authors highlighted how the four stages of the experiential learning cycle (concrete experience, reflective observation, abstract conceptualization, and active experimentation) helped students develop evaluation skills in a group educational setting. Desai et al. (2018) tested the efficacy of Project-Based Learning (PBL), an experiential learning approach, by comparing students' academic performance in two colleges. One group used PBL to solve real-world problems, while the other followed traditional lecture-based methods. The results of T-tests revealed a significant improvement in students' performance in Semester End Exams (SEE) and placements in the PBL group. It showed that experiential learning benefits students in the light of creativity and innovation, and problem-solving skills are needed for excellent academic performance.

Several studies have leveraged learning management system (LMS) data in educational data analytics to improve student achievement. Aldowah, Al-Samarraie, Wan Mohamad (2019), and Chiappe and Rodriguez (2017) have utilized LMS data to identify patterns that can inform interventions to improve student performance.

Ma and Chia (2020) developed a learning analytics course centered around PBL, focusing on solving real-world problems. The course received positive student feedback, and a follow-up study by Ma and Chia (2023) demonstrated how predictive models—such as decision trees, regression, and neural networks—could be used to predict student's cumulative grade point averages (CGPA) based on course performance. The regression model yields the lowest mean absolute error (MAE), suggesting its effectiveness in predicting the students' CGPA.

Based on the literature review, a notable gap emerges in using simulation-based learning to predict students' academic performance. Several authors have demonstrated the positive outcomes of simulation as it enhances students' engagement and improves their problem-solving ability. However, few have explored using the data generated through simulation activities to predict students' academic performance.

In the subsequent sections of this paper, we explore pedagogical frameworks designed to integrate simulations into our course successfully. We outline how simulations can be integrated and structured to support experiential learning and data collection for predictive analysis. In section four, we focus on how the learner activities, such as student interactions within the simulation game, can serve as meaningful data points to predict students' final scores. We explained the development of regression models and shared some actionable insights.

# 3 PEDAGOGICAL FRAMEWORKS

In this section, we focus on the pedagogical framework with the underlying teaching philosophy, teaching methods, and assessment methods to ensure the proper delivery of the course. We focus on the student's learning process, ensuring students have a high engagement level with the course materials and a comprehensive understanding of business functions. At the beginning of the course, simulation-based learning forms a core component, with MonsoonSIM providing a cloud-based dynamic

platform allowing students to play the game onsite or remotely at their convenience. Students are excited about playing the simulation game, where students immerse themselves in interactive scenarios that mimic real-world business operations. This hands-on experience allows students to apply theoretical knowledge to practical situations, enhancing their action-planning and strategic thinking abilities.

This compulsory course for all undergraduate business students aims to provide a comprehensive understanding of core business functions and their interrelationships within an organization. Through a combination of experiential learning techniques such as business simulation games, industry-driven case studies, and spreadsheet-based analysis students will develop critical skills in problem identification, decision-making, and business modeling.

### 3.1 Learning Objectives

The course is designed with six learning outcomes in mind:

- Formulate business problems using Spreadsheet techniques
- Apply data analysis skills for better decisionmaking
- Identify business strategies to deal with changes.
- Provide students with a holistic understanding of business operations and decision-making.
- Encourage collaboration and teamwork through group-based tasks.
- Foster critical thinking and problem-solving skills through simulation.

#### 3.2 Experiential Learning Approach

The framework emphasizes experiential learning, where students "learn by doing" in the MonsoonSIM simulation game. At the outset of the course, each lecturer will randomly assign all the students to a team of at most five at the beginning of the first seminar. Each team will manage a business selling products at retail, e-commerce, and wholesale to be financially substantial, with the highest revenues and profit at the end of the game. In a regular class, about 40 students forming eight teams will compete and be ranked based on some key financial indicators. Students are encouraged to watch the video on how to play the game before the lesson. During the session, the instructor dedicates approximately one hour to explaining the key functions of the virtual business environment. The lecturer will also show a demo of running the simulation game live, briefly

touching most of the functions. Before we started the game, lecturers gave students fifteen minutes for discussion. During the discussion, students identify their tasks and job roles in the game based on their prior knowledge of departments and experiences. Most students felt lost as it differed from most of the mobile phone games they had played. The setting for the actual game lasts for an hour, at least 75 simulated days, and each day will last about 45 seconds to minutes. It is an extensive, competitive, and interactive session where students actively manage a virtual business entity, navigating and coordinating the operations of various interdependent departments. The departments in the simulations are B2B or Wholesale, Customer Service, E-commerce, Finance and Accounting, Human Resources, Logistics and Warehouse, Maintenance, Marketing, MRP, Forecasting and Planning, Procurement, Production, and Retail.

During the simulation activities, detailed records of learner activities are maintained, providing valuable data for the authors to develop a predictive model. The simulation generates extensive transactional, operational, and financial data, which students can analyze after the game, using their data analysis and problem-solving skills. By interpreting these data, students formulate new business strategies to improve key performance indicators such as profit and loss, production efficiency, and inventory turnover ratios in the subsequent games.

Over the twelve-week semester, students engage in multiple offsite simulation games, learning through hands-on experience. Experiential learning allows students to explore many business functions under various scenarios and diverse business strategies. Through iterative gameplay, they refine their approaches, leveraging the insights gained from data analysis to optimize outcomes. While students may initially possess limited knowledge of business operations, the experiential learning process enables them to develop a deep understanding of the roles and interdependencies of various business departments.

# 3.3 Self-Directed Learning Approach

More than 70% of our university's students are working adults. Thus, their time at the university is limited. They want more emphasis on autonomy and independence. We upload all the teaching materials, including the study guide and e-textbook, which are available to all enrolled students six weeks before the start of the course. Attendance is strongly encouraged, but if the students cannot attend the class physically due to overseas work travel or commitment, there will be a means for them to continue learning. We provide a video recording of each semester, and students can self-learn by referring to these resources at their own pace and in their flexible time. We design pre-class quizzes to encourage students to self-learn and complete them online before class to promote knowledge acquisition. With the new technological advancement in learning management systems (LMS), we encourage students to develop self-directed learning and lifelong learning habits.

#### 3.4 Assessment Methods Overview

Our assessment method comprises several components designed to comprehensively evaluate students' understanding and application of course material. Here is the breakdown of each assessment component and its weight in the overall grade:

#### i. Pre-Class Quizzes (20%)

We administer four pre-class quizzes to actively motivate students to study the material before each lesson to evaluate their foundational understanding of essential concepts. Pre-class quizzes are part of the self-directed learning approach and equip students with meaningful participation in the upcoming class discussion. The pre-class quizzes are multiple choice questions (MCQ) and have twenty questions for each. Students can complete it within a week before the deadline. These quizzes account for 20% of the overall grade, which is critical in promoting proactive and consistent learning.

#### ii. Individual Assignment on Business Modeling (30%)

A substantial assessment component focuses on an individual assignment involving business modeling using spreadsheet tools. This assignment also includes a reflective question based on the outcomes of a simulation game. Typically, students excel in this assignment, demonstrating strong performance on this task and underscoring the importance of the learning process. This assignment contributed 30% of their overall grade. The assignment paper is published online at the start of the course, giving students four weeks to complete it independently. This extra timeline promotes comprehensive research and a thorough understanding of the course material.

#### iii. Simulation Games and Final Presentation (20%)

Students actively engage in multiple simulation game sessions throughout the course to improve their scores and ranking. Students' performance in the simulation is assessed through a comprehensive scoring matrix, which calculates a weighted average of multiple key performance metrics. The scoring matrix includes crucial financial indicators such as profit or loss, cash on hand, the customer satisfaction index from B2B and e-commerce, and the staff turnover ratio. These factors play a significant role in evaluating overall performance, reflecting the various aspects of a business's success. Instructors can select from a diverse range of over 30 combinations of key performance indicators (KPIs) tailored to different learning objectives and scenarios. This flexibility allows educators to create a customized assessment framework that aligns with the course goals and the specific skills they wish to evaluate. We finalized the scoring matrix at the beginning of the course. We shared it with the students at the first game, ensuring it was firmly established and consistent throughout all simulation games. Consistency is essential for accurately measuring and performance comparing students' across different rounds, as it helps to eliminate variability that could arise from changing evaluation criteria. By maintaining a stable scoring matrix, we can provide students with precise and reliable performance feedback, enhancing their learning experience and helping them improve their business acumen.

In week twelve, these game sessions culminate in a group presentation where students articulate their findings and strategic approaches developed during the simulations. The assessment of this presentation is guided by a detailed rubric evaluating key dimensions, including the quality of presentation delivery, the rigor of strategic application within the simulation, the depth and precision of data analysis, and the significance of the learning outcomes derived from the experience. The activity constitutes 20% of the overall course assessment, emphasizing its vital role in developing collaborative learning, critical thinking, effective communication, and teamwork.

#### iv. Final Examination (30%)

The course concludes with an open-book examination to assess students' comprehensive understanding of the course content. Students can use the Internet, wifi, and laptops during the two-hour exams, which feature two businessfocused questions. These questions require the development of spreadsheet models to solve complex, real-world problems, emphasizing the practical application of course concepts. The final examination accounts for 30% of the total assessment, one of the highest weights for the course assessment, similar to the assignment. Even though we encourage collation, at least 80% of the course assessment is based on the individual work effort. Setting the exam paper is quite a challenge for the instructors. It is required to meet at least 60% of the learning outcome and to ensure students can integrate and apply knowledge effectively in a structured, problemsolving context.

Typically, students find it challenging to excel in this final examination component. The difficulty arises because the problems presented are often unforeseen, requiring students to state their assumptions, work with unknowns, employ critical thinking, and adapt swiftly. Moreover, they face the added pressure of completing the exam within a strict two-hour time limit, which can exacerbate feelings of anxiety and hinder their ability to perform at their best. Even with the extensive online resources, such as study guides, eTextbooks, educational websites, and AI tools designed to assist with problem-solving, many students still struggle to achieve satisfactory results in this exam. This act of moderation enables the educator to accurately assess students' ability to apply their skills to real-world, unfamiliar problems, genuinely reflecting their proficiency.

# 4 PREDICTIVE MODELING WITH REGRESSION

When students engage in the simulation game, the platform meticulously tracks their activities by recording the number of transactions they perform during gameplay. Data collection is essential for analyzing how students interact with the game and can provide insights into their learning processes.

After the first match, the instructors can download all relevant data from the website, facilitating further analysis and review. We want to build a predictive model to use the data from the first week to predict the students' final course scores. The predictive model will help us identify students with low scores so we can engage those at-risk students early to improve their engagement and final academic achievement.

To maintain confidentiality and protect students' identities, we have taken measures to mask identifiable information and have assigned new student IDs exclusively for this analysis. The new student IDs are the primary key to the data analysis. We collected nearly a hundred student records from the most recent three semesters participating in the simulation games. Table 1 shows the data structure of the student data.

Table	1:	Student	data
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Description	Data Field	
Student ID	Categorical	
Learner activity count (X1)	The number of activities done by students in the first game.	
Pre-class quiz score (X2)	First Quiz score (0 - 100)	
Final score (Target: Y)	Final score (0 - 100)	

	Learner activity count	Pre-class quiz score	Final score
Mean	23.21	81.41	71.19
Standard Error	1.94	1.64	0.85
Median	19.	85	72.13
Mode	20	90	75.10
Standard Deviation	19.05	16.09	8.34
Minimum	0	0	45.1
Maximum	85	100	88.9

Table 2: Summary statistics of students' data.

Next, we will explore the descriptive statistics of the input variables to gain insights into student performance and engagement, as shown in Table 2. The activity count recorded during the simulation game is 23.2, with a standard deviation of 19. The significant standard deviation indicates considerable variability in students' activity levels, suggesting that some students were highly engaged while others had limited interaction with the game. The activity counts range from a minimum of zero to a maximum of 85, highlighting the diverse engagement experiences among participants. As educators, we can identify students whose learner activity count is less than ten for a consultation session. Based on the author's experience, students who are inactive in the game are struggling to keep up with the game's dynamics and feel at a loss. They cannot contribute and continue the game as other team members progress. They feel peer pressure and cannot perform due to their lack of skills and knowledge. Thus, setting up additional games to practice with the Robot (BOT) before the next game will help them gain more confidence and enhance their contribution and participation in future games.

Regarding academic performance, the mean preclass quiz score is 81.4, which can be categorized as relatively high, which indicates that students generally entered the course with a good understanding of the material since the course materials are available to them six weeks before the commencement of the course in the online learning portal. The average final score for the course is 71.2, with a mode of 75.1, suggesting that while many students performed around this score, there was also a spread in individual performances. The standard deviation for the final scores is 8.34, reflecting some variation in how students perform in the course.

Next, the authors will develop the regression predictive model to predict the student's final score (Y) using two input variables: learners' activities in the first simulation game (X1) and the first pre-class quiz (X2). Regression is a statistical model that finds the relationship between the independent variable Y and one or more dependent or explanatory variables X. The method assumes a linear relationship between the dependent variables (X)'s and the independent variable (Y). In this context:

Let *i* represent a student, where i = 1, 2, ..., N.

Let  $Y_i$  denote the final score of student *i*.

Let  $X1_i$  represent the learner activity count of student *i*.

Let  $\hat{Y}_i$  be the predicted final score of student *i*.

**Model 1** is a regression model that predicts the final score  $\hat{Y}_i$  solely based on the learner activity count (X1). Using the regression analysis, the linear equation derived is:

$$\hat{Y} = 0.0177 \,\text{X1} + 70.78 \tag{1}$$

We can use equation (1) to compute the predicted final score for any student. For example, if a student's activity count (X1) is 60, the predicted score ( $\hat{Y}$ ) can be calculated as:

$$\hat{Y} = 0.0177 * 60 + 70.78 = 71.84$$
 (2)

We compare the predicted score ( $\hat{Y}$ ) to the actual final score (Y) to evaluate the model. Suppose the

actual score (Y) for this student is 75. The absolute percentage error (APE) is computed as:

$$APE = \frac{|Y - \hat{Y}|}{Y} * 100\% = \frac{|75 - 71.84|}{75} * 100\% = 4\%$$
(3)

We use the Mean Absolute Percentage Error (MAPE) to measure the overall accuracy of the model, which is calculated for all students:

MAPE = 
$$\frac{\sum_{i=1}^{i=n} \frac{|Y_i - \hat{Y}_i|}{Y_i}}{n} * 100\%$$
 (4)

This metric summarizes the model's predictive accuracy as a percentage error. Using the formula for absolute percentage error, we can calculate the error for each student and then determine the average absolute percentage error to evaluate the model's accuracy. **Model 1** achieves a Mean Absolute Percentage Error (MAPE) of **8.47%**, indicating that students' activity counts can reasonably predict their final scores. However, the model has a significant limitation.

The activity count (X1) ranges from 0 to 85, and based on the regression equation,  $\hat{Y} = 0.0177 \text{ X1} +$ 70.78, the minimum predicted score for students with no recorded activity (X1 = 0) is 70.78, corresponding to the y-intercept. The prediction is problematic because it assumes that students with no activity will score at least 70.78. Historical data shows that approximately 30% of students score below 70, contradicting this assumption. Additional explanatory variables must be incorporated to address this issue and improve the model's accuracy. These variables could capture other aspects of student behavior, engagement, or external factors influencing performance. By incorporating more predictors, we aim to develop a more comprehensive model that aligns better with the observed distribution of scores and accounts for students scoring below the current minimum prediction.

To address Model 1's limitations and expand its predictive capability, we introduce an additional variable: the score from the pre-class quiz conducted during the first lesson. The first quiz is administered alongside simulation games in the same week, offering an early indicator of students' understanding and engagement with the course content. We intend to incorporate the pre-class quiz score into model 1 and aim to provide a more accurate prediction of final scores. If this variable proves to be a significant predictor, it will allow us to identify students at risk who are underperforming early in the course. Let  $w_1, w_2$ , represent the weights assigned to learner activity count and pre-class quiz score.

Let  $W_i$  be the weighted score of student *i*.

Let  $X1_i$  represent the learner activity count of student *i*.

Let  $X2_i$  represent the pre-class quiz score of student *i*.

Let  $\hat{Y}_i$  represent the predicted final score of student *i*.

**Model 2** uses the weighted score derived from the learner activity and pre-class quiz. In this model,  $\hat{Y}$  represents the predicted final score based on the combined contributions of X1 and X2, weighted by the coefficients  $w_1$  and  $w_2$ .

We initially assign equal weightage to the learner activity count and the pre-class quiz score, each contributing 50% to the weighted score. The score for each student i is calculated as follows:

$$W_i = w_1 * X1_i + w_2 * X2_i \tag{5}$$

where  $w_1 = 0.5$  and  $w_2 = 0.5$ .

The general regression line to predict the student's score is:  $\hat{Y}$  = intercept + (slope \* weighted score ).

Using regression analysis, we derive the linear equation:

$$\hat{Y} = 59.33 + 0.2267 \,\mathrm{W} \tag{6}$$

Using the above formula, we compute the absolute percentage error for each student and calculate the average to obtain the Mean Absolute Percentage Error (MAPE) given in equation (4).

**Model 2** achieves a MAPE of **7.96%**, demonstrating that combining the learner activity count and the preclass quiz score as predictors reduces the error compared to using a single variable. This indicates that the two variables provide a more accurate final score prediction. Next, we aim to determine the optimal weightage for the two components  $(w_1 and w_2)$  that minimizes the MAPE. The optimization is subject to the following constraint:

$$w_1 + w_2 = 1$$
 (7)

Equation (7) ensures that the total weight sum equals 1. We can identify the weight distribution that yields the lowest error by systematically adjusting  $w_1$  and  $w_2$  while recalculating the MAPE for each combination. For example,  $w_1$  could range from 0 to 1 in increments, with  $w_2 = 1 - w_1$ . The weighted score  $W_i$  and the corresponding MAPE is computed for each pair. This optimization process would allow us to assign the most balanced and optimal weightage between the learner activity count and the pre-class quiz score, improving the model's predictive performance.

Using the Excel solver tool, we identify the optimal weight distribution for the two predictors, assigning 30% weight ( $w_1 = 0.3$ ) to the learner activity and 70% weight ( $w_2 = 0.7$ ) to the pre-class quiz. Figure 1 produces the minimum MAPE of 7.80%, demonstrating a better predictive model than other weight combinations. This regression model is suitable for predicting the students' final scores with over 90% accuracy.

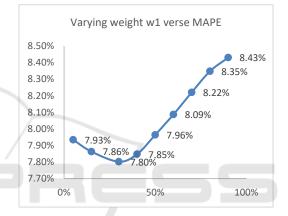


Figure 1: Varying weightage for the learner activity count and MAPE.

In conclusion, applying the optimal weight distribution to the predictive model offers educators a valuable tool for identifying academically at-risk students (those with predicted final scores of less than 60) who lack commitment to the course. Using this early detection, the model allows educators to make timely interventions, such as providing additional coaching, mentoring, and tailored additional support to help students strengthen their ability to learn and cope with the difficulties they face.

The active approach improves their academic performance and minimizes the likelihood of course failure, reducing the risk of attrition in their first semester. Ultimately, the predictive model serves as a critical resource for fostering student success and reducing long-term attrition rates at the university.

# **5** CONCLUSIONS

In this paper, the authors explore simulation tools in a tertiary education business program, highlighting their effectiveness in enhancing student engagement and promoting experiential learning. By developing a core business module, the authors share their pedagogical framework and assessment methods, providing valuable insights for educators considering similar course designs. The instructors also face challenges, such as scheduling simulation games after office hours and the dynamic nature of the gaming environment, which sometimes leave students feeling demotivated when strategies fail.

Incorporating predictive analytics into the pedagogical framework further amplified its impact by enabling early identification of at-risk students. By leveraging data from simulation activities and preclass quizzes, predictive models accurately forecasted student performance and facilitated timely interventions. These actionable insights improved academic outcomes and underscored the importance of analytics-based decision-making in education.

Future research could explore a more profound integration of simulations with other teaching methodologies to maximize their impact. With these advancements, simulation-based learning can evolve as a transformative educational tool, preparing students for success in an increasingly dynamic professional landscape.

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