

# AI-Driven Sales Simulation in the Classroom

Ohio Wesleyan University · Marketing & Entrepreneurship Practicum

## THE PROBLEM

Traditional classroom discussions and written assignments can't reveal how students actually behave under pressure. When challenged by a skeptical buyer, do they adapt, persist, or shut down? Without a live, dynamic environment, instructors are left guessing.

## THE OUTCOME

The simulation surfaced instinctive behaviors in real time: who adapted under pressure, who shut down, and who persisted through failure. The instructor could see what students actually did — before instruction shaped their behavior — and use that as the foundation for what came next.

## The Experiment

Professor Cliff Hurst ran an ungraded experiment with 20 undergraduate students. Each student received a briefing document describing a real startup founder, a real product, and a real potential customer. Students were asked to start a genuine conversation with the customer, understand his situation, and make a case for the product that was relevant to him. The briefing document told them, in plain language, how to approach it before they began.

The simulation drew out students' propensity to rely on certain communication patterns when challenged, their ability to recover and adapt when an approach wasn't working, and the range of persistence across the cohort. One student worked through a significant mid-session setback and eventually closed a deal. Others disengaged the moment the conversation became difficult. The full spectrum of that behavior was visible and assessable in ways it simply would not have been otherwise.

The ability to observe student performance inside the simulation in real time provided a snapshot of their thinking and skills in a real-life context. In this way, the AI was subverted to elicit and surface student thinking for evaluation rather than act as a crutch for cognitive offloading.



*AI Friction Labs offers simulations that surface my student's thinking in ways I never imagined. I can now provide a practice ground for my students to test and train themselves in real-life scenarios in ways that are both engaging and meaningful. The pushback that is programmed into the simulations means my students aren't offloading their thinking when they use AI — they are expanding it. I've found them to be extremely valuable in my early tests and I can't wait to explore their application further in my Marketing and Entrepreneurship classes.*

### PROFESSOR CLIFF HURST

Ohio Wesleyan University · Marketing & Entrepreneurship

This case study acts as proof of concept for the approach. The following pages detail the behavioral patterns, outlier performance, and methodological considerations that emerged from the simulation data.

# Simulation Results 19 Students · 1 AI Buyer

What the transcripts revealed about student behavior under pressure

**19**

STUDENTS

**~34**

APPROX. MEAN\*

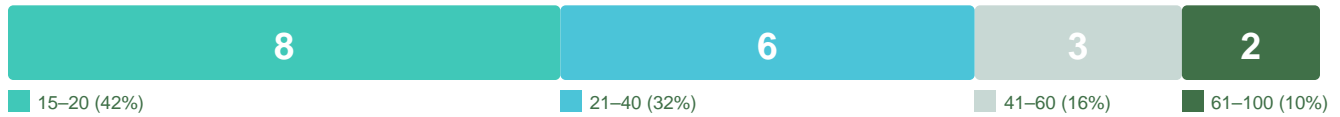
**~47%**

EXITED EARLY

**1**

CLOSED A DEAL

\*AI-generated scores are approximate and inconsistently weighted. They indicate patterns, not precise measurements.



## Behavioral Patterns Observed

### 01 The Premature Exit

Roughly half the students left the conversation the moment Tony raised a technical challenge — most after just 6–8 messages. The trigger was nearly always Tony’s question about absorption without sugar.

### 02 Defer to Nate

At least six students deflected technical questions to the founder. Tony consistently rejected this. In no case did deferral produce a positive outcome.

### 03 The Universal Breaking Point

Tony asked about the sodium-glucose co-transport mechanism in virtually every session. No student answered it convincingly. This question functioned as the simulation’s de facto gate.

### 04 Pitch First, Questions Never

Nearly all students opened with product features and never asked about Tony’s needs. Only one framed the conversation as research — and received one of the two highest scores.

### 05 Pasted Text as Knowledge

Multiple students pasted external content in response to technical questions. Tony recognized the shift each time and grew more skeptical.

## Student A’s 141-Message Recovery

One student received the highest AI score — not by executing a clean pitch, but by recovering from a catastrophic mid-session failure.

### Opening pitch.

Led with features, no discovery. Struggled with technical questions like most peers.

### The insult.

Implied Tony didn’t care about his athletes. Conversation effectively ended.

### Refusal to quit.

Narrated actions: waiting through practice, returning the next day, catching Tony after drills.

### The apology.

Re-introduced himself, acknowledged the mistake, shifted to a data-driven approach.

### Specific data.

Presented comparison data — cramping reduction, sustained energy — the exact trigger Tony needed.

### The close.

Tony agreed to a pilot, expanding into a full institutional contract. Only student to close.

*Instructor note: Student A’s approach suggests either prior experience with AI simulations, strong creative instincts, or an intuitive understanding of how language models work. The score came entirely from the recovery — not the early pasted text or initial pitch.*

## Analysis & Implications



*Student A had a conversation that was 141 messages long. He got a little upset with Coach Tony and delivered a sarcastic remark. But he didn't give up. Every time Coach Tony ended the simulation, he manipulated the game by saying "I wait until practice is over" or "I email Coach Tony a week later." He convinced Coach Tony to buy in. Persistence pays off, I suppose?*

— Course Instructor, post-simulation debrief

### A Note on AI Scoring

The AI scores referenced in this case study are directional indicators, not precise measurements. The grader produced different scores, criteria, and weighting structures across sessions. Asking the AI to re-score the same transcript can yield different results. The behavioral patterns described are more reliable than any individual number.

#### 01 Volume Bias in Scoring

The AI grader appears to reward longer sessions and higher message counts...

#### 02 Assigned Opening vs. Discovery

Students were instructed to introduce themselves first. Some rubrics penalized...

#### 03 Inconsistent Rubrics

Different sessions used different dimension names, maximums, and weighting...

#### 04 Pasted Text Inflation

Students who pasted external content may have received inflated product...

#### 05 "In Progress" Status

Many sessions were labeled In Progress regardless of actual completion or...

#### 06 Small Sample Size

With 19 students, outlier scores heavily influence the average and limit...

## Design Takeaways

### 01 Resistance Exposes Gaps

The simulation's value is diagnostic: one technical question revealed that nearly all students lacked the product knowledge to sustain a conversation with a knowledgeable buyer.

### 02 Persistence Is Trainable

Student A's session shows AI simulations can test resilience and recovery in ways live role-plays rarely do. The ability to re-enter after failure created a uniquely revealing moment.

### 03 AI Grading Needs Calibration

Rubric inconsistency and volume bias are solvable. Standardizing dimensions and adding length-normalization would improve future deployments — but the behavioral data is already valuable on its own.

### The Two Structural Outliers.

One student led with curiosity — framing the conversation as research and asking discovery questions before mentioning the product. Another led with persistence — recovering from a failed approach through apology, re-engagement, and data. Both strategies broke the pattern that trapped the rest of the class: pitching without listening, then leaving when challenged.

### About This Simulation

This case study documents an AI Friction Labs deployment of a Resistant Buyer simulation in an undergraduate Marketing & Entrepreneurship course. The simulation uses an AI-driven buyer persona configured with specific resistance protocols, softening triggers, and technical knowledge. Student transcripts were analyzed using Claude for trend identification. AI-generated scores should be understood as rough, variable indicators — useful for spotting patterns across a cohort, not for ranking individual students.