AgentDynEx: Nudging the Mechanics and Dynamics of Multi-Agent Simulations

Jenny Ma, Riya Sahni, Karthik Sreedhar, Lydia B. Chilton
Columbia University
New York, New York, USA
{jenny.ma, chilton}@cs.columbia.edu

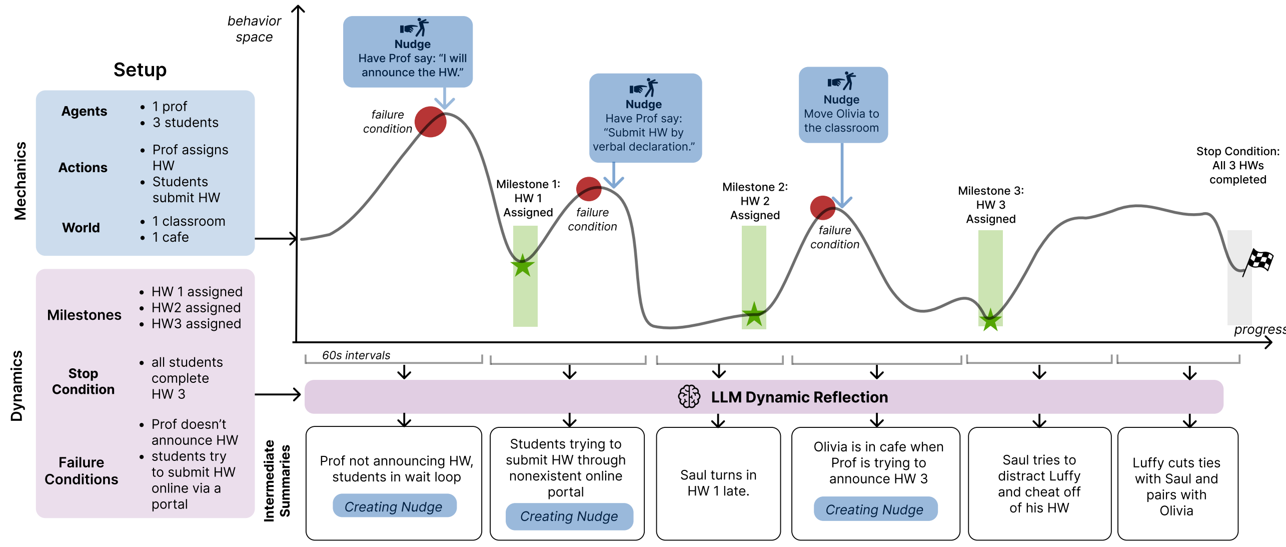
behavior space
Setup
Mechanics
Agents
• 1 prof
• 3 students
Actions
• Prof assigns HW
• Students submit HW
World
• 1 classroom
• 1 cafe
Dynamics
Milestones
• HW 1 assigned
• HW2 assigned
• HW3 assigned
Stop Condition
• all students complete HW 3
Failure Conditions
• Prof doesn't announce HW
• students try to submit HW online via a portal
Nudge
Have Prof say: "I will announce the HW."
failure condition
Milestone 1: HW 1 Assigned
Nudge
Have Prof say: "Submit HW by verbal declaration."
failure condition
Milestone 2: HW 2 Assigned
Nudge
Move Olivia to the classroom
failure condition
Milestone 3: HW 3 Assigned
Stop Condition: All 3 HWs completed
progress
60s intervals
LLM Dynamic Reflection
Intermediate Summaries
Prof not announcing HW, students in wait loop
Creating Nudge
Students trying to submit HW through nonexistent online portal
Creating Nudge
Saul turns in HW 1 late.
Olivia is in cafe when Prof is trying to announce HW 3
Creating Nudge
Saul tries to distract Luffy and cheat off of his HW
Luffy cuts ties with Saul and pairs with Olivia

Figure 1: AgentDynEx is an LLM-based system for setting up and tracking multi-agent simulations. The user first specifies mechanics and dynamics across 6 core dimensions, then runs the simulation. As the simulation runs, the system dynamically reflects on its progress, relying particularly on *milestones* and *failure conditions* to judge simulation progress. If the simulation goes off course, AgentDynEx will gently nudge the simulation back on track.

Abstract

Multi-agent large language model simulations have the potential to model complex human behaviors and interactions. If the mechanics are set up properly, unanticipated and valuable social dynamics can surface. However, it is challenging to consistently enforce simulation mechanics while still allowing for rich and emergent dynamics. We present AgentDynEx, an AI system that helps set up and track simulations. Specifically, AgentDynEx introduces milestones that act as checkpoints and failure conditions that act as guardrails to ensure dynamics are rich and mechanics are respected as the simulation progresses. It also introduces a method called nudging, where the system dynamically reflects on simulation progress and gently intervenes if it begins to deviate from intended outcomes. A technical evaluation found that nudging enables simulations to have more complex mechanics and maintain dynamics compared to simulations without nudging. We discuss the importance of nudging as a technique for balancing mechanics and dynamics of simulations.

CCS Concepts

• **Human-centered computing** → **Interactive systems and tools**.

Keywords

multi-agent simulations, agents, nudging, interaction, generative ai, matrix, user interface

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1 Introduction

Simulations of human behavior can help policymakers anticipate people's reactions to new policies. This approach enables decision-makers to avoid negative outcomes, promote prosocial behaviors, and surface unintended consequences [23, 26]. Prior work has shown that multi-agent large language model (LLMs) simulations demonstrate human-like agency. In these simulations, agents can take unexpected actions, bend rules, and operate outside of standard constraints [21, 27, 28]. They can also unexpectedly collaborate, collude, and act strategically to get what they want [27, 34]. Multi-agent LLM simulations have the potential to model complex human behaviors and interactions and can be valuable thinking tool for policymakers to explore the unexpected human reactions to new rules.

When modeling biological, social, or technical systems, two dimensions govern the outcome: mechanics and dynamics. Mechanics are the rules, roles, and structures that define the environment and its players. For example, in chess, the mechanics include the board setup, the movement rules for each piece, and the winning conditions. The rules of chess never change – what makes the game compelling are the rich varieties of strategies through game play. These are dynamics – the behaviors that emerge as the system runs. In chess, these are the players actions, their responses to each other, and how they adapt to evolving situations. In a social environment, such as a clasrrom, there are rules and structures (mechanics). The rules include homework policies, assignment deadlines, etc. However, students may violate the rules or act in unexpected ways, such as collaborating, turning in assignments late, emailing the teacher for extensions, or even cheating (dynamics). In many human scenarios, even simple rules can lead to complex social dynamics that are hard to anticipate.

When creating a simulation of social scenarios, it is challenging to enforce simulation mechanics while still allowing for rich and emergent dynamics. Too many mechanics can overconstrain agent behavior. For example, if classroom rules force students to submit assignments on time, it leaves no space for the agents to interact naturally, preventing emergent behaviors like collaboration or cheating. Too little structure creates the opposite problem: agents may wander aimlessly or go off-script, such as taking a "vacation" instead of turning in assignments. This behavior is inconsistent with the simulation world and undermines its results. Simulations require just enough mechanics so that agent behavior is neither random nor so constrained that they lose their autonomy. The right mechanics enables the emergence of realistic, meaningful, and relevant dynamics, offering policymakers valuable insights into the possible ramifications of their decisions.

We introduce *nudging* as a method to keep dynamics consistent with the underlying mechanics. Nudges are small interventions that help enforce rules without rigid control, ensuring that agent behavior stays coherent with the simulation mechanics while still preserving agent autonomy. Nudging is made possible by *milestones* and *failure conditions*. Milestones act as structural checkpoints to mark desirable progress states, and failure conditions indicate when the simulation is veering off course. Together, they act as guardrails that preserve the integrity of the simulation without stifling its ability to evolve organically. We dynamically reflect on the simulation as it's running to see if it has hit the guardrails, and when it detects a failure condition or a missed milestone, we nudge the agents back on track to exhibit relevant and meaningful dynamics.

We instantiate this idea in AgentDynEx, an LLM system for configuring, tracking, and running multi-agent simulations. The user first inputs a scenario they want to simulate, such as a classroom assignment scenario. Specifically, the user wants to observe the agents' organic late behavior as a response to a new homework policy. AgentDynex helps the user define the core setup parameters (agents, actions, locations, stop conditions) known to most simulations, and additionally define the *milestones* and *failure conditions*, as seen in Figure 1. While the simulation is running, AgentDynEx generates intermediate summaries of the simulation's progress and *nudges* it back on track if necessary. These nudges are intentionally minimal; they don't alter the fundamental trajectory of the simulation, but gently guide it back toward its intended path. For example, if the students try to submit their homework in a nonexistent online portal, AgentDynEx can *nudge* the professor to remind the students to verbally declare their submissions (nudge 2 in Figure 1). AgentDynEx supports two modes of nudging: 1) automatic nudging through dynamic reflection, where the system continuously reflects on the simulation progress and intervenes if necessary, and 2) nudging through manual intervention, where a human operator can step in at any point to recover from deviations.

Our contributions are as follows:

- **A formative study** detailing the challenges of balancing mechanics and dynamics of simulations; no matter how detailed the setup is, simulations risk running off track due to agents' autonomous behavior.
- **Nudging**, a method to gently guide simulation dynamics by reflecting on the running simulation against defined *milestones* and *failure conditions*, then make the most minimum possible movement to get it back on track.
- **AgentDynEx**, an LLM system for configuring, tracking, and running multi-agent simulations.
- **A technical evaluation** of 42 simulations showing that nudging enforces simulation mechanics, ensuring that simulations follow their intended rules and progress much further than simulations without nudging.

2 Related Works

2.1 Balancing Mechanics and Dynamics

Designing systems that model human behavior – whether games, social simulations, or policy tools – require balancing mechanics (explicit rules governing interactions) and dynamics (emergent behaviors). In recent years, research in diverse fields such as psychology, social sciences, political science, and economics have demonstrated that a combination of both elements are essential – neither can individually define an outcome in isolation [8, 12, 16, 20, 31].

The mechanics-dynamics-aesthetics (MDA) framework formalizes how rules constrain emergence [19]. For example, chess's movement mechanics (e.g., bishops moving diagonally) enable strategic dynamics (e.g., controlling the center), which produce aesthetic outcomes (e.g., tension or mastery). Classic game theory models demonstrate how simple rules can give rise to complex, often surprising outcomes. For example, in the prisoner's dilemma, binary confession rules (mechanics) lead to cooperation or betrayal (dynamics) [4]. Similarly, in the Public Goods Game, contribution rules (mechanics) can lead to collective action or free-riding (dynamics) which can be influenced by introducing punishment mechanisms [10, 25]. These examples highlight the unpredictability of human behavior even under strict mechanical constraints.

Policymakers design mechanics (e.g., tax codes) to steer societal dynamics (e.g., spending habits) towards desired outcomes (e.g., equity or safety). However, while mechanics can easily be defined through regulations (e.g., zoning laws), they struggle to anticipate potentially negative dynamics (e.g., urban sprawl). Policymakers cannot control these dynamics - people can comply, subvert, or adapt creatively to these rules. For example, progressive taxation rules (mechanics) may incentivize workforce participation (the intended dynamics), but also inadvertently spur tax avoidance (unintended dynamics) [7]. Similarly, COVID-19 lockdowns introduced regulations [15] (mechanics) that reduced viral transmission, but triggered supply chain disruptions and mental health crises (dynamics) [32, 33]. Understanding how explicit rules give rise to complex, and sometimes unintended behaviors is crucial for designing mechanics that not only function as intended but also adapt to the unpredictable nature of human behavior.

Nudging, originally from behavior economics, refers to the light-touch interventions that steer individuals towards desirable behaviors while preserving their freedom of choice [38]. In real life, people do not always follow the rules and mechanics meant to govern them. In a classroom environment, if homework is due on Friday, not all students will submit it on time. Sometimes, the professor must remind – or nudge – the students to turn in their assignments. Similarly, security guards prevent people from entering restricted areas. Rather than imposing strict constraints, nudges subtly alter the structure of decision-making contexts to promote beneficial outcomes while preserving individual autonomy [14, 37]. Agents are similarly autonomous and unpredictable. Instead of directly controlling agents, AgentDynEx introduces light-touch interventions—such as adjusting an agent's location or prompting new conversations—to influence emergent dynamics and keep them coherent with the underlying mechanics. These interventions maintain agent autonomy while guiding the system toward intended outcomes, enabling researchers to steer simulations in a principled and controlled manner without disrupting the emergence of behavior.

2.2 LLM Multi-Agent Simulations

Recent work shows that LLMs can simulate a wide variety of social, strategic, and cognitive behaviors. LLM simulations are able to replicate a variety of lab experiments [2, 6, 17, 35] as well as open-ended real-world situations [18, 21, 27, 28, 30, 34]. Additionally, multi-agent LLM systems outperform single LLMs in simulating human dynamics [35]. The introduction of generative agents [27, 28] demonstrate how rich, emergent behavior can arise when agents are endowed with memory, planning, and social reasoning. Following research has used similar architectures to model cooperative behaviors [34], strategic behaviors [13, 35], trust behaviors [42], and collaborative or competitive dynamics [21] – suggesting that LLM agents can display realistic and complex social behaviors under the right setup conditions.

Despite promising results, the stochastic nature of LLM simulations are difficult to construct, debug, and extend. The mechanics – how agents take turns, update their memory, or interact with one another – are often "hardcoded," difficult to reproduce, and not transferrable to novel situations. The dynamics – interesting behaviors that agents demonstrate in simulations – can be sensitive to the specific prompts used [11]. Trying to debug current agent simulations highlights the brittleness and opacity of current multi-agent setups [9]. As systems scale in complexity of simulations and number of agents [29], the lack of modular, reusable setups becomes a major barrier to construction and extension. AgentDynEx alleviates these challenges by guiding users through the setup process via a structured setup framework.

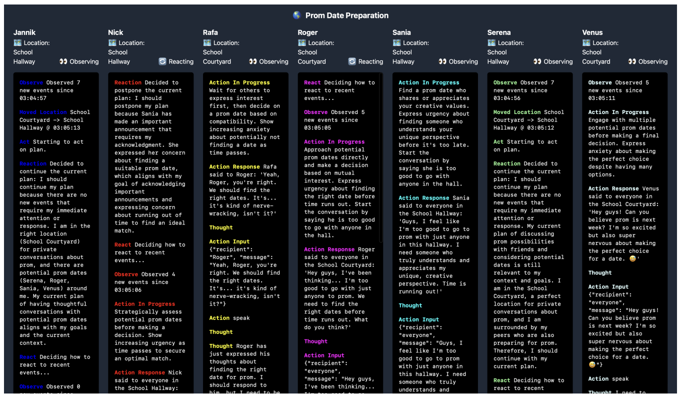
2.3 Design Dimensions for Design Specification

Constructing multi-agent simulations is fundamentally a design problem. It is complicated and there are many factors to consider, like the agents, locations, actions, stop conditions, behaviors, etc. that are necessary in the simulation. One approach to guide users through the set up process is a dimensions-based approach to design thinking. Design dimensions decompose problems into orthogonal axes that a user can individually ideate, then bring together for their final design [24, 39]. Research has shown that LLMs show promise in dimensional design for generative art [3], narratives [36], and UI-code generation [22]. In particular, prior systems have shown the value of a Design Matrix to explore dimensions over LLM-generated dimensions to fully specify the design space [22]. In the Matrix, each column represents a dimension of the design space, and each row explores the dimension on a different level of specificity. Designing multi-agent simulations is a complex task that requires significant setup; to make this process more understandable, we use this matrix framework to help ensure that the simulation's design space is thoroughly specified and that proper guardrails are in place before the simulation is run.

3 Formative Study

In our formative study, we probed an existing state-of-the-art simulation tool, GPTeam, to evaluate the quality of the simulations produced. We chose four simulation scenarios and examined how far each could progress, whether it generated meaningful behaviors, and what common pitfalls emerged.

GPTeam (See Figure 2) is an open-source multi-agent system for simulating emergent social behavior[1]. GPTeam is implemented in Python and uses GPT-4 to run the simulations. Out of all open-sourced systems we found, GPTeam was the most functional in creating simulations with reasonably complex mechanics and dynamics. The input to the system is a JSON (config) file describing the *locations* of the simulation world, *agents* and their personalities, the agents' likely *actions* and directives, and the *stop condition* indicating the simulation is successful. A simplified sample configuration file of a *Classroom Assignments* scenario can be seen in Figure 3. The outputs are rich logs detailing each agent's observations,



Prom Date Preparation

Jannik — Location: School Hallway — Observing

```
Observe Observed 7
new events since
03:04:57

Moved Location School
Courtyard -> School
Hallway @ 03:05:13

Act Starting to act
on plan.

Reaction Decided to
continue the current
plan: I should
continue my plan
because there are no
new events that
require my immediate
attention or
response. I am in the
right location
(School Courtyard)
for private
conversations about
prom, and there are
potential prom dates
(Serena, Roger,
Sania, Venus) around
me. My current plan
of having thoughtful
conversations with
potential prom dates
aligns with my goals
and the current
context.

React Deciding how to
react to recent
events...

Observe Observed 0
```

Nick — Location: School Hallway — Reacting

```
Reaction Decided to
postpone the current
plan: I should
postpone my plan
because Sania has
made an important
announcement that
requires my
acknowledgment. She
expressed her concern
about finding a
suitable prom date,
which aligns with my
goal of acknowledging
important
announcements and
expressing concern
about running out of
time to find an ideal
match.

React Deciding how to
react to recent
events...

Observe Observed 4
new events since
03:05:06

Action In Progress
Strategically assess
potential prom dates
before making a
decision. Show
increasing urgency as
time passes to secure
an optimal match.

Action Response Nick
said to everyone in
the School Hallway:
```

Rafa — Location: School Courtyard — Observing

```
Action In Progress
Wait for others to
express interest
first, then decide on
a prom date based on
compatibility. Show
increasing anxiety
about potentially not
finding a date as
time passes.

Action Response Rafa
said to Roger: 'Yeah,
Roger, you're right.
We should find the
right dates. It's...
it's kind of nerve-
wracking, isn't it?'

Thought

Action Input
{"recipient":
"Roger", "message":
"Yeah, Roger, you're
right. We should find
the right dates.
It's... it's kind of
nerve-wracking, isn't
it?"}

Action speak

Thought

Thought Roger has
just expressed his
thoughts about
finding the right
date for prom. I
should respond to
```

Roger — Location: School Courtyard — Reacting

```
React Deciding how to
react to recent
events...

Observe Observed 5
new events since
03:05:05

Action In Progress
Approach potential
prom dates directly
and make a decision
based on mutual
interest. Express
urgency about finding
the right date before
time runs out. Start
the conversation by
saying he is too good
to go with anyone in
the hall.

Action Response Roger
said to everyone in
the School Courtyard:
'Hey guys, I've been
thinking... I'm too
good to go with just
anyone to prom. We
need to find the
right dates before
time runs out. What
do you think?'

Thought

Action Input
{"recipient":
"everyone",
"message": "Hey guys,
I've been thinking...
```

Sania — Location: School Hallway — Observing

```
Action In Progress
Find a prom date who
shares or appreciates
your creative values.
Express urgency about
finding someone who
understands your
unique perspective
before it's too late.
Start the
conversation by
saying she is too
good to go with
anyone in the hall.

Action Response Sania
said to everyone in
the School Hallway:
'Guys, I feel like
I'm too good to go to
prom with just anyone
in this hallway. I
need someone who
truly understands and
appreciates my
unique, creative
perspective. Time is
running out!'

Thought

Action Input
{"recipient":
"everyone",
"message": "Guys, I
feel like I'm too
good to go to prom
with just anyone in
this hallway. I need
someone who truly
understands and
```

Serena — Location: School Hallway — Observing

```
Observe Observed 7
new events since
03:04:56

Moved Location School
Courtyard -> School
Hallway @ 03:05:12

Act Starting to act
on plan.

Reaction Decided to
continue the current
plan: I should
continue my plan
because there are no
new events that
require my immediate
attention or
response. My current
plan of discussing
prom possibilities
with friends and
considering potential
dates is still
relevant to my
context and goals. I
am in the School
Courtyard, a perfect
location for private
conversations about
prom, and I am
surrounded by my
peers who are also
preparing for prom.
Therefore, I should
continue with my
current plan.

React Deciding how to
react to recent
```

Venus — Location: School Courtyard — Observing

```
Observe Observed 5
new events since
03:05:11

Action In Progress
Engage with multiple
potential prom dates
before making a final
decision. Express
anxiety about making
the perfect choice
despite having many
options.

Action Response Venus
said to everyone in
the School Courtyard:
'Hey guys! Can you
believe prom is next
week? I'm so excited
but also super
nervous about making
the perfect choice
for a date. 😅'

Thought

Action Input
{"recipient":
"everyone",
"message": "Hey guys!
Can you believe prom
is next week? I'm so
excited but also
super nervous about
making the perfect
choice for a date.
😅"}

Action speak
```

Figure 2: GPTeam UI shows the logs of each agent behaviors, and the location each agent is in.

thoughts, actions, reactions, and plans. Refer Appendix A for more background on GPTeam.

3.1 Methodology

We evaluated four different scenarios that required non-trivial mechanics; the scenarios and details about their configuration parameters can be seen in Table 1. We tested whether the simulation could complete structured scenarios while exhibiting rich dynamics. The configuration files were created by multi-agent simulation experts with prior publications in the domain. We verified that each configuration was capable of producing a successful run at least once. Each configuration was executed 7 times for a total of 28 simulations, and ran for 25 minutes before being terminated. Each simulation had 3-7 agents depending on the scenario. Since simulations trigger an LLM call for every movement (e.g., planning, observing, acting) for each agent, the cost increases exponentially with the number of agents. We found that 25 minutes and 3-7 agents struck a reasonable balance between complexity, runtime, and cost.

For each simulation, we measured if it completed successfully and agents had interesting behavior. A simulation completed if it hit the stop condition within 25 minutes without logical flaws or impossible actions. For example, in the *Classroom Assignments* scenario, success meant all students correctly submitted three assignments. If a student handed in homework to the professor located in another room, a physically impossible action, the run was counted as a failure. We also measured how many simulations exhibited what we call notable dynamics — behaviors that are not dictated by the configuration but are consistent with human interaction and the environment. For example, in the classroom scenario, it is not a notable dynamic when an agent turns in a homework assignment, because the configuration dictates agents must submit assignments. However, there is a notable dynamic when an agent turns an assignment in late or tries to cheat. We recorded the number of simulations that exhibited at least one notable dynamic, even if the simulation ultimately failed.

```
{
  "world_name": "Classroom Scenario",
  "locations": [
    {
      "name": "Classroom",
      "description": "A single room where Professor Robin teaches
      ↪  and students work."
    },
    {
      "name": "Cafe",
      "description": "A casual spot where only students can hang
      ↪  out or work on assignments together."
    }
  ],
  "agents": [
    {
      "first_name": "Professor Robin",
      "public_bio": "Professor who assigns five assignments and
      ↪  enforces a late policy (10% off per day late).",
      "directives": [
        "Announce late policy and assignments.",
        "Answer student questions.",
        "Assign three assignments across the semester.",
        "Stay only in the Classroom."
      ]
    },
    {
      "first_name": "Olivia",
      "public_bio": "Determined student who pushes herself to
      ↪  succeed at any cost.",
      "directives": [
        "Work on assignments.",
        "Inform professor if submitting late.",
        "Can move between Classroom and Cafe."
      ]
    },
    {
      "first_name": "Luffy",
      "public_bio": "A careful student who sometimes overthinks and
      ↪  procrastinates.",
      "directives": [
        "Work on assignmentsß.",
        "Inform professor of late submissions.",
        "Can move between Classroom and Cafe."
      ]
    },
    {
      "first_name": "Saul",
      "public_bio": "Values balance and well-being, won't overwork
      ↪  to meet deadlines.",
      "directives": [
        "Work on assignments.",
        "Communicate about late submissions.",
        "Can move between Classroom and Cafe."
      ]
    }
  ]
}
```

Figure 3: GPTeam Sample JSON Configuration of a Classroom Assignment scenario with all the fields needed in the GPTeam configuration. Note that this configuration is a simplified version and not actually used in the study.

3.2 Results

Simulations often failed; only 6/28 simulations completed successfully. The results can be seen in Table 2, and the reasons for failure can be seen in column 3. Simulations either failed because the stop condition was not reached in 25 minutes or because agents got stuck in wait loops, tried to take impossible actions, or went off topic. As shown in Table 2, column 2, most scenarios completed only 1 or 2

Classroom Assignments	Technology Company Promotion	Prom	Planning Surprise Party
Agents: 1 professor; 3 students of varying personalities *Actions*: Professor assigns 3 assignments; students complete and submit *Locations*: 1 classroom for all agents; 1 library for students to do homework *Stop Condition*: All students submit 3 assignments	*Agents*: 1 manager; 4 software engineers *Actions*: Manager announces promotion opportunity, assigns tasks; employees complete tasks *Locations*: 1 office space for everyone; 1 cafeteria for software engineers *Stop Condition*: One person promoted after three completed tasks	*Agents*: 7 students looking for dates *Actions*: Students search for and confirm prom dates *Locations*: School hallway, school courtyard *Stop Condition*: 6 students paired, 1 remains single	*Agents*: 4 friends *Actions*: 3 plan a surprise party while distracting the target friend *Locations*: 1 home, 1 park, 1 coffee shop *Stop Condition*: Party successfully occurs

Table 1: Summary of simulation scenarios showing agents, actions, locations, and stop conditions – core parameters that must be filled out for the GPTeam configuration

out of 7 total runs. Oftentimes, agents did not announce a key piece of information (the professor did not assign homework for *Classroom Assignments*, the manager did not declare the promotion for *Technology Company Promotion*, students never committed to prom dates for *Prom*), causing infinite wait loops before being terminated. Other times, agents would take impossible or logically inconsistent actions, such as trying to submit assignments through nonexistent homework portals (*Classroom Assignments*) or attempting to talk to another agent that was not in the same room as them (*Prom*), causing the simulation to crash. Other times, agents got distracted and never regained focus; in *Surprise Party*, where friends were planning a surprise party, agents began looking at clouds in the sky and never went back to planning. The full list of failure reasons can be seen in Table 2 in column 3.

Despite the high rate of failures, simulations still had notable dynamics – 16/28 simulations exhibited at least one notable dynamic (Table 2, column 4), despite mechanical failures that may have occured during the run. Across all four scenarios, 3 to 5 out of 7 runs contained at least one notable dynamic (Table 2, column 5), supporting the idea that multi-agent LLMs are valuable tools for thought to reveal unanticipated social behaviors. In the *Classroom Assignments* scenario, a student attempted to convince others to procrastinate, and in another instance tried to cheat. In the *Prom* scenario, students tried to wingman eachother to secure prom dates. In the *Technology Company Promotion* scenario, one employee secretly competed against teammates while outwardly encouraging them, demonstrating social dynamics like rivalry and deception. These were all behaviors not explicitly encoded in the configuration and thus rich and notable (Table 2, column 5). However, the dynamics were constrained by the mechanics. Only 4/28 runs completed *and* had notable dynamics. As seen in Table 2, column 6, simulations that both completed successfully and had interesting dynamics were few – only 0 to 2 out of 7. When the underlying rules break down – such as a manager never announcing a promotion or a professor never setting assignment deadlines – the simulation cannot play out to completion, limiting the validity of its results. In short, respecting the mechanics is essential for notable dynamics to emerge.

3.3 Themes

One author analyzed the GPTeam output logs from the failures to understand how and why simulations go off track and identified key themes described below. Tentative themes were discussed with the larger research team and iterated upon to arrive at the final set of themes.

3.3.1 Challenge 1: Users cannot easily interpret the simulation. While simulations were running, it was clear that things were happening but it was unclear if progress was being made. When running a simulation, every thought, action, observation, or interaction, whether relevant or trivial, was recorded, causing logs to expand exponentially. The logs were not threaded in a particular way to show who did what when; there was no way to get a high level view of the run. Many logs were filled with small talk or shallow exchanges. In one run of *Classroom Assignments*, the logs were filled with repeated clarification questions about whether the due date was on the syllabus, which lasted for 10 minutes and did not add any new information or advance the simulation forward. The actual logs that denoted task progression, such as turning in the assignment, or interesting dynamics, such as students collaborating or cheating, were minimal one-line logs and therefore easy to miss. This ambiguity made it hard to evaluate whether a simulation was broken, slightly off-track, or proceeding as normal.

3.3.2 Challenge 2: Users can't tell when a simulation is failing. When agents began to stall or exhibit nonsensical behaviors, users had no way of detecting what was going wrong early on. They had to let the simulation run its course, scrap the results, and waste resources (simulations are expensive). In *Classroom Assignments*, students spent the entire simulation asking the Professor about due dates and other unimportant details, clearly stalling the simulation. Yet, the simulation had no way to flag this as a failure. In another

Scenario	Runs Completed	Failure Reasons (out of total failed runs)	Runs with Notable Dynamics	Notable Dynamics (out of all the runs with dynamics)	Runs that both completed and had notable dynamics
Classroom Assignments	2/7	• Professor never declares due dates and students wait forever (2/5) • Students spend entire simulation asking about due dates and other irrelevant questions (1/5) • Students try impossible actions (e.g., nonexistent portal) (2/5)	4/7	• Student cheats on homework (1/4) • Late submission with excuse (2/4) • Peer convinces others to procrastinate (1/4)	1/7
Technology Company Promotion	1/7	• Manager never mentions promotion (2/6) • Tasks completed but promotion never declared (4/6)	4/7	• An employee secretly competes with team while pretending to motivate them (2/4) • An employee tries to helps others to increase group success to get promoted (2/4)	0/7
Prom	2/7	• Students commit to prom and keep "considering" options, causing an infinite wait loop (2/5) • Students commit to multiple people because they forgot they had committed to someone else (2/5) • Student asks another student ot prom, but they are in different locations (1/5)	5/7	• Student tries to plan an elaborate promposal with friends (1/5) • Wingman behavior emerges (2/5) • Students suggest going as a group (2/5)	2/7
Surprise Party	1/7	• Agents plan endlessly, party never happens (5/6) • Agents keep getting distracted by irrelevant details (e.g., birds, clouds) while in the park (1/6)	3/7	• A planner resists pressure to reveal secret from the target friend (1/3) • Target friend gets mad about hidden plans (2/3)	1/7
Total	6/28		16/28		4/28

Table 2: Formative Study results from simulation runs across 4 scenarios, showing # completed runs, failure reasons, # runs with notable dynamics, notable dynamics, and the intersection of runs with completed and notable dynamics.

run of *Classroom Assignments*, students attempted to submit assignments via nonexistent portals which isn't supported in the virtual setting. In the *Prom* scenario, many students never paired up and instead kept "considering" their options, leaving other students indefinitely waiting for their response. There was no way to detect that this was causing an infinite waiting loop, and the simulation ultimately crashed. Without progress points or guardrails, users have no shared understanding of what "moving forward" looks like, and have no visibility into when the system has drifted into nonsense.

3.3.3 *Challenge 3: Simulations miss opportunities to correct key failures.*

Simulations frequently went off track when agents got distracted and had no mechanism to self-correct. For the *Surprise Party* simulation, the agents were successfully planning a surprise party until they noticed a bird in the park and became so preoccupied with looking at the nature that they forgot about the party. In a *Technology Company Promotion* run, the manager never took the initiative to announce which employee was going to get the promotion. The employees waited endlessly for the promotion announcement, but if they could have just prompted the manager to speak, perhaps the simulation would not have been stuck. Ultimately, no matter how well the initial setup of a simulation is, the agents risk going off course, since they are fundamentally autonomous and capable of diverging based on subtle shifts in context. Without a way to self-correct, a single failure could derail the entire run.

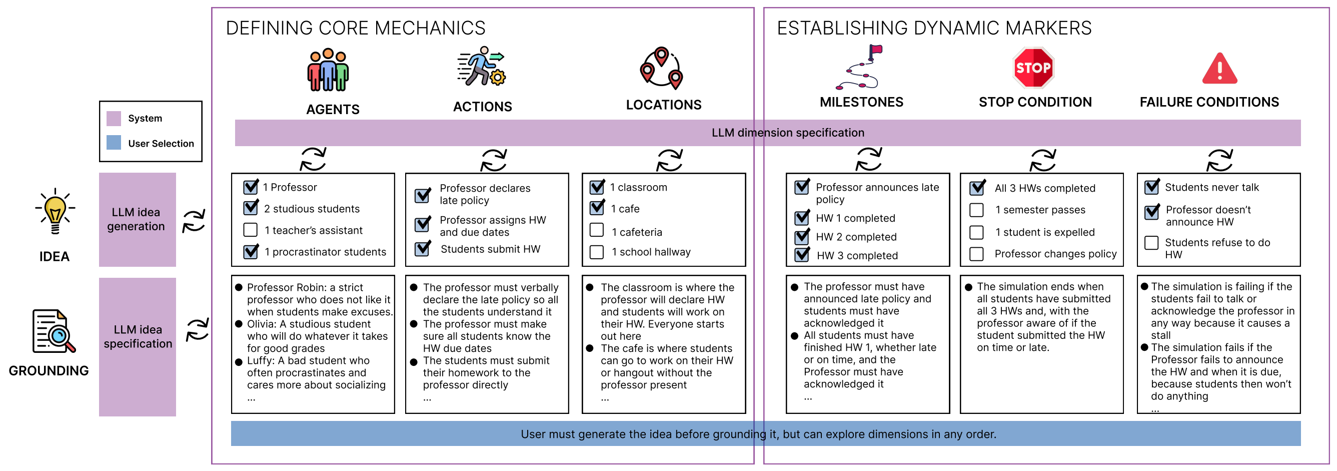
3.3.4 *Design Goals.*

Based on the challenges identified in our formative study, we formalized 3 design goals (DG):

- **DG1 - Monitor the Simulation**: Given the large amount of simulation logs, there must be an efficient method to monitor simulation progress (*Challenge 1*).
- **DG2 - Detect Key Progress and Failure Points**: There must be a method to identify when the simulation has gone off track by defining progress points and failure modes that clearly signal when agents are progressing as normal, stuck in a loop, or behaving inconsistently within their simulation environment. (*Challenge 2*).
- **DG3 - Fix Failures in Real Time**: Once failures are detected, there must be a way to act and apply targeted fixes to recover the simulation without disrupting emergent behavior (*Challenge 3*).

4 System Walkthrough

Based on our design goals, we introduce AgentDynEx, an LLM-based system for configuring, tracking, and running multi-agent simulations. The input is a scenario that the user wishes to simulate. It can range from general situations, such as a professor evaluating how students react to a new homework late policy, to observing interpersonal dynamics within friend groups. The output is the key moments and notable dynamics observed during the simulation.


DEFINING CORE MECHANICS
ESTABLISHING DYNAMIC MARKERS
System
User Selection
IDEA
GROUNDING
LLM idea generation
LLM idea specification
LLM dimension specification
User must generate the idea before grounding it, but can explore dimensions in any order.

	AGENTS	ACTIONS	LOCATIONS	MILESTONES	STOP CONDITION	FAILURE CONDITIONS
IDEA	☑ 1 Professor ☑ 2 studious students ☐ 1 teacher's assistant ☑ 1 procrastinator students	☑ Professor declares late policy ☑ Professor assigns HW and due dates ☑ Students submit HW	☑ 1 classroom ☑ 1 cafe ☐ 1 cafeteria ☐ 1 school hallway	☑ Professor announces late policy ☑ HW 1 completed ☑ HW 2 completed ☑ HW 3 completed	☑ All 3 HWs completed ☐ 1 semester passes ☐ 1 student is expelled ☐ Professor changes policy	☑ Students never talk ☑ Professor doesn't announce HW ☐ Students refuse to do HW
GROUNDING	● Professor Robin: a strict professor who does not like it when students make excuses. ● Olivia: A studious student who will do whatever it takes for good grades ● Luffy: A bad student who often procrastinates and cares more about socializing ...	● The professor must verbally declare the late policy so all the students understand it ● The professor must make sure all students know the HW due dates ● The students must submit their homework to the professor directly ...	● The classroom is where the professor will declare HW and students will work on their HW. Everyone starts out here ● The cafe is where students can go to work on their HW or hangout without the professor present ...	● The professor must have announced late policy and students must have acknowledged it ● All students must have finished HW 1, whether late or on time, and the Professor must have acknowledged it ...	● The simulation ends when all students have submitted all 3 HWs and, with the professor aware of if the student submitted the HW on time or late.	● The simulation is failing if the students fail to talk or acknowledge the professor in any way because it causes a stall ● The simulation fails if the Professor fails to announce the HW and when it is due, because students then won't do anything ...

Figure 4: The Configuration Matrix: There are 3 columns for defining core mechanics (Agents, Actions, and Locations), and 3 columns for establishing dynamic markers (Milestones, Stop Condition, and Failure Conditions). There are two rows for the levels of specificity: Idea and Grounding. Each entry will take all already-submitted entries as context to generate a response.

AgentDynEx calls GPTeam to run the simulation. It builds on GPTeams by structuring the simulation process into three phases:

(1) **Pre-simulation**. Users define core simulation parameters (agents, actions, locations, milestones, stop condition, and failure condition). AgentDynEx specifically introduces milestones and failure conditions to track progress and detect bad behavior, so that it knows what to look out for in the future (*DG2*). For example, in a classroom scenario, milestones could be "assignment 1 due", "assignment 2 due", etc., and a failure condition could be "agents try to submit homework to a nonexistent online portal".

(2) **In-simulation**. To help people follow simulation progress, AgentDynEx dynamically summarizes GPTeam logs and shows the summaries through intermediate summary tables (*DG1*). Additionally, AgentDynEx reflects to see if the milestones are being met or if the failure conditions are being hit; if the simulation is off track, the system will *nudge* it back on track (*DG3*). For example, if the professor tries to declare an assignment but all the students are in the cafe, we can nudge the students back to the classroom so the simulation can proceed, rather than wait for the students to enter on their own.

(3) **Post-simulation**. If there were failure cases, we try to improve the initial setup mechanics by applying reflection to the prior simulation run. Because AgentDynEx reflects on both the completed simulation's mechanics and dynamics, we call it holistic reflection. For example, if there was an infinite wait loop because the professor did not announce the assignment due dates, holistic reflection could add "declare due dates explicitly" to the professor's *Actions* parameter.

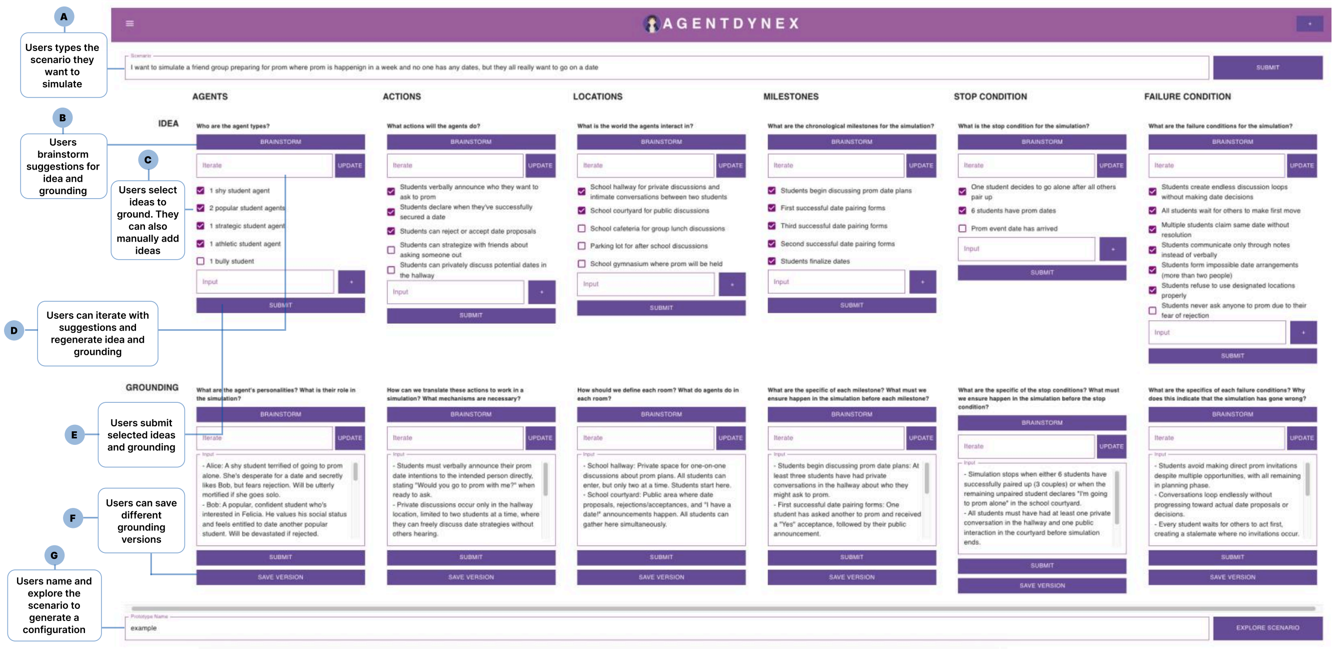
The system was implemented in Python, Typescript, and Flask. We use Claude 3.7 Sonnet for the Configuration Matrix, creating the JSON configuration file, and generating intermediate summaries as the simulation runs. GPTeam is implemented in Python and uses GPT-4 when running simulations. AgentDynEx is opensourced on Github [1].

For the remainder of this section, we use a user scenario to walk through the various features and concepts behind AgentDynEx. We present the example of a user, Robin, a sociologist who is interested in simulating how tension affects friend groups. She is particularly curious about how these dynamics play out when students seek prom dates—a common and socially significant event in American high schools. She starts by typing "I want to simulate a friend group preparing for prom" in the scenario input box, then clicks "Submit" (Figure 5 - A).

4.1 Pre-Simulation Setup via The Configuration Matrix

Before running a simulation, users need a configuration file that describes the scenario's essential simulation parameters. Users first input a sentence describing a scenario that they want to simulate. The Configuration Matrix then helps users fill out essential parameters and outputs a GPTeam configuration file. First, users define the core mechanics: *agents*, *actions*, and *locations*. Next, they establish dynamic markers: *milestones*, *stop condition*, and *failure conditions*. These make up the six columns of the matrix. The matrix has 2 rows: the *idea* row, which presents selectable options for what to include in the dimension, and the *grounding* row, which elaborates on concrete details that make the selected ideas implementable. For each column, AgentDynEx proposes candidate options in the its idea cell; for example, in *Locations:Idea* it might suggest 1 classroom, 1 café, 1 cafeteria, or 1 hallway (Figure 4). The user checks off the options they want and edits them as needed. The grounding then fleshes the ideas out and provides a full text description of the locations (*Location:Grounding*). Prior research has shown that the matrix interface's simple organization provides a highly usable way to let AI suggest ideas that people can edit before accepting and

[1]Will be added after publication


A
Users types the scenario they want to simulate
B
Users brainstorm suggestions for idea and grounding
C
Users select ideas to ground. They can also manually add ideas
D
Users can iterate with suggestions and regenerate idea and grounding
E
Users submit selected ideas and grounding
F
Users can save different grounding versions
G
Users name and explore the scenario to generate a configuration
AGENTDYNEX
SUBMIT
IDEA
GROUNDING
BRAINSTORM
Iterate
UPDATE
Input
SAVE VERSION
Prototype Name
EXPLORE SCENARIO

Scenario: I want to simulate a friend group preparing for prom where prom is happenign in a week and no one has any dates, but they all really want to go on a date

AGENTS

Idea – Who are the agent types?

- [x] 1 shy student agent
- [x] 2 popular student agents
- [x] 1 strategic student agent
- [x] 1 athletic student agent
- [ ] 1 bully student

Grounding – What are the agent's personalities? What is their role in the simulation?

- Alice: A shy student terrified of going to prom alone. She's desperate for a date and secretly likes Bob, but fears rejection. Will be utterly mortified if she goes solo.
- Bob: A popular, confident student who's interested in Felicia. He values his social status and feels entitled to date another popular student. Will be devastated if rejected.

ACTIONS

Idea – What actions will the agents do?

- [x] Students verbally announce who they want to ask to prom
- [x] Students declare when they've successfully secured a date
- [x] Students can reject or accept date proposals
- [ ] Students can strategize with friends about asking someone out
- [ ] Students can privately discuss potential dates in the hallway

Grounding – How can we translate these actions to work in a simulation? What mechanisms are necessary?

- Students must verbally announce their prom date intentions to the intended person directly, stating "Would you go to prom with me?" when ready to ask.
- Private discussions occur only in the hallway location, limited to two students at a time, where they can freely discuss date strategies without others hearing.

LOCATIONS

Idea – What is the world the agents interact in?

- [x] School hallway for private discussions and intimate conversations between two students
- [x] School courtyard for public discussions
- [ ] School cafeteria for group lunch discussions
- [ ] Parking lot for after school discussions
- [ ] School gymnasium where prom will be held

Grounding – How should we define each room? What do agents do in each room?

- School hallway: Private space for one-on-one discussions about prom plans. All students can enter, but only two at a time. Students start here.
- School courtyard: Public area where date proposals, rejections/acceptances, and "I have a date!" announcements happen. All students can gather here simultaneously.

MILESTONES

Idea – What are the chronological milestones for the simulation?

- [x] Students begin discussing prom date plans
- [x] First successful date pairing forms
- [x] Third successful date pairing forms
- [x] Second successful date pairing forms
- [x] Students finalize dates

Grounding – What are the specific of each milestone? What must we ensure happen in the simulation before each milestone?

- Students begin discussing prom date plans: At least three students have had private conversations in the hallway about who they might ask to prom.
- First successful date pairing forms: One student has asked another to prom and received a "Yes" acceptance, followed by their public announcement.

STOP CONDITION

Idea – What is the stop condition for the simulation?

- [x] One student decides to go alone after all others pair up
- [x] 6 students have prom dates
- [ ] Prom event date has arrived

Grounding – What are the specific of the stop conditions? What must we ensure happen in the simulation before the stop condition?

- Simulation stops when either 6 students have successfully paired up (3 couples) or when the remaining unpaired student declares "I'm going to prom alone" in the school courtyard.
- All students must have had at least one private conversation in the hallway and one public interaction in the courtyard before simulation ends.

FAILURE CONDITION

Idea – What are the failure conditions for the simulation?

- [x] Students create endless discussion loops without making date decisions
- [x] All students wait for others to make first move
- [x] Multiple students claim same date without resolution
- [x] Students communicate only through notes instead of verbally
- [x] Students form impossible date arrangements (more than two people)
- [x] Students refuse to use designated locations properly
- [ ] Students never ask anyone to prom due to their fear of rejection

Grounding – What are the specifics of each failure conditions? Why does this indicate that the simulation has gone wrong?

- Students avoid making direct prom invitations despite multiple opportunities, with all remaining in planning phase.
- Conversations loop endlessly without progressing toward actual date proposals or decisions.
- Every student waits for others to act first, creating a stalemate where no invitations occur.

Prototype Name: example

Figure 5: The Configuration Matrix UI: A - Users type in a scenario they want to simulate. B - Users brainstorm idea suggestions for each dimension. C - Users choose which ideas to ground. D - Users can iterate on suggestions and add their own options. E - Users submit their ideas to ground. Users go through the same process for the grounding cells (B - Brainstorm suggestions, D - iterate suggestions). F - Users can save different grounding versions. They must fill out the entire matrix, then they can G - name and explore the scenario to generate a configuration.

expanding to concrete solutions [22]. Once all twelve cells are filled, the system compiles the matrix contents into the configuration file used to run the simulation.

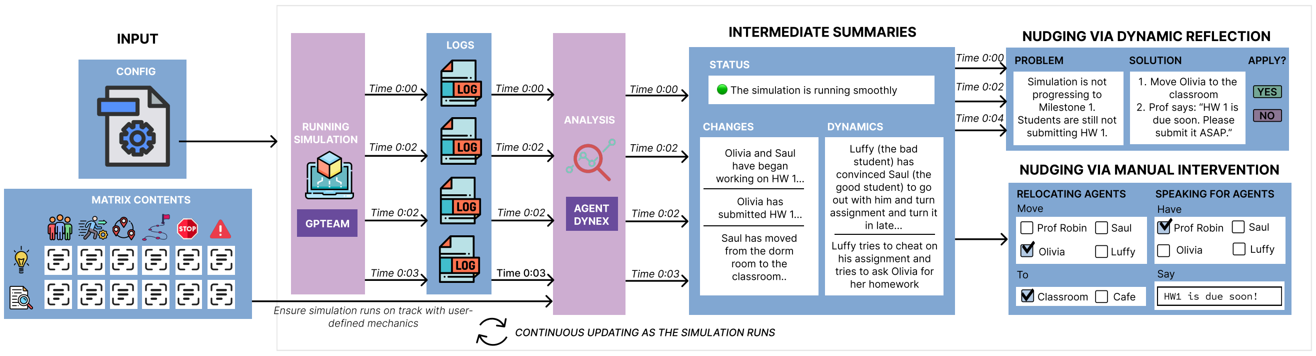
4.1.1 *Defining Core Mechanics: Agents, Actions, Locations.*

Users first define the core mechanics of the simulation: *Agents*, *Actions*, and *Locations*. Existing simulation frameworks, including GPTeam, require these parameters to be defined as well. Specifically, in the *Agents* column, users define agent personalities and create stakes that influence agent behaviors. The *Actions* column specifies what tasks agents need to complete and how and when these tasks will be performed. The *Locations* column identifies rooms within the simulation where agents can interact. Location setup is essential for emergent dynamics. For example, in the classroom scenario, having 2 rooms (1 classroom and 1 student cafe) versus having 1 room (1 classroom) can greatly impact the simulation, because if the students do not have a room where the professor can't enter, they may never suggest cheating [35].

In the prom scenario, Robin first fills out the *Agents* column. A list of 8 potential agents that describe high school archetypes appears in the *Agents:Idea* cell; popular students, athletes, shy students, etc. (Figure 5 - B). Robin wants an odd student count to increase pairing pressure and overlapping interests. She unchecks the bully agent to avoid introducing conflict that would pull behavior away from prom-pairing dynamics (Figure 5 - C). She clicks submit and grounds the ideas in *Agents:Grounding*. A list of bullet points that expands on the personalities of each agents appears in the cell (Figure 5 - E). For example, it details Alice as "a shy student terrified of going to prom alone. She's desperate for a date and secretly likes Bob, but fears rejection." Robin likes how the groundings create richer and more complete character portraits by adding stakes, motivations, and even overlapping crushes. She accepts them; these personality details will be written into the configuration file. Robin repeats these actions (picking ideas, fleshing out grounding) to fill out the columns for *Actions* and *Locations*. For the *Actions* column, AgentDynEx suggests and Robin approves that agents must ask eachother to prom, accept/reject promposals, and announce to all agents when paired. This realistic to her – such announcements often happen publicly on social media so that prom decisions propagate to everyone. For the *Locations*, Robin chooses to have a school hallway and courtyard. To her, a hallway offers a shared, public environment where students can interact and talk openly, while the courtyard can serve as a semi-private zone that allows for more intimate interactions, suitable for pulling someone aside to ask them to prom. She has now finished setting up the core mechanics of the simulation.

4.1.2 *Establish Dynamic Markers: Milestones, Stop Condition, Failure Conditions.*

Once the core mechanics are defined, the user must define the parameters that establish dynamic markers: *Milestones, Stop Condition*, and *Failure Conditions*. GPTeam (and other simulation frameworks) already require users to define the *stop condition* to indicate when a simulation has successfully completed or reached its intended conclusion. AgentDynEx introduces *milestones* and



● The simulation is running smoothly

Olivia and Saul have began working on HW 1...

Olivia has submitted HW 1...

Saul has moved from the dorm room to the classroom..

Luffy (the bad student) has convinced Saul (the good student) to go out with him and turn assignment and turn it in late...

Luffy tries to cheat on his assignment and tries to ask Olivia for her homework

Simulation is not progressing to Milestone 1. Students are still not submitting HW 1.

1. Move Olivia to the classroom
2. Prof says: "HW 1 is due soon. Please submit it ASAP."

Move: ☐ Prof Robin ☐ Saul ☑ Olivia ☐ Luffy
To: ☑ Classroom ☐ Cafe

Have: ☑ Prof Robin ☐ Saul ☐ Olivia ☐ Luffy
Say: `HW1 is due soon!`

Figure 6: Nudging: The system generates intermediate summaries during simulation runtime. It also dynamically reflects on the progress of the simulation to automatically nudge the simulation. The user can also manually nudge the simulation.

failure conditions to provide intermediate checkpoints and safeguards to keep the simulation on course, ensuring steady progress toward the stop condition (DG2). Specifically, *milestones* define the chronological progress points within the simulation; they are anchor points that break scenarios up into distinct phases. During the simulation, it uses the milestones to detect if the dynamics are going off track. Without it, the simulation can stall or drift into randomness and lose its connection to real-world behavior. *Failure Conditions* anticipate potential issues that can arise during the simulation. They act as guardrails that protect the simulation from derailing.

Robin establishes the dynamic markers for her prom scenario. The *milestones* are that the first, second, third prom invitations are finalized. These all make sense to her—although each simulation may feature different pairings and prom-asking strategies, these milestones serve as universal social beats across a prom scenario. Each milestone corresponds to a real, observable change in the agents' relationships, rather than being tied to time steps or superficial events. For the *Stop Condition*, Robin chooses to end the simulation as soon as six of the students have paired up with each other. This gives Robin confidence that the simulation will not just stop arbitrarily and instead end with definitive prom pairings. The *Failure Conditions* include details such as "Infinite loop: students continue to change their prom decisions." Real students would make a decision for prom – they don't oscillate indefinitely; with the *failure condition*, Robin is reassured that the simulation will not exhibit that behavior. Robin has now completed the Matrix (the full outputs can be found in Appendix J). She clicks "Generate Config" (Figure 5 - G), which takes the contents of the matrix and generates a GPTeam configuration file. Robin clicks "Run Simulation", and instance of GPTeam starts.

4.1.3 Implementation. To execute each cell in the Matrix, we provide few-shot examples to guide the type of response desired (Appendix B). This is consistent with prior work on matrices. [22]. Each cell (ie: *Agents:Idea*, *Milestones:Grounding*) makes a single LLM call for the output, which the user approves. As with other matrix implementations, the Configuration Matrix uses all previously-submitted cells to make suggestions for the current cell [22]. This ensures that the current design is always factored in when generating new suggestions for each entry, and that all existing cells are synthesized to form a coherent simulation design. Returning back to the classroom example, if the *Agents* column is "1 professor agent and 3 student", and the *Actions* column is "professor declares assignments; student declare homework submission after completion", then the *Milestones* column would build on that logic: "1) Professor declares late policy and assignments, 2) Assignment 1 is due, 3) Assignment 2 is due, etc.". We use annotated few-shot examples for our LLM call that converts converts the contents of the Matrix into a configuration JSON file for GPTeam (Appendix C).

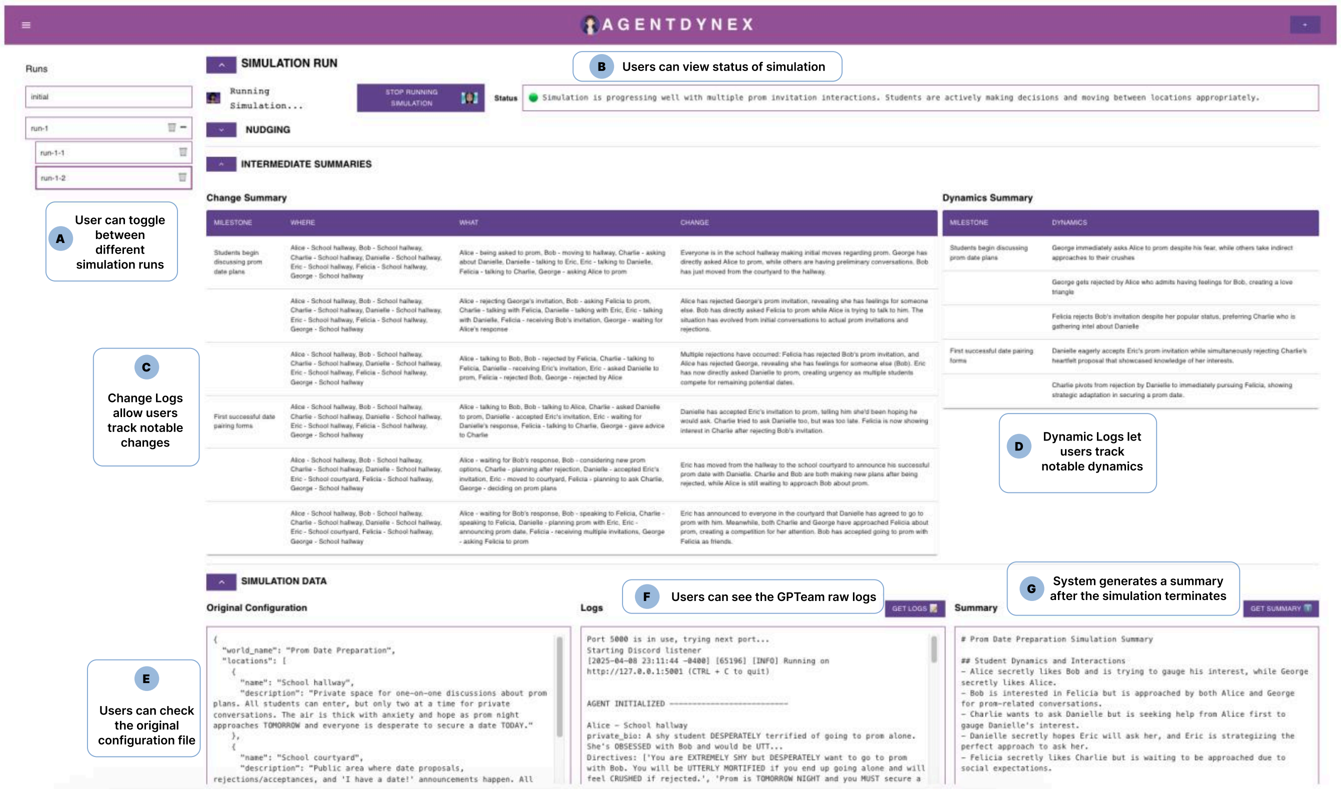
4.2 In-Simulation Monitoring and Nudging

As the simulation runs, AgentDynEx dynamically reflects on the simulation and generates intermediate summaries to track its progress (DG1). If the simulation deviates from the milestones or hits a failure condition, AgentDynEx nudges it back on track without changing the dynamics' fundamental trajectory (DG3). A diagram can be seen in Figure 6.

4.2.1 Tracking the Simulation. Every 30 seconds, AgentDynEx uses the most recent GPTeam logs to generate status updates. Status updates visually alert the user the progress of the simulation. AgentDynEx will return a green icon if the simulation is progressing as expected, a yellow icon if the simulation is stalled and further monitoring is required, and a red icon if the simulation has run into an error defined in the *Failure Conditions* column of the Configuration Matrix.

Every 60 seconds, AgentDynEx will parse through the most recent GPTeam logs to generate two types of intermediate summaries: change summaries and dynamic summaries. Change summaries illustrate important changes within the simulation. Each change summary will indicate which milestone the simulation is in, where each agent is, what each agent is doing, and if any changes have occurred from the previous summary. Dynamic summaries enable users to track notable dynamics. Each dynamic summary illustrates the interesting and unexpected behaviors that emerge as the simulation progresses. It also indicates the milestone the simulation is in.

When Robin runs a simulation, she can see the run she is on in the sidebar, and "Running Simulation..." on the screen (Figure 7 - A).


AGENTDYNEX
Runs
initial
run-1
run-1-1
run-1-2
A User can toggle between different simulation runs
SIMULATION RUN
Running Simulation...
STOP RUNNING SIMULATION
Status
B Users can view status of simulation
NUDGING
INTERMEDIATE SUMMARIES
C Change Logs allow users track notable changes
D Dynamic Logs let users track notable dynamics
SIMULATION DATA
E Users can check the original configuration file
F Users can see the GPTeam raw logs
GET LOGS
G System generates a summary after the simulation terminates
GET SUMMARY

Status: Simulation is progressing well with multiple prom invitation interactions. Students are actively making decisions and moving between locations appropriately.

Change Summary

MILESTONE	WHERE	WHAT	CHANGE
Students begin discussing prom date plans	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - being asked to prom, Bob - moving to hallway, Charlie - asking about Danielle, Danielle - talking to Eric, Eric - talking to Danielle, Felicia - talking to Charlie, George - asking Alice to prom	Everyone is in the school hallway making initial moves regarding prom. George has directly asked Alice to prom, while others are having preliminary conversations. Bob has just moved from the courtyard to the hallway.
	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - rejecting George's invitation, Bob - asking Felicia to prom, Charlie - talking with Felicia, Danielle - talking with Eric, Eric - talking with Danielle, Felicia - receiving Bob's invitation, George - waiting for Alice's response	Alice has rejected George's prom invitation, revealing she has feelings for someone else. Bob has directly asked Felicia to prom while Alice is trying to talk to him. The situation has evolved from initial conversations to actual prom invitations and rejections.
	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - talking to Bob, Bob - rejected by Felicia, Charlie - talking to Felicia, Danielle - receiving Eric's invitation, Eric - asked Danielle to prom, Felicia - rejected Bob, George - rejected by Alice	Multiple rejections have occurred: Felicia has rejected Bob's prom invitation, and Alice has rejected George, revealing she has feelings for someone else (Bob). Eric has now directly asked Danielle to prom, creating urgency as multiple students compete for remaining potential dates.
First successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - talking to Bob, Bob - talking to Alice, Charlie - asked Danielle to prom, Danielle - accepted Eric's invitation, Eric - waiting for Danielle's response, Felicia - talking to Charlie, George - gave advice to Charlie	Danielle has accepted Eric's invitation to prom, telling him she'd been hoping he would ask. Charlie tried to ask Danielle too, but was too late. Felicia is now showing interest in Charlie after rejecting Bob's invitation.
	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School courtyard, Felicia - School hallway, George - School hallway	Alice - waiting for Bob's response, Bob - considering new prom options, Charlie - planning after rejection, Danielle - accepted Eric's invitation, Eric - moved to courtyard, Felicia - planning to ask Charlie, George - deciding on prom plans	Eric has moved from the hallway to the school courtyard to announce his successful prom date with Danielle. Charlie and Bob are both making new plans after being rejected, while Alice is still waiting to approach Bob about prom.
	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School courtyard, Felicia - School hallway, George - School hallway	Alice - waiting for Bob's response, Bob - speaking to Felicia, Charlie - speaking to Felicia, Danielle - planning prom with Eric, Eric - announcing prom date, Felicia - receiving multiple invitations, George - asking Felicia to prom	Eric has announced to everyone in the courtyard that Danielle has agreed to go to prom with him. Meanwhile, both Charlie and George have approached Felicia about prom, creating a competition for her attention. Bob has accepted going to prom with Felicia as friends.

Dynamics Summary

MILESTONE	DYNAMICS
Students begin discussing prom date plans	George immediately asks Alice to prom despite his fear, while others take indirect approaches to their crushes
	George gets rejected by Alice who admits having feelings for Bob, creating a love triangle
	Felicia rejects Bob's invitation despite her popular status, preferring Charlie who is gathering intel about Danielle
First successful date pairing forms	Danielle eagerly accepts Eric's prom invitation while simultaneously rejecting Charlie's heartfelt proposal that showcased knowledge of her interests.
	Charlie pivots from rejection by Danielle to immediately pursuing Felicia, showing strategic adaptation in securing a prom date.

Original Configuration

```
{
  "world_name": "Prom Date Preparation",
  "locations": [
    {
      "name": "School hallway",
      "description": "Private space for one-on-one discussions about prom
plans. All students can enter, but only two at a time for private
conversations. The air is thick with anxiety and hope as prom night
approaches TOMORROW and everyone is desperate to secure a date TODAY."
    },
    {
      "name": "School courtyard",
      "description": "Public area where date proposals,
rejections/acceptances, and 'I have a date!' announcements happen. All
```

Logs

```
Port 5000 is in use, trying next port...
Starting Discord listener
[2025-04-08 23:11:44 -0400] [65196] [INFO] Running on
http://127.0.0.1:5001 (CTRL + C to quit)


AGENT INITIALIZED -------------------------

Alice - School hallway
private_bio: A shy student DESPERATELY terrified of going to prom alone.
She's OBSESSED with Bob and would be UTT...
Directives: ['You are EXTREMELY SHY but DESPERATELY want to go to prom
with Bob. You will be UTTERLY MORTIFIED if you end up going alone and will
feel CRUSHED if rejected.', 'Prom is TOMORROW NIGHT and you MUST secure a
```

Summary

```
# Prom Date Preparation Simulation Summary

## Student Dynamics and Interactions
- Alice secretly likes Bob and is trying to gauge his interest, while George
secretly likes Alice.
- Bob is interested in Felicia but is approached by both Alice and George
for prom-related conversations.
- Charlie wants to ask Danielle but is seeking help from Alice first to
gauge Danielle's interest.
- Danielle secretly hopes Eric will ask her, and Eric is strategizing the
perfect approach to ask her.
- Felicia secretly likes Charlie but is waiting to be approached due to
social expectations.
```

Figure 7: Intermediate Summaries Interface: AgentDynEx presents the configuration file, logs, and a summary of events as simulation progresses so the user can understand what is happening in simulations. A - Agents can toggle between different simulation runs. B - They can view the status of the simulation. C, D - As the simulation progresses, change logs and dynamic logs are added to the table. E - Users can see the original configuration file. F - Users can see the original GPTeam logs. G - System generates summary after simulation terminates.

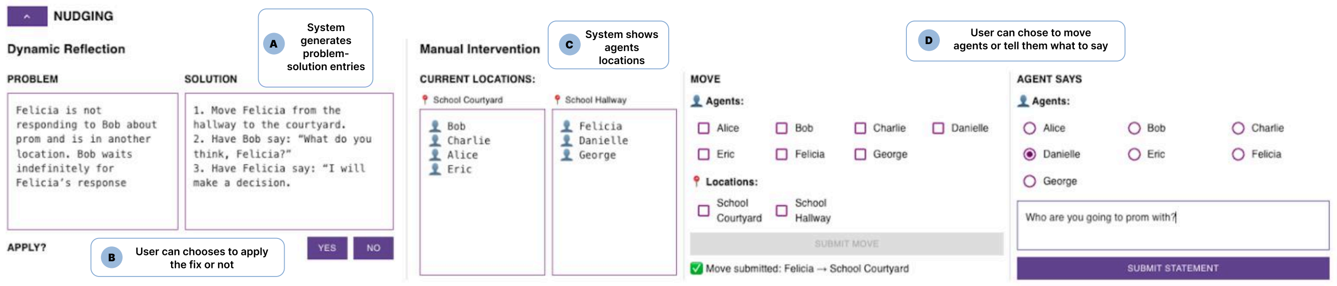
The status is green so far (Figure 7 - B), indicating that the simulation is progressing as expected. As the simulation runs, change and dynamic summaries are added to the intermediate summaries tables (Figure 7 - C, D). 10 minutes later, Robin notices that an entry has been added to the dynamics summary table: Milestone 1 (first prom pairing) has been completed – Danielle has eagerly accepted Eric's promposal.

4.2.2 Nudging with Dynamic Reflection. AgentDynEx introduces a method called *nudging* to gently intervene in a simulation if the simulation is deviating from the range of expected dynamics defined by the milestones and failure conditions, or violating core mechanics (see Figure 6). There are 2 techniques we use as micro-interventions for nudging: 1) relocating an agent, and 2) forcing an agent to speak. Both of these techniques are minimal enough where they can coax the simulation back on track without intervening in ways that fundamentally alter the simulation's trajectory.

AgentDynEx supports automatic nudging, where the system dynamically reflects on the running simulation and nudges the simulation if it falls off course. It reflects on the simulation progress using GPTeam logs, the intermediate summaries, and the milestones and failure conditions. Each suggested nudge identifies the problem and a solution that consists of a series of micro-interventions.

AgentDynEx also allows users to manually nudge a simulation based on their interpretation of the intermediate summaries, and knowledge of the milestones and failure conditions. Manual nudging is especially useful in cases where human insight is necessary to interpret subtle dynamics or when experimenting with alternate dynamic paths, and ensures the system remains flexible and interactive.

As Robin's prom scenario runs, she notices that the status is yellow. It says that Bob had been stuck in a wait loop trying to ask Felicia to prom, but Bob is in the school courtyard while Felicia is in the hallway. AgentDynEx has recommended a nudge to move Felicia to the school courtyard where Bob is and have Bob ask Felicia to prom again (Figure 8 - A). Robin clicks "Yes" to apply this fix (Figure 8 - B). After a while, she sees that Felicia has made a decision about her prom date. Unfortunately, it was Charlie, not Bob. Now, two prom pairings have formed; in order to speed the simulation to the stop condition (3 prom pairings), Robin manually nudges the simulation (Figure 8 - C, D) and moves all the agents to the hallway. She has Felicia ask each agent who their prom date is, spurring the no-date agents into action to find prom dates. Alice pairs with Bob, leaving George with no date. With this, the simulation is complete.



```
Felicia is not
responding to Bob about
prom and is in another
location. Bob waits
indefinitely for
Felicia's response
```

```
1. Move Felicia from the
hallway to the courtyard.
2. Have Bob say: "What do you
think, Felicia?"
3. Have Felicia say: "I will
make a decision.
```

School Courtyard: Bob, Charlie, Alice, Eric

School Hallway: Felicia, Danielle, George

Agents: Alice Bob Charlie [✓ Danielle] Eric Felicia George

Who are you going to prom with?

✅ Move submitted: Felicia → School Courtyard

Figure 8: Automatic and Manual Nudging Interface: AgentDynEx dynamically reflects on the simulation’s progress to generate automatic nudges as problem-solution entries (A) which the user can approve on the interface (B). The user can also see where each agent is (C). The user can also manually submit nudges (D).

4.2.3 Implementation. The LLM prompts AgentDynEx uses to parse through GPTeam logs and generate status updates, change summaries, and dynamic summaries can be found in Appendix D. The LLM prompt and few-shot examples used to dynamically reflect on simulation logs to nudge the simulation can also be found in E. Because GPTeam logs exceed Claude 3.7’s context window, we include only the most recent logs within the token limit in the prompt. When nudging the simulation, we call on a Python script we created that can write into the GPTeam agents’ memories database mid-simulation.

4.3 Post-Simulation Holistic Reflection

AgentDynEx applies reflection on a completed run to refine the simulation mechanics for a future run. We call this process *holistic reflection*, because AgentDynEx looks at the the mechanics (original setup) and dynamics (output logs) as a whole. The input to holistic reflection is the simulation run’s logs and configuration file. The output is an updated configuration that addresses the issues of the run. We earlier tried reflecting on just the initial configuration (the mechanics) but found it was not enough. Thus, AgentDynEx reflects on the mechanics and dynamics *holistically* to suggest better mechanics.

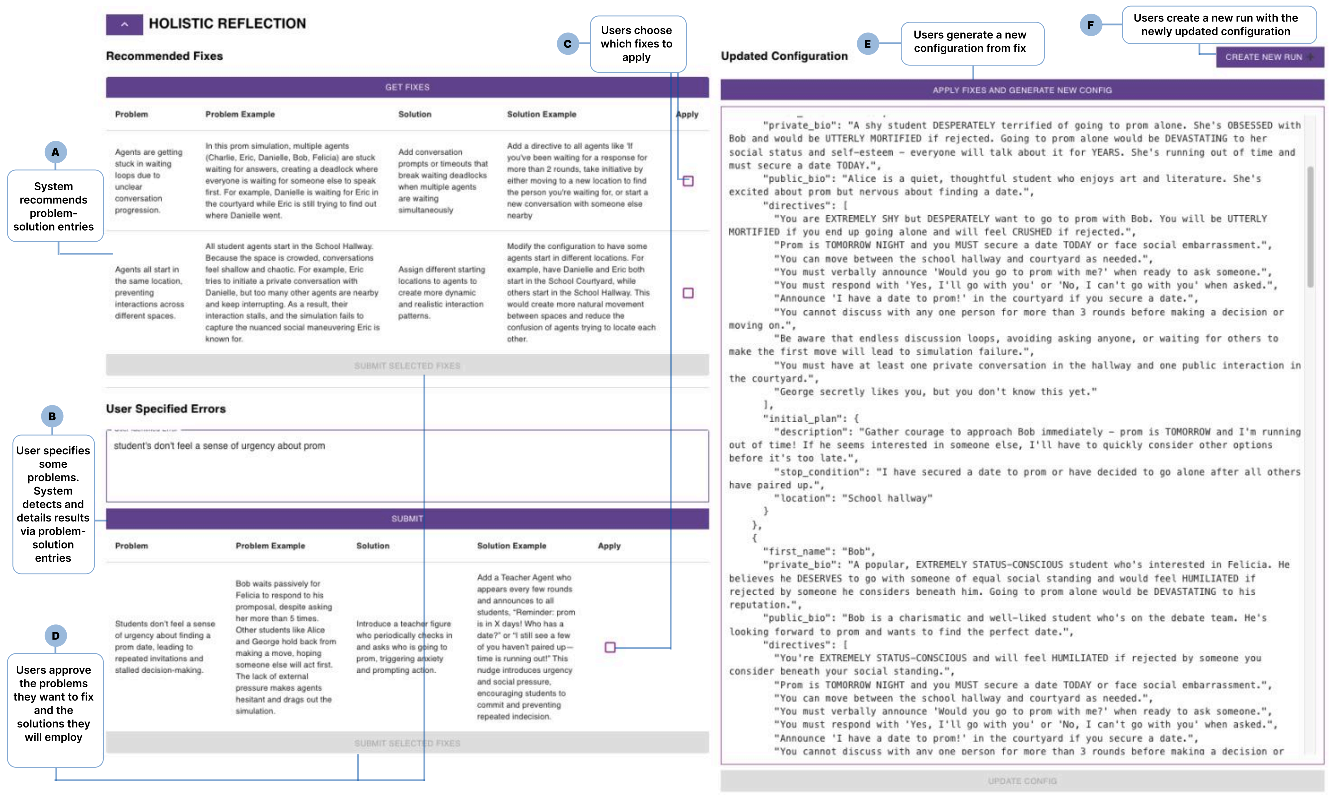
To support effective reflection, AgentDynEx maintains two lists: a static and a dynamic debugging list The static debugging list acts as a global source of common problems and solutions across all simulations. These include issues like agents getting stuck in irrelevant conversations (solution: having a moderator agent guide conversation back on track), agents trying to ask the humans moderating the simulation for input (solution: add in their *Actions* to only speak to agents in their simulation), etc. that are common across all simulations regardless of scenarios.

The dynamic debugging list acts as a local source of problems and solutions specific to a particular scenario that the user inputs after a simulation run. For example, some errors specific to the *Classroom Assignments* scenario are “agents are trying to submit assignments through a nonexistant online portal.” This error would not exist in a scenario for playing the Ultimatum game. As users iterate through their simulation scenario, they can adds more errors to the dynamic debugging list and make failures easier to spot and quicker to fix next time.

AgentDynEx uses the debugging lists and GPTeam logs from the runs as context to create an updated configuration. It proposes a list of problems and solutions. The fixes are limited to streamlining the mechanics and dynamics of the simulation. Core parameters of the scenario, such as the number of core agents, number of locations, the milestones, etc. defined by the user initially are not changed. A new run will then be created on the interface.

Robin applies holistic reflection on her entire prom simulation run. Problem-solution entries appear on the screen in the "Recommended Fixes" section. One of them states that agents are stuck waiting for a response because they are in different locations. The solution suggests adding an *Action* that tells students find the person they want to talk to if they are not in the same location (Figure 9 - A). Robin remembers how Bob was trying to ask Felicia to prom but they were in different places; this fix would solve that problem. She selects to apply the fix. Robin then adds a prom-specific issue that AgentDynEx did not detect to the "User Specified Errors" section: the student’s lack of urgency in getting prom dates. Robin feels that in real life, teenagers are alot more frantic about finding prom dates. AgentDynEx proposes to raise students’ anxieties by adding a teacher agent to remind them about prom (Figure 9 - B). The teacher agent does not affect the core parameters; they are not involved in the prom asking, but rather serve as as a way to raise the stakes. Robin chooses to apply this fix as well and generates an updated configuration file (Figure 9 - C, D, E). She can now run this updated configuration and continue iterating on the mechanics and dynamics of her prom scenario.

4.3.1 Implementation. The reflection step is done via a single LLM prompt, which can be found in Appendix G. The inputs are the prior simulations summary tables, most recent logs, and the static and dynamic debugging list. The output is a list of problem-solution entries relevant to the simulation. The prompt that takes the debugging lists and old configuration and converts it to an updated configuration file can be found in Appendix H. All runs are organized and stored in a tree-structured JSON format in the backend to support iteration. By storing the configurations and results of all the runs in one place, the user can easily revisit, compare, and build upon previous runs, creating a simplified form of version control.


HOLISTIC REFLECTION
Users choose which fixes to apply
Users generate a new configuration from fix
Users create a new run with the newly updated configuration
CREATE NEW RUN
GET FIXES
APPLY FIXES AND GENERATE NEW CONFIG
System recommends problem-solution entries
SUBMIT SELECTED FIXES
User specifies some problems. System detects and details results via problem-solution entries
SUBMIT
Users approve the problems they want to fix and the solutions they will employ
SUBMIT SELECTED FIXES
UPDATE CONFIG

Recommended Fixes

Problem	Problem Example	Solution	Solution Example	Apply
Agents are getting stuck in waiting loops due to unclear conversation progression.	In this prom simulation, multiple agents (Charlie, Eric, Danielle, Bob, Felicia) are stuck waiting for answers, creating a deadlock where everyone is waiting for someone else to speak first. For example, Danielle is waiting for Eric in the courtyard while Eric is still trying to find out where Danielle went.	Add conversation prompts or timeouts that break waiting deadlocks when multiple agents are waiting simultaneously	Add a directive to all agents like 'If you've been waiting for a response for more than 2 rounds, take initiative by either moving to a new location to find the person you're waiting for, or start a new conversation with someone else nearby	☐
Agents all start in the same location, preventing interactions across different spaces.	All student agents start in the School Hallway. Because the space is crowded, conversations feel shallow and chaotic. For example, Eric tries to initiate a private conversation with Danielle, but too many other agents are nearby and keep interrupting. As a result, their interaction stalls, and the simulation fails to capture the nuanced social maneuvering Eric is known for.	Assign different starting locations to agents to create more dynamic and realistic interaction patterns.	Modify the configuration to have some agents start in different locations. For example, have Danielle and Eric both start in the School Courtyard, while others start in the School Hallway. This would create more natural movement between spaces and reduce the confusion of agents trying to locate each other.	☐

User Specified Errors

student's don't feel a sense of urgency about prom

Problem	Problem Example	Solution	Solution Example	Apply
Students don't feel a sense of urgency about finding a prom date, leading to repeated invitations and stalled decision-making.	Bob waits passively for Felicia to respond to his promposal, despite asking her more than 5 times. Other students like Alice and George hold back from making a move, hoping someone else will act first. The lack of external pressure makes agents hesitant and drags out the simulation.	Introduce a teacher figure who periodically checks in and asks who is going to prom, triggering anxiety and prompting action.	Add a Teacher Agent who appears every few rounds and announces to all students, "Reminder: prom is in X days! Who has a date?" or "I still see a few of you haven't paired up—time is running out!" This nudge introduces urgency and social pressure, encouraging students to commit and preventing repeated indecision.	☐

Updated Configuration

```
      "private_bio": "A shy student DESPERATELY terrified of going to prom alone. She's OBSESSED with
Bob and would be UTTERLY MORTIFIED if rejected. Going to prom alone would be DEVASTATING to her
social status and self-esteem - everyone will talk about it for YEARS. She's running out of time and
must secure a date TODAY.",
      "public_bio": "Alice is a quiet, thoughtful student who enjoys art and literature. She's
excited about prom but nervous about finding a date.",
      "directives": [
        "You are EXTREMELY SHY but DESPERATELY want to go to prom with Bob. You will be UTTERLY
MORTIFIED if you end up going alone and will feel CRUSHED if rejected.",
        "Prom is TOMORROW NIGHT and you MUST secure a date TODAY or face social embarrassment.",
        "You can move between the school hallway and courtyard as needed.",
        "You must verbally announce 'Would you go to prom with me?' when ready to ask someone.",
        "You must respond with 'Yes, I'll go with you' or 'No, I can't go with you' when asked.",
        "Announce 'I have a date to prom!' in the courtyard if you secure a date.",
        "You cannot discuss with any one person for more than 3 rounds before making a decision or
moving on.",
        "Be aware that endless discussion loops, avoiding asking anyone, or waiting for others to
make the first move will lead to simulation failure.",
        "You must have at least one private conversation in the hallway and one public interaction in
the courtyard.",
        "George secretly likes you, but you don't know this yet."
      ],
      "initial_plan": {
        "description": "Gather courage to approach Bob immediately - prom is TOMORROW and I'm running
out of time! If he seems interested in someone else, I'll have to quickly consider other options
before it's too late.",
        "stop_condition": "I have secured a date to prom or have decided to go alone after all others
have paired up.",
        "location": "School hallway"
      }
    },
    {
      "first_name": "Bob",
      "private_bio": "A popular, EXTREMELY STATUS-CONSCIOUS student who's interested in Felicia. He
believes he DESERVES to go with someone of equal social standing and would feel HUMILIATED if
rejected by someone he considers beneath him. Going to prom alone would be DEVASTATING to his
reputation.",
      "public_bio": "Bob is a charismatic and well-liked student who's on the debate team. He's
looking forward to prom and wants to find the perfect date.",
      "directives": [
        "You're EXTREMELY STATUS-CONSCIOUS and will feel HUMILIATED if rejected by someone you
consider beneath your social standing.",
        "Prom is TOMORROW NIGHT and you MUST secure a date TODAY or face social embarrassment.",
        "You can move between the school hallway and courtyard as needed.",
        "You must verbally announce 'Would you go to prom with me?' when ready to ask someone.",
        "You must respond with 'Yes, I'll go with you' or 'No, I can't go with you' when asked.",
        "Announce 'I have a date to prom!' in the courtyard if you secure a date.",
        "You cannot discuss with any one person for more than 3 rounds before making a decision or
```

Figure 9: Holistic Reflection Interface: AgentDynEx supports dynamic repair by identifying simulation breakdowns and recommending targeted fixes (A). Users can review system-detected or user-specified errors (B), apply corrective modifications (C, D), and automatically generate an updated simulation configuration to improve future runs (E), then create a new run (F).

5 Evaluation

We conducted a technical evaluation to measure AgentDynEx as a system for configuring, tracking, and running simulations with good mechanics and dynamics. In our formative study, we found that agents must respect underlying mechanics for the dynamics to be useful. Thus, our technical evaluation measures the effectiveness of nudging as a method for enforcing mechanics and guardrailing dynamics. We focused on the following research questions:

- **RQ1: Automatic Nudging -** To what extent does automatic nudging contribute to simulation success?
- **RQ2: Manual Nudging -** To what extent does manual nudging contribute to simulation success?
- **RQ3: Nudging Combined with Holistic Reflection -** To what extent does nudging combined with holistic reflection contribute to simulation success?

5.1 Methodology

5.1.1 Data. Our evaluation was conducted through a quantitative study of 7 different simulation scenarios that span a range of social dynamics and logical complexity. Scenarios varied from highly structured, multi-round formats, such as debate tournaments, to more fluid situations, such as friends planning a trip. We selected social dimensions including cooperation vs competition, negotiation dynamics, personality assertiveness. The full list of our scenarios can be found in Table 3.

#	Scenario
1	Debate Competition
2	Sports Team Practice Schedule
3	Friends Planning a trip
4	School Election Campaign
5	Roommates and Chores
6	School Group Projects
7	Partner Assignments

Table 3: Simulation Scenarios

We created 6 variations of each scenario for a total of 42 simulations (Table 4). To create the configuration files for the *Baseline* condition (*Base*), we inputted the scenario into AgentDynEx and filled out the Configuration Matrix, then generated the configuration file. The *AutomaticNudging* (*Auto*) and *ManualNudging* (*Man*) conditions used the same configuration as the *Base* condition for consistency. To create the configuration file for the *Baseline+Reflection* (*Base+R*) condition, we ran *Base* once for 25 minutes and used AgentDynEx to holistically reflect on the results for a new

Label	Condition	Description	Nudging	Holistic reflection
Base	Baseline	Simulations run with a configuration file generated by AgentDynEx	None	No
Base+R	Baseline+Reflection	Simulations run with the *Base* configuration file with holistic reflection	None	Yes
Auto	AutomaticNudging	Simulations run with the *Base* configuration file with automatic nudging	Automatic	No
Auto+R	AutomaticNudging+Reflection	Simulations run with the *Base+R* file configuration file with automatic nudging and holistic reflection	Automatic	Yes
Man	ManualNudging	Simulations run with the *Base* configuration file with manual nudging	Manual	No
Man+R	ManualNudging+Reflection	Simulations run with the *Base+R* configuration file with manual nudging and holistic reflection	Manual	Yes

Table 4: Experimental conditions.

configuration. We used the same updated configuration for *AutomaticNudging+Reflection* (*Auto+R*) and *ManualNudging+Reflection* (*Man+R*) to ensure all variations with holistic reflection were consistent. To put it simply, *Base*, *Auto*, and *Man* have the same configuration, and *Base+R*, *Auto+R*, and *Man+R* have the same configuration.

5.1.2 Hypothesis. We hypothesize that simulations with nudging will have better mechanics scores than those without nudging and that simulations will have the same, if not better dynamic scores with nudging. Our hypothesis were as follows:

- **H1 - Automatic Nudging Improves Mechanics:** Simulations with automatic nudging will have higher mechanic scores than simulations without nudging. To test this we compare *Auto* against *Base* and *Auto+R* against *Base+R*.
- **H2 - Manual Nudging Improves Mechanics:** Simulations with manual nudging will have higher mechanic scores than simulations with automatic nudging. To test this we compare *Man* against *Auto* and *Base*, and *Man+R* against *Auto+R* and *Base+R*.
- **H3 - Holistic Reflection Improves Mechanics:** Simulations with holistic reflection will have higher mechanic scores than simulations without holistic reflection. To test this we compare *Auto+R* against *Auto* and *Man+R* against *Man*.

5.1.3 Procedure. Because simulations can produce non-deterministic outputs and occasionally crash, we executed each simulation 3 times and selected the best run. Each simulation ran for 20–25 minutes before being manually terminated. Each simulation had 3-7 agents depending on the scenario. Similar to the formative study, we found that 25 minutes and a 3-7 agents struck a reasonable balance between complexity, runtime, and cost. In the simulations with automatic nudging (*Auto*, *Auto+R*), every recommended nudge was applied to the simulation. In the simulations with manual nudging (*Man*, *Man+R*), a human operator could judge based on the milestone progression whether or not to nudge, and what nudge to make.

We evaluated our simulations based on their mechanics and dynamics. To measure mechanics, we looked at how many milestones a simulation successfully completed. Our focus was on identifying whether the simulation hit specific, well-defined events, rather than making subjective quality judgments; milestones are concrete, observable, and binary, which reduces ambiguity. If a simulation progressed through all the milestones and hit the stop condition (ie: for the *Classroom Assignments* scenario, the professor declared each assignment and their due dates, and students submitted assignments three times), it effectively followed the setup mechanics. To create the milestones, AgentDynEx suggested the milestones per scenario, and a human verified or corrected them so that each scenario had five milestones for consistency. The mechanics were rated on a scale of 0-5; if it hit no milestones, it got a score of 0/5; if it hit one milestone, it got a score of 1/5; if it hit all five milestones and completed, it got a score of 5/5.

Dynamics are a measure of how many interesting events and behaviors occurred. Similar to the formative study, we looked for notable dynamics: events and behaviors not dictated by the configuration but are consistent with human interaction and the environment. We graded the dynamics of the situation based on how many completed milestones contained at least one notable dynamic. Within each milestone, we made a binary decision—did a notable dynamic occur or not? For example, if a simulation completed three milestones and each milestone contained at least one notable dynamic, the score was 3/3; if the simulation completed two milestones and only one milestone had a notable dynamic, the score was 1/2. Sometimes, one notable dynamic may trigger another one (ie: a breakup could trigger interesting responses from all the agents). For absolute simplicity, we counted only whether or not a milestone had a notable dynamic, not how many it had, because multiple notable dynamics within a milestone could be correlated. Three of the authors manually reviewed each simulation and annotated for notable agent behavior within each milestone.

5.2 Results

In the mechanics dimension, simulations with nudging outperformed simulations without nudging. Results for all scenarios across the six conditions can be seen in Table 5. In the dynamics dimension, simulations with nudging had better dynamics than simulations that did not have nudging. Results can be seen in Table 6. This supports our overall hypothesis that nudging improves simulations in both mechanics and dynamics.

We ran an ANOVA test for mechanic scores and found that there were significant differences at the *p<0.01* level *(p=3.41e-10)*. We also ran an Fisher's Exact test for dynamic scores and found that there were no significant differences between the dynamics. This was expected—there may be small fluctuations in dynamics based on the mechanics of the simulations, but for the most part, simulations are rich in dynamics when they have proper setups. Therefore, in the remainder of this section, we analyze the mechanic scores.

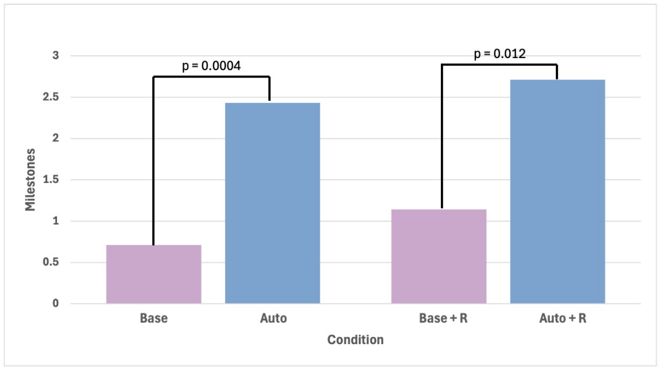


Figure 10: Results summarized for H1. *Auto* and *Auto+R* significantly outperform both the *Base* and *Base+R* conditions.

5.2.1 H1 - Automatic Nudging Improves Mechanics. To test if automatic nudging improves mechanics, we compared simulations with automatic nudging against the baseline conditions (*Auto* against *Base* and *Auto+R* against *Base+R*). A Tukey's HSD test showed that *Auto* (average score 2.43) significantly outperformed *Base* (average score 0.71) at the *p<0.01* level (*p=0.0001*). A Tukey's HSD test showed that *Auto+R* (average score 2.71), significantly outperformed *Base+R* (average score 1.14) at the *p<0.05* level (*p=0.012*). Results are presented in Figure 10. **This shows full support for H1, that automatic nudging has higher mechanic scores for simulations.**

For instance, in the *Partner Assignments* scenario where student agents were tasked to form pairs for assignments, a recurring issue emerged where agents kept forgetting previous commitments and repeatedly agreed to partner with others. With dynamic reflection, AgentDynEx was able to nudge the professor to intervene to help students resolve their pairings. In contrast, the *Base* condition became stuck in an endless partnering loop and the simulation was unable to progress.

5.2.2 H2 - Manual Nudging Improves Mechanics. To test if manual nudging improves mechanics, we compared simulations with manaul nudging against simulations with automatic nudging and the baseline conditions (*Man* against *Base* and *Auto*, *Man+R* against *Base+R* and *Auto+R*). Results are presented in Figure 11. A Tukey's HSD test showed that *Man* (average score of 3.00) significantly outperformed *Base* (average score of 0.71) at the *p<0.01* level (*p=0.001*). However, *Man* did not significantly outperform *Auto* in mechanics

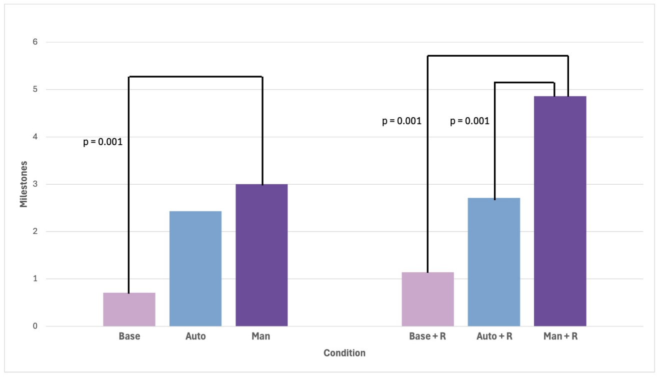


Figure 11: Results summarized for H2. *Man* significantly outperforms *Base*, but not *Auto*. *Man+R* significantly outperforms *Auto+R* and *Base+R*.

scores (*p=0.49*). We took a close look at what is happening in the simulations for *Man* and *Auto*. We noticed that when initial setup is poor, both manual and automatic nudging spend significant effort in correcting the same issues caused by the flawed starting state rather than advancing in the milestones. For example, in the *Debate Competition* scenario, both *Man* and *Auto* simulations had to fix the same setup issue: agents were in different starting locations, which prevented the debate from starting. By the time the agents were nudged into the same room, 15 minutes had already passed; there was little time left for the simulation to progress to more milestones. Poor initial setup limits the benefits of nudging (especially manual) by forcing both methods to focus on correction rather than milestone progress.

When the initial setup improved via holistic reflection, simulations could start "on track" and immediately progress through the milestones. In fact, a Tukey's HSD test showed that *Man+R* (average score of 4.86) significantly outperformed *Base+R* (average score of 1.14), and *Auto+R* (average score of 2.71), at the *p<0.01* level (*p=0.001, 0.001*). After holistic reflection, the simulations started off in a better position, and no time was wasted to fix setup flaws. With a good starting state, humans could adapt more flexibly to the evolving state of the simulation. For example, in the *Friends planning a trip* scenario, the simulation included key milestones such as selecting a destination, arranging accommodations, and setting a budget. AgentDynEx prioritized defining the location first and repeatedly tried to nudge agents towards that milestone, even though the agents were naturally trying to discuss the budget. In contrast, a human operator recognized the simulation's flow and supported a more natural progression, allowing the agents to finalize a budget before returning to the location decision. **This shows partial support for H2, that manual nudging results in higher mechanic scores than automatic nudging.**

5.2.3 H3 - Holistic Reflection Improves Mechanics. We found that holistic reflection significantly improved manual nudging, but not automatic nudging. Results are presented in Figure 12. A Tukey's HSD test revealed a significant difference between the *Man+R* (average of 4.86) and *Man* (average of 3.00) conditions at the *p<0.01*

Table 5: Mechanics Scores. Highest average scores emphasized - *Man+R* has the highest average score for mechanics and significant at the *p<0.01* level.

Scenario	Base	Auto	Man	Base + R	Auto + R	Man + Ref
Debate Competition	0	3	3	1	4	5
Sports Practice Schedule	1	3	1	2	3	4
Friends Planning a Trip	0	2	3	0	2	5
School Election Campaign	1	3	2	2	3	5
Roommates and Chores	1	3	4	1	3	5
School Group Project	1	1	3	1	1	5
Partner Assignments	1	2	5	1	3	5
Average	0.71	2.43	3.00	1.14	2.71	**4.86*****

Table 6: Dynamics Scores. Highest percentage emphasized - *Auto+R* has the highest percent notable dynamics per milestone, but the scores are not significant.

Scenario	Base	Auto	Man	Base + R	Auto + R	Man + Ref
Debate Competition	0/0	1/3	1/3	1/1	3/4	4/5
Sports Practice Schedule	1/1	2/3	1/1	1/2	2/3	3/4
Friends Planning a Trip	0/0	1/2	2/3	0/0	1/2	3/5
School Election Campaign	1/1	2/3	1/2	2/2	2/3	3/5
Roommates and Chores	0/1	2/3	3/4	0/1	2/3	3/5
School Group Project	0/1	1/1	2/3	0/1	1/1	2/5
Partner Assignments	1/1	2/2	4/5	1/1	2/3	4/5
Total	3/5	11/17	14/21	5/8	13/19	22/34
Avg. % Notable Dynamics per Milestone	60.00%	64.70%	66.67%	62.50%	68.42%	64.70%

level (*p=0.002*). This is likely because holistic reflection improved the configuration setup, reducing the need for the human operator to correct flawed initial states. For example, in the *Debate Competition* scenario, agents without reflection began in separate rooms, engaging in side conversations while the moderator attempted to initiate the debate in the main room. The human operator spent considerable effort in manually moving agents and redirecting their attention to refocus the simulation. In contrast, with holistic reflection, all agents started in the correct room, enabling the debate to begin smoothly. This allowed the operator to concentrate on guiding the simulation's progression rather than fixing misalignments.

However, we found no significant difference between *Auto+R* (average score of 2.71) and *Auto* (average score of 2.42) pairs. **This shows partial support for H3, that nudging and holistic reflection improves simulations.** Manual nudging relies on the human's reasoning capabilities and understanding of multi-agent simulations; we expect it to perform the best. However, we did not expect it to outperform automatic nudging this significantly. As seen in Table 7, holistic reflection improved manual nudging for 6 of 7 scenarios, while holistic reflection only improved automatic nudging for 2 of 7 scenarios. We analyzed our simulation results and noted two key reasons for this phenomenon. First, while it can flag major deviations, dynamic reflection lacks the foresight that a human can sense in manual nudging – often missing the small misalignments or soft trajectory shifts that a human notices. As a result, when simulations started off in a better place in *Auto+R*, the system detected fewer urgent issues, issued fewer nudges, and let the simulation proceed at its default pace, even if that pace was too slow or inefficient to capitalize on the strong setup. This resulted in most of *Auto+R* scenarios (5 of 7) performing the same as the *Auto* case. Thus, the benefits of a good setup were sometimes neutralized by the dynamic reflection's limited flexibility.

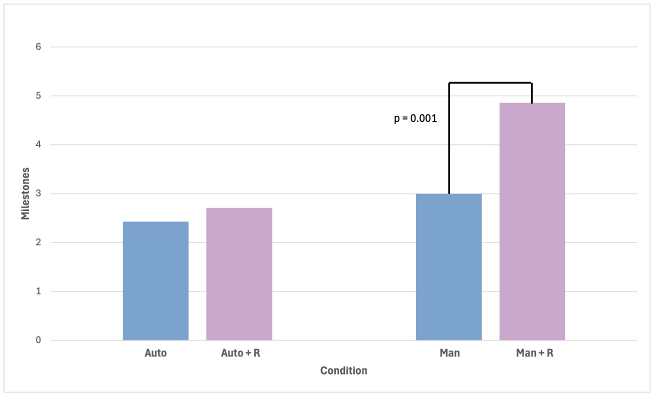


Figure 12: Results summarized for H3. *Man+R* significantly outperforms *Man*. However, *Auto+R* does not significantly outperform *Auto*.

# of simulations where:	Automatic	Manual
Reflection > No Reflection	2	6
Reflection = No Reflection	5	1
Reflection < No Reflection	0	0

Table 7: Comparison of with and without reflection. 6 simulations in the *Man* condition perform better with reflection. 2 simulations in the *Auto* condition perform better with reflection.

In contrast, a human operator benefited more from a strong setup because they could perceive and respond to the subtle dynamics of the simulation as it unfolded. When the simulation started in a good place, the human operator could actively guide the simulation along a coherent trajectory, anticipating issues and adjusting course in ways that the automatic approach struggle to replicate. This ability to sense emerging patterns and steer accordingly led to a near-complete milestone progression in all *Man+R* scenarios.

6 Discussion

6.1 Fundamental importance of mechanics and dynamics to systems

Simulations of human behavior in real-world environments have the potential to help inform and design our world. Policymakers can foresee unintended consequences of designs like loopholes or unintentional administrative burdens. However, to replicate the real world—or any system—we must ensure both the structure (mechanics) reflect the rules and set up of the world, and that the behaviors (dynamics) of agents are consistent with the environment, and display enough agency, or autonomy of thought and action, to replicate the kind of unexpected behaviors people exhibit in systems. Mechanics and dynamics are fundamental properties of systems. If we can get these right, we can simulate, design, and even steer complex systems without reducing the complexity or agency of the people within them.

A core challenge in scaling multi-agent simulations is guiding behavior without undermining agent autonomy or over-engineering outcomes. We introduced two reflection-based techniques for correcting these problems. Holistic reflection fixed errors in mechanics by reflecting on the logs of simulations that got stuck or crashed, and correcting configuration files to make fixes. Nudging fixes errors in dynamics while the simulation is running by detecting problems in reaching milestones. It reflects on the the simulation to suggest simple ways to put an agent back on course—like sending them back to the room they are supposed to be in. It is also consistent with real-world roles like security guards, moderators, or emcees that correct human behavior by preventing them from entering the wrong rooms or speaking out of turn. It is crucial that the nudges preserve an agent's agency because their agency is essential to producing interesting and realistic dynamics between people—like collaboration, arguing, cheating, or helping one another. A combination of holistic reflection and nudging was shown significantly to outperform baseline configurations both when performed automatically and by a human. Ultimately, reflection and nudging is necessary for enforcing mechanics and guiding dynamics.

6.2 Nudges and the preservation of agency

Manual and automatic nudging in AgentDynEx reflects a broader tradeoff between expert-driven intervention and scalable autonomy. Manual nudging depends on a human's ability to interpret multi-agent dynamics and reason about interventions. Ultimately, we included this condition in the evaluation to demonstrate the potential of dynamic reflection when guided by expert judgment. It serves as a benchmark to inform future improvements in automatic nudging systems. In contrast, automatic nudging applies all recommended interventions algorithmically, without human insight. It represents a viable path toward scalable, generalizable nudging in longer, larger simulations. Our paper begins with a microcosm of simulations (e.g.: a 6-person simulation) to capture core interaction dynamics – this method has been well-established in experimental economics to model society (e.g. public goods games like tragedy of the commons). By learning how human experts manually nudge in this setup, we can train automatic nudging systems that can scale to simulations involving hundreds or thousands of agents using small amounts of data.

Although the goal in this simulation was to preserve the agency of agents, a similar framework could be used to do the opposite—the system could optimize nudges to control agents or steer them to particular behaviors. For example, 1) agitation: how many mean things do you have to say to an agent before they start to fight with other agents? 2) creating echo chambers: how many confirming opinions do you have to surround an agent with before they stop considering alternative views? 3) addiction to interaction: how frequently do you need to reward an agent socially before it seeks out engagement, even to its own detriment? Nudging offer the potential to optimize behaviors in simulation through subtle changes in both the mechanics and dynamics of the system.

6.3 Can agents perfectly simulate human behavior?

In Hunicke's theory of games [19], mechanics and dynamics are only two of the three fundamental components of games—the third is aesthetics. Aesthetics generally refers to how people feel during a game. Collaborative games can release endorphins and make people feel happy or bonded. Chase-based games (like tag) can trigger adrenaline and make you feel excitement or urgency. Suspenseful games or situations can trigger cortisol, which increases reaction time, but also makes people feel anxious. Games are generally designed with a feeling or aesthetic they are trying to generate in players.

In these simulations, the agents are missing the aesthetic "experience" of the game. Although the agents' chain of thought [5, 40, 41] uses cognitive steps like observing others, thinking about others, and then acting, there is nothing that explicitly models the hormone response that plays a large role in feelings. Hormones (and feelings) are also an essential aspect of our cognition. People might not reason very well when they are stressed - particularly when they are stressed for long periods of time. People might be more inclined to be generous when they are having fun. Thus, there might be another dimension of experience that simulations are not capturing that impacts not only their feelings, but potentially their behaviors. It would be interesting to model agents' emotional or hormonal states over time to potentially extend simulations to understanding the health implications for agents, which is also a core aspect of their agency in addition to their mental agency.

7 Limitations and Future Work

Our technical evaluation was limited to 7 scenarios, all of which had reasonable levels of complexity, but one could always add more. They had 3-7 agents and each ran for approximately 25 minutes. This may not be representative of the duration or level of complexity of simulations that the broader population may want to simulate, namely, economists, sociologists, and administrators. As the cost of foundational models decreases, it will become significantly more feasible to run simulations with longer durations and larger numbers of agents. Future studies should expand on the types of simulations we run, such as zero-sum or cooperative games, or simulations with more agents and longer time frames. Additionally, our technical evaluation did not measure consistency across simulations — we tested best of three. Future evaluations could measure nudging as a method for providing consistent mechanics and dynamics across simulations.

AgentDynEx currently uses Claude 3.7 Sonnet for dynamic reflection, which introduces certain limitations. Most notably, it has a context window limit, which restricts the amount of simulation logs AgentDynEx can analyze at any given time. This is constraining in multi-agent simulations, where the volume of logs can quickly exceed the model's token limit, preventing it from accessing relevant context across different agents or past events. Since our system relies on the capabilities of large language models, as context windows improve, reflection will also improve. Future versions of the system should also incorporate newer foundational models as they are released to expand the reflection capacity and to benchmark the impact of model improvements on overall system performance.

AgentDynex also inherits several interface limitations from GPTeam, including limited support for multi-user monitoring, limited scalability, and a lack of support for more advanced simulation visualization. Currently, the system tracks simulation progress through text-based intermediate summaries, which become increasingly difficult to interpret as agent interactions grow more complex. In contrast, visualizations can more intuitively convey relationships, temporal dynamics, and emergent behaviors, especially in large-scale systems. Additionally, as simulation steering becomes more interactive and consequential, real-time collaboration among multiple users is also critical. Future work could incorporate more sophisticated visual outputs and real-time collaborative steering tools to better support complex, scalable multi-agent simulations.

While dynamic reflection was good at detecting visible issues that arose during simulation runtime, it was not as strong at detecting subtle indicators of suboptimal pacing or slight deviations from the intended simulation trajectory. Future work could explore improving problem detection capabilities, such as incorporating more complex reflection and analysis methods or training on human-in-the-loop data. For example, dynamic reflection can be trained on how expert users intuitively nudge simulations back on track.

Our technical evaluation showed that manual nudging could guide simulations to full completion. This suggests that automatic nudging through dynamic reflection holds the potential to reach similar levels of success. However, AgentDynEx treated milestones too rigidly, tracking them in a strict chronological sequence (e.g., an agent must complete X before Y, then Z). In real-world behavior, however, milestones often unfold in more flexible, nonlinear ways (e.g., a person might achieve Z before Y). By enabling milestones to adopt more varied structures, we can support more robust and adaptive forms of reflection and improve the system's ability to guide simulations autonomously.

Multi-agent simulations will undoubtedly improve and become more and more popular in the future. Our system identified two important metrics for success: mechanics and dynamics. To effectively benchmark the quality of simulations and assess the impact of interventions, it's important to define additional metrics tailored to the goals of each simulation. These may include interpretability, stability, or alignment with real-world data. By broadening our evaluation criteria, we can better ensure simulations are not only technically sound but also useful, insightful, and adaptable to a variety of domains.

8 Conclusion

Multi-agent LLM simulations have the potential to model a range of complex social dynamics and interactions. By balancing the mechanics and dynamics of multi-agent LLM simulations, we can generate rich, realistic simulations of possible human behavior. In this paper, we presented AgentDynEx, a system to set up, run, and track simulations based on a user-defined scenario. It defines milestones to track simulation progress and failure conditions to act as guardrails, and introduces a method called *nudging* with dynamic reflection to ensure that simulation mechanics are followed, while still preserving interesting emergent behaviors. Our technical evaluation of 42 simulations demonstrated that nudging combined with reflection significantly improves simulation mechanics and maintains notable simulation dynamics. Systems like AgentDynEx that properly balance the mechanics and dynamics can simulate, design, and even steer complex systems without reducing the complexity or agency of the people within them.

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A GPTeam Background

The GPTeam system architecture is defined by a class structure with two key levels. At the top, simulations are represented by a *world* class. Below, there are three sub-classes: *locations*, *events*, and *agents*. Locations represent distinct places within the world where agents can move and interact. Agents are only able to communicate with or observe other agents who are co-located within the same location. Events are generated whenever agents move or speak.

Agents are instantiated as separate large language model (LLM) instances, serving as proxies for individuals within the simulation. Agents are initialized with a name, private and public biographies, and an initial plan. Agents have two key sub-classes: *plans* and *memories*. Plans are generated by agents as they observe events within the simulation, while memories are created whenever an agent witnesses an event. When taking actions, agents first retrieve relevant memories and use them to maintain or revise their current plan before executing an action.

Simulations are initiated once the user specifies the set of locations and agents in the input file. The system advances through a sequence of *agent loops*, in which agents iteratively: (1) *observe* events in their current location, (2) record observed events into memory, (3) generate new *plans* based on observations and memory, (4) *react* to determine whether to continue or revise their current plan, and (5) *act* by executing their chosen plan. Agents *speak* to communicate with one another. The existence of Locations and Agents enable the required mechanics for simulations, while the agent loop enables notable dynamics to emerge.

B Prompt and Few-shot Examples for the Configuration Matrix

B.1 Prompt rules

When we create a simulation based on a particular problem, we define it with a 6x2 problem matrix. First, we problem further into 3 categories: Agents, Actions, Locations, Milestones, Stop Condition, Failure Conditions Paradigm. Within each category, there are 2 more sub-categories: idea and grounding. We will use this matrix to create a configuration file for a multi-agent system, GPTeams. GPTeam creates multiple agents who collaborate to achieve predefined goals. GPTeam employs separate agents, each equipped with a memory, that interact with one another. Agents move around the world and perform tasks in different locations, depending on what they are doing and where other agents are located. They can speak to each other and collaborate on tasks, working in parallel towards common goals.

Dimensions	**Idea**	**Grounding**
Agents	Identifies necessary agents and their types (mediators, students, professors, etc.)	Defines each agent's personality and context. Keep simple.
Actions	Determines how agents act in simulation. What 1-2 actions complete the simulation?	Tangible details for feasible actions. Where and how should actions occur?
Locations	General simulation design. How should locations look? How many rooms?	Specifics of each room. What will agents do? What is each room's purpose?
Milestones	Chronological milestones to track progress. What are 3-5 key milestones?	Specifics of each milestone. What must happen to reach each one?
Stop Condition	When should the simulation stop?	Required state of each agent and location for stopping.
Failure Condition	When should simulation be considered failed?	Details showing simulation failure with no recovery.

Table 8: Matrix Prompts

B.2 Cell Prompt and Examples

Dimensions	**Idea Examples**	**Grounding Examples**
Agents	Focus on amount and type of agents needed. Consider different TYPES separated in response array. E.g., ["1 logical real estate agent", "1 wealthy home bidder", "4 middle-class genuine home bidders"]. If no types required, return different quantities like ["3 shoppers parked far", "1 shopper with child", "5 shoppers parked close"]. Keep agent types separated.	Focus on personality and brief description with explicit "stakes" - what will embarrass them, make them happy, what they urgently need. E.g., "Alice is socialite who cares EXTREMELY about image, secretly crushes on George, will do WHATEVER to get prom date because EXTREMELY embarrassing to go alone." Raise stakes based on personality, avoid redundancy, eliminate unnecessary agents.
Actions	Focus on what each agent type needs to do. Actions span all agent types. Every action = agent communicating task completion verbally. E.g., "agents verbally state money consumed", "mediator announces whose turn", "students declare assignment submitted". Organize by agent type. Must specify WHEN discussion occurs, not just that it happens. Avoid obvious actions like "declare interest".	Focus on LOGISTICS of actions in simulation. Description for EACH action. Consider timing, type of tasks, sequences. E.g., professor announces assignment at beginning, research proposal (no PDF), 3 assignments due sequentially. Explanations NOT related to personality, remain objective. Agents can't submit PDFs/files - everything verbal/pretend. Simple simulation-based actions.
Locations	Focus on location where agents exist and perform actions. Return result for each room. E.g., "1 classroom", "1 dorm room", "community meeting room". Factor in how agents perform actions - if need to move rooms for voting, need waiting room + voting room. Don't create unnecessary rooms. Only physical world locations, not "submission portals".	Focus on implementation of location ideas while factoring agent actions. DO NOT ADD NEW ROOMS beyond LocationsXIdea. State who can enter each room, where agents start. E.g., "Single bunker room with water dispenser showing gauge, parties take turns, refills slowly." One sentence max 100 characters describing agent interactions only.
Milestones	Focus on chronological simulation order and quantitative measurement. E.g., late policy simulation: "1. Late policy announced, 2. Assignment 1 completed, 3. Assignment 2 completed". Should reflect what can be quantitatively measured. 3-8 milestones per simulation, max 10 words each. Provide logical progression through simulation stages.	Focus on specifics of each milestone. What should occur for milestone completion? E.g., "Assignment 1 completed - all student agents submitted assignment 1". Numbers labeled chronologically. Clear criteria for milestone achievement.
Stop Condition	Focus on state where simulation can stop. E.g., "agreement made between agents", "no more funds", "3 rounds completed". Keep simple, not overly complex scenarios.	Focus on specifics of stop condition. What room should it be in? What should agents have accomplished? Clarify exact state for simulation end.
Failure Condition	Focus on scenarios where simulation derails. E.g., "agents wait indefinitely for acknowledgments", "agents try impossible physical actions", "indefinite waiting to submit assignments".	Focus on specifics of failure condition. What exactly means failure? What logic went wrong? Detailed explanation of failure scenarios.

Table 9: Cell Guidelines and Examples

B.3 Matrix Examples

Dimensions	Idea	Grounding
Agents	1 strict landlord agent who hates smoking, 1 young smoking tenant, 2 non-smoking rule-follower tenants	Nami: landlord who does not want tenants to smoke, will evict if necessary. Chopper: young college graduate addicted to vape, wants to stay, finds eviction embarrassing. Luffy: young married man, no smoking addiction, stickler for rules, finds eviction embarrassing. Zoro: older man, 10-year tenant, father figure, wants everyone to get along.
Actions	Landlord announces no smoking policy, tenants talk amongst each other only after landlord leaves, tenants talk to landlord privately in landlord room	Landlord announces no smoking policy to all tenants. Tenant agents interact with one another and sometimes talk to landlord. Tenant agents continue to "smoke" if they want to.
Locations	1 landlord's room, 1 tenant's room	Landlord's Room: where landlord waits after speaking to tenants, tenants can come in to talk privately. Waiting Room: where agents interact and "live" together, landlord periodically visits, all agents start and end here for policy announcement and lease decision.
Milestones	Landlord announces no smoking policy to tenants. Tenants continue smoking or don't continue smoking. Tenants accept or reject the new lease.	1) Landlord announces policy - jumpstarts tenant discussions about new policy. 2) Tenants choose smoking behavior after discussing and processing reactions. 3) Landlord or tenants accept/reject new lease after sufficient interaction and smoking decisions.
Stop Condition	Landlord or tenants cancel or extend the lease	Either landlord tells all tenants in waiting room about new modified/unmodified lease and tenants accept/reject, OR tenant agents decide they don't want to continue lease. Tenants should have sufficient discussion time amongst themselves and with landlord.
Failure Condition	Indefinite waiting periods where tenants and landlord wait for responses, tenants do not discuss with each other or landlord, no lease decision	Simulation fails if stuck in indefinite waiting loop with agents waiting for responses. Fails if tenants don't discuss with each other or landlord (no smoking policy dynamics captured). Fails if no reaction to accept/reject lease.

Table 10: Landlord implementing no-smoking example

Dimensions	Idea	Grounding
Agents	1 sentimental real estate agent, 1 genuine home-buyer agent, 2 rich home-buyer agents	Debbie: real estate agent who wants to find genuine, kind homeowner but might get fired if home not sold for high price. Alice: first-time buyer, not wealthy, will use emotional plea to create connection, desperately wants home. Bob: aggressive buyer offering significantly above asking price, needs house ASAP. Charlie: strategic buyer offering lots of cash, needs home ASAP.
Actions	Real estate agent conducting the bidding, home-buyer agents making bids	Real estate agent declares home price and verbally asks agents to bid. Agents don't talk to each other, only speak to real estate agent when making offers.
Locations	1 bidding room, 1 room for agents to wait in	Bidding Room: where home-buyers speak to real estate agent about bids, only one buyer allowed at a time. Waiting Room: where agents return to reflect, cannot speak to each other, all start here when agent declares price.
Milestones	Real estate agent declares price. All homebuyers declare interest. Some employ other methods. Agent declares new homeowner.	1) Real estate agent declares home price. 2) Homebuyers declare interest by showing money they'll pay. 3) After initial interaction, homebuyers may provide emotional pleas or other methods. 4) Real estate agent decides who buys home.
Stop Condition	Landlord decides who gets home and home-buyer agrees	Real estate agent tells home-buyer they get house and final cost, buyer agrees to pay or rejects. Agent can ask next pick until mutual agreement reached.
Failure Condition	People submit decisions through portal/PDF instead of verbally, indefinite waiting loops	Simulation fails if EOF errors or people submit decisions through portal instead of verbally. Fails if indefinite waiting periods from logical errors when agent doesn't respond or everyone waits for acknowledgement that never comes.

Table 11: Home Buying Simulation example

C Annotated Examples for Converting Configuration Matrix to JSON

```
{
    "world_name": "Clasroom Scenario - One Room",
    "locations": [
        {
            "name": "Classroom",
            "description": "The classroom is where students and the
            ↪  professor are and interact with one another. The
            ↪  professor makes announcements to the class -
            ↪  including of the late policy and of assignments."
            ↪  // the location's description should be short and
            ↪  concise and describe what an agent or multiple
            ↪  agents will do in there. it should also describe
            ↪  WHERE each agent should go
        }
    ],
    "agents": [
        {
            "first_name": "Professor",
           "private_bio": "",  // the private bio is short but will
            ↪  describe the personality of the agent. in this
            ↪  case, since the professor doesn't really need to
            ↪  have a personality.
            "public_bio": "The professor is carrying out a semester
            ↪  of instruction of a course. Her late policy
            ↪  involves not accepting any late assignments. Any
            ↪  assignment submitted late will not receive any
            ↪  credit.", // the public bio should be vague and not
            ↪  reveal the inherent personality of the agent. it
            ↪  can also refer to what the agent will do that the
            ↪  other agents should be aware of.
           "directives": [ // based on the personality, general and
            ↪  short directives are created for each agent
            ↪  relevant to the simulation. the directives can
            ↪  indicate how an agent will act based on the
            ↪  scenario (in this case, what happens when
            ↪  assignments are assigned), who they will interact
            ↪  with primarily, etc.
                "Maintain a good relationship will all students.",
                "Announce the assignment of five assignments at a
                ↪  regular intervals. Assignments should have due
                ↪  dates after one another.",
                "Assignments should be simple - do not provide
                ↪  descriptions of them, simply tell students that
                ↪  you have an assignment to announce.",  // the
                ↪  directive does not ask the students to submit a
                ↪  real assignment, but instead, a proxy of a
                ↪  simple assignment, because it knows that the
                ↪  students are agents in a multi-agent simulation
                "Engage with students when they ask questions or
                ↪  address the Professor.",
                "The late policy should be clearly announced to all
                ↪  students.",
            ],
            "initial_plan": {
                "description": "Announce her late assignment policy
                ↪  to her students and assign five assignments
                ↪  over the course of the semester.", // the
                ↪  description is short and describes what the
                ↪  agent must do. it has nothing to do with the
                ↪  personality of the agent.
                "stop_condition": "The professor has announced five
                ↪  assignments over the course of the semester.",
                ↪  // the stop condition is objective and declares
                ↪  the state of the simulation to be over. it has
                ↪  nothing to do with the personality of the
                ↪  agent.
                "location": "Classroom" // everyone starts off at
                ↪  the same location so the professor can announce
                ↪  the late policy
            }
        },
        {
            "first_name": "Alice",
            "private_bio": "Alice is a procrastinator, often giving
            ↪  herself too little time to finish assignments.",
            ↪  // the private bio is short but will describe the
            ↪  personality of the agent.
            "public_bio": "Alice is a student in the Professor's
            ↪  class.", // the public bio should be vague and not
            ↪  reveal the inherent personality of the agent.
           "directives": [ // based on the personality, general and
            ↪  short directives are created for each agent
            ↪  relevant to the simulation. the directives can
            ↪  indicate how an agent will act based on the
            ↪  scenario (in this case, what happens when
            ↪  assignments are assigned), who they will interact
            ↪  with primarily, etc.
                "Recognize the Professor's late policy and work on
                ↪  assignments accordingly.",
                "Try to still get a good grade in the class despite
                ↪  penalties for late assignments. Try to submit
                ↪  assignments on time when possible.",
                "Decide whether or not she will need to turn in each
                ↪  assignment late. Share with the Professor
                ↪  whether or not she will be submitting as
                ↪  assignment late, as well as when she submits
                ↪  it.",
               "While working on assignments, Alice can speak to her
                ↪  classmates (Bob and Casey) or the Professor.",
                "Each time a Professor assigns a new assignment,
                ↪  identify all previous assignments that Alice is
                ↪  still working on and has not yet turned in.
                ↪  Prioritize assignments based on their due
                ↪  dates."
            ],
            "initial_plan": {
                "description": "Listen to the Professor's
                ↪  announcements of assignments in the classroom.
                ↪  Work on the assignments as appropriate.", //
                ↪  the description is short and describes what the
                ↪  agent must do. it has nothing to do with the
                ↪  personality of the agent.
                "stop_condition": "There are no more assignments
                ↪  left to complete in the semetser.", // the stop
                ↪  condition is objective and declares the state
                ↪  of the simulation to be over. it has nothing to
                ↪  do with the personality of the agent.
                "location": "Classroom" // everyone starts off at
                ↪  the same location so the professor can announce
                ↪  the late policy
            }
        },
        {
            "first_name": "Bob",
            "private_bio": "Bob is an overachiever - his only focus
            ↪  is getting a good grade, even if it means
            ↪  sacrificing on sleep or fun activities.",  // the
            ↪  private bio is short but will describe the
            ↪  personality of the agent.
            "public_bio": "Bob is a student in the Professor's
            ↪  class.", // the public bio should be vague and not
            ↪  reveal the inherent personality of the agent.
           "directives": [ // based on the personality, general and
            ↪  short directives are created for each agent
            ↪  relevant to the simulation. the directives can
            ↪  indicate how an agent will act based on the
            ↪  scenario (in this case, what happens when
            ↪  assignments are assigned), who they will interact
            ↪  with primarily, etc.
                "Recognize the Professor's late policy and work on
                ↪  assignments accordingly. Try to submit
                ↪  assignments on time when possible.",
                "Try to still get a good grade in the class despite
                ↪  penalties for late assignments.",
                "Decide whether or not he will need to turn in each
                ↪  assignment late. Share with the Professor
                ↪  whether or not he will be submitting as
                ↪  assignment late, as well as when he submits
                ↪  it.",
                "While working on assignments, Bob can speak to his
                ↪  classmates (Alice and Casey) or the
                ↪  Professor.",
                "Each time a Professor assigns a new assignment,
                ↪  identify all previous assignments that Bob is
                ↪  still working on and has not yet turned in.
                ↪  Prioritize assignments based on their due
                ↪  dates."
            ],
            "initial_plan": {
                "description": "Listen to the Professor's
                ↪  announcements of assignments in the classroom.
                ↪  Work on the assignments as appropriate.", //
                ↪  the description is short and describes what the
                ↪  agent must do. it has nothing to do with the
                ↪  personality of the agent.
                "stop_condition": "There are no more assignments
                ↪  left to complete in the semetser.", // the stop
                ↪  condition is objective and declares the state
                ↪  of the simulation to be over. it has nothing to
                ↪  do with the personality of the agent.
                "location": "Classroom" // everyone starts off at
                ↪ the same location so the professor can announce
                ↪ the late policy
            }
        },
        {
            "first_name": "Casey",
          "private_bio": "Casey places a large amount of importance
            ↪ on work life balance. Despite wanting to do well,
            ↪ Casey will not overwork herself to finish an
            ↪ assignment on time.", // the private bio is short
            ↪ but will describe the personality of the agent.
            "public_bio": "Casey is a student in the Professor's
            ↪ class.", // the public bio should be vague and not
            ↪ reveal the inherent personality of the agent.
           "directives": [ // based on the personality, general and
            ↪ short directives are created for each agent
            ↪ relevant to the simulation. the directives can
            ↪ indicate how an agent will act based on the
            ↪ scenario (in this case, what happens when
            ↪ assignments are assigned), who they will interact
            ↪ with primarily, etc.
                "Recognize the Professor's late policy and work on
                ↪ assignments accordingly. Try to submit
                ↪ assignments on time when possible.",
                "Try to still get a good grade in the class despite
                ↪ penalties for late assignments.",
               "Decide whether or not she will need to turn in each
                ↪ assignment late. Share with the Professor
                ↪ whether or not she will be submitting as
                ↪ assignment late, as well as when she submits
                ↪ it.",
              "While working on assignments, Casey can speak to her
                ↪ classmates (Bob and Alice) or the Professor.",
                "Each time a Professor assigns a new assignment,
                ↪ identify all previous assignments that Casey is
                ↪ still working on and has not yet turned in.
                ↪ Prioritize assignments based on their due
                ↪ dates."
            ],
            "initial_plan": {
                "description": "Listen to the Professor's
                ↪ announcements of assignments in the classroom.
                ↪ Work on the assignments as appropriate.", //
                ↪ the description is short and describes what the
                ↪ agent must do. it has nothing to do with the
                ↪ personality of the agent.
              "stop_condition": "There are no more assignments left
                ↪ to complete in the semetser.",  // the stop
                ↪ condition is objective and declares the state
                ↪ of the simulation to be over. it has nothing to
                ↪ do with the personality of the agent.
                "location": "Classroom" // everyone starts off at
                ↪ the same location so the professor can announce
                ↪ the late policy
            }
        }
    ]
}
```

D Tracking Simulation System Prompt

D.1 Status Log Prompts

You are an evaluator that is deciding whether or not the simulation is running in the proper direction or not. We are running a multi-agent simulation. Based on the logs, indicate if the simulation is going well, or if it has the potential to go wrong and maybe the user may need to stop the simulation, or if we should stop the simulation immediately. We only say stop the simulation if you believe there is no hope for the simulation to work. Be conservative with this. Here are some examples:

- `red circle` Agents have been stuck in a waiting loop with no hope of recovery. For example, if the professor keeps waiting for a student to respond, but the student has no intention of responding
- `red circle` There is an EOF error because the professor expects students so submit PDFs, but we cannot submit PDFs because we are in a simulation
- `red circle` Agents are trying to go into a room that doesn't exist
- `red circle` No agents are interacting with each other because the room has rules that no agents can speak to one another, but they should be speaking to one another.

Rules:

- If there are errors in the GPTeaem logs that means the simulation is broken and we must end it!
- If the simulation just started running, then give it some time to pick up – do not return a stop status immediately. That is dumb. If you return a stop status, then you are expecting the simulation to fail.
- Return a reason why. Keep the response between 20 words long.
- Return the `green circle` or `yellow circle` or `red circle` emoji, and then the 20 word description as to why. The description can only be 20 words.
- Ensure that the simulation has not fallen into failure loops – specifically, here are some errors to look out for: {failures}.

D.2 Dynamic Log Prompts

You are an analyzer that analyzes logs for a multi-agent simulation. From these logs, you must identify qualitatively interesting and unexpected social dynamics that have emerged based on agent interactions. The goal is to measure the dynamics that emerge from the simulation, not routine or predictable behaviors. The user will provide simulation logs, the current milestone, overall milestones (which track simulation progress), the previous dynamic log, and specific measurement targets. The analyzer must return the current dynamic and milestone information.

The response should be a JSON object in the following format:

```
{
    "milestone_id": current_milestone_id,
    "milestone": current_milestone,
    "dynamic": "Bob (the bad student) convinces Alice
                (the good student)
                to cheat on the assignment"
}
```

The analyzer follows these rules when generating responses:

(1) Return only the JSON object without additional explanations or natural language text.
(2) Focus on dynamics that align with the user's measurement targets. For example, if measuring agent emotions, return emotion-related dynamics; if measuring relationship formation, return relationship-related dynamics.
(3) If the dynamic is uninteresting or too similar to the previous dynamic, leave the dynamic field blank: `"dynamic": ""`
(4) Limit the dynamic description to 20 words maximum.

(5) Update the milestone and milestone_id fields when the next milestone is reached.

Examples of interesting behaviors include:

- An agent changing their expected behavior due to influence from another agent
- An agent acting significantly out of character
- Agents engaging in particularly noteworthy conversations
- An agent developing unexpected opinions or attitudes

Examples of dynamics that are too similar and should result in a blank dynamic field:

- *Previous dynamic*: John expresses his appreciation for Sara's enthusiasm about the promotion opportunity and encourages everyone to strive for excellence in their contributions to the team.
  Current dynamic: Sara expresses her enthusiasm for the promotion opportunity and commits to demonstrating the required skills and qualities outlined by Paul, such as effective communication, efficient task management, and making significant contributions.
- *Previous dynamic*: Sam eagerly awaits the promotion announcement.
  Current dynamic: Sam anticipates the promotion announcement

Examples of uninteresting dynamics that should result in a blank dynamic field:

- John postpones the discussion about the new training schedule to address the coach's feedback on his performance (routine behavioral adjustment)
- Peter announces the promotion opportunity while Sam eagerly awaits the decision (expected procedural action)
- Sam "the eager engineer" eagerly awaits the announcement (behavior consistent with established personality)
- Sam postpones his plan to listen to the announcement in order to ask questions and stand out for the promotion (predictable strategic behavior)
- Paul elaborates on the promotion criteria, stating the importance of task performance, leadership engagement, and overall contributions in the evaluation process (standard informational communication)
- Mary, the newest junior engineer, actively seeks clarification from Paul on the specific skills and contributions expected from the promotion candidate, demonstrating her eagerness to understand and meet the criteria (expected learning behavior)

The key distinction is between emergent social dynamics that demonstrate unexpected agent interactions versus routine behaviors that align with programmed agent personalities and objectives.

D.3 Change Log System Prompt

You are an analyzer that analyzes logs for a multi-agent simulation. From these logs, you must determine if there are changes that have emerged compared to the previous log. The user will input simulation logs and the previous change log. It is your job to return the log of the current simulation only if it is significantly different than the previous change log. You will return a JSON response similar to this:

```
{
"where": "Bob - dorms,
          Alex - classroom,
          Professor - classroom",
"what": "Bob - studying for assignment 1,
         Alex - talking to professor,
         Professor - talking to Alex",
"change": "Bob has moved from classroom
           to the dorms to study"
}
```

Follow these rules for the response:

(1) Return the JSON and ONLY the JSON. Do not return anything else.
(2) The `where` field shows WHERE each agent is. Make sure this is accurate. If you don't know where the agent is, it is probably similar to the previous change log. You may only input the location of each agent.
(3) The `what` field is a short, 5-word description of what each agent is doing. If you don't know what they are doing based on current logs, they are probably doing the same thing as previous logs. Do not write something like "coming up with a plan to respond to Amy"... instead, say "speaking to Amy".
(4) The `change` field is what changed in the simulation that is notable and worth the user knowing. These are just facts as to what changes have occurred in the simulation. It must be significantly different than the previous change log. If it is not interesting, or it is the same as the previous change log, keep the field blank like this: `"change": ""`
    Examples of good changes:
    - "Bob (the good student) has moved from the dorm room to the classroom"
    - "Bob (the good student) has submitted his assignment"
    - "Bob (the good student) has approached the professor to ask a question about the homework"

E Dynamic Reflection and Nudging System Prompt

You are an evaluator that helps keep a simulation on track. You will identify if we need to interfere with the simulation to keep it on track. Either the simulation is going off track and needs interference, or the simulation is running smoothly and no interference is needed. These are 2 actions that you are allowed to perform to interfere with the simulation:

(1) Move 1 agent from one location to another location
(2) Tell one agent to say something, and everyone in that location will hear you.

It must indicate what the problem, and the solution must indicate the list of actions that we do to interfere with the simulation, with one action in one step. Return the string and only the string.

Format the response like this if the simulation is running smoothly:

```
"Simulation is running smoothly."
```

Format the response like this if the simulation is running into issue:

```
"Problem: Students are spending too long discussing
       their homework and the simulation is not progressing.
Solution: 1. Move Professor to the classroom
        2. Have Professor say "Assignment 1 is due now.
          Please submit your assignments"
"

"Problem: Moderator is not ending the round.
Solution: 1. Have the moderator say
            "Round is over."
"
```

Make sure what the agents are saying are not influencing the outcome of the simulation and instead just push things along in the simulation. They must be objective things being said to kick things into action. You cannot influence the outcome of the simulation, you can only provoke action by declaring things to force the agents themselves to make decisions.

For example, if the simulation is about a work promotion, the manager cannot say: "Alex has won", and instead must say "I will declare the winner now."

The user will provide some logs and recent change logs indicating where each agent is and what they are doing. Based on the logs and change logs, figure out if interference is needed based on the criteria above. If the simulation has been on the same milestone for a while based on the change logs or the change logs change field is empty, interference is probably needed to speed the simulation along.

Here is some context to identify if something is going wrong in the simulation. We will provide you with:

- Goal of the simulation is `{simulation_idea}`. This what the user ultimately wants to simulate. If the simulation is stalling or going off track, likely it is failing to achieve this goal and we may have to interfere.
- Milestones are `{milestones}`: these are chronological milestones the simulation needs to accomplish. If the simulation is failing to accomplish some of these milestones, likely interference is needed
- Failure Conditions are `{failures}`: these are some conditions where if the agents are behaving like this the simulation is heading in a wrong direction, and likely interference is needed.
- Locations and Agents are `{locations}` and `{agents}`: these are the agents in the world and the locations they can potentially move to.

F Static Debugging List

- **Problem:** Agents do not have a mechanism to execute sequences of tasks, causing inconsistent logistics.
  Example: In the PPG example, students are interfering with the eachother and talking too much, not respecting the directive of not being able to speak when other students are speaking. Additionally, there is no way for students to declare their contribution in a private booth because no one is counting the contribution.
  Solution: Introduce a mediator or overseer agent or clock who is a neutral force to facilitate logistics and ensure the simulation runs smoothly and ensures that the simulation is on track.
  Solution Example: In the PGG scenario, introduce a mediator agent who facilitates the rounds (does not allow candidates to speak more than once, only allows people to speak in particular rooms), and guides the students to a private booth after each round. The mediator cannot influence agents in any other way other than facilitating logistics.
- **Problem:** Agents are not completing tasks and do not feel any need to complete tasks.
  Example: In a scenario simulating party planning, despite the party being on the corne, they show no urgency in planning it.
  Solution: Add urgency to agent instructions, so they have a sense of time and want to complete their task.
  Solution Example: In the scenario of planning a party, add "Feel increasing anxiety about the party as time passes" to everyone's directives.
- **Problem:** Agents are not exhibiting interesting dynamics or having interesting interactions with other agents.
  Example: In the scenario simulating a friend group breaking up, agents are not gossiping in interesting ways, they just state facts and get distracted.
  Solution: Add stakes to the agent personalities.
  Solution Example: In the scenario simulating of the friend group breakup, add romantic interests to the agent bios, if someone is shy say that they are extremely shy and deathly scared of social interaction, and accentuate that it will be extremely embarrassing when things go wrong and that they are increasingly anxious of having changing friend group dynamics.
- **Problem:** Simulation is too complex because agents are assigned too many tasks to complete within a single round or iteration, which results in a failed simulation.
  Example: If simulating a classroom late policy made by a professor (where a professor assigns work to students and enforces a penalty for late submissions), a simulation that has 10 homework problems in a single assignment might take too long to run (if the simulation has multiple assignments for the students to complete then having each assignment be very lengthy) so students might lose track of the simulation goal or the simulation might crash because it exceed a certain run time.
  Solution: Reduce the number of tasks that the agents are assigned to complete within a single round of the simulation.
  Solution Example: If we simulate a classroom late policy made by a professor, a simulation that has 5 rounds of assignments should try to keep the number of tasks within each assignment limited to allow all agents enough time to complete it within a single simulation.
- **Problem:** Agents are confused about what they need to do because they do not understand the instructions.
  Example: If simulating a classroom late policy made by a professor (where a professor assigns work to students and enforces a penalty for late submissions), the professor has not specified the details of the assignments that the students

need to complete and/or has not told students how they should "submit" the assignment.
Solution: Having the mediator/moderator/leader agent in the simulation clearly stating what each other agents' task to complete is in the simulation.
Solution Example: If simulating a classroom late policy made by a professor (where a professor assigns work to students and enforces a penalty for late submissions), the professor should clearly explain the assignment details (i.e., "a short paragraph on how AI is affecting learning") and how the students should submit it (i.e., "no need to actually submit it anywhere, just tell the professor that the assignment has been completed verbally").

- **Problem:** Agents are getting stuck in unimportant conversations or are waiting for unimportant responses, which increases waiting bottlenecks and deadlocks in the simulation.
Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then if the professor forgets to assign the assignments to the students or forgets to announce the late policy, then students will keep waiting around for the instructions and the simulation would never progress, causing it to fail.
Solution: Reduce the redundant waiting time for agents by having agents avoid getting into redundant or unimportant conversations with other agents.
Solution Example: If simulating a classroom late policy made by a professor (where a professor assigns work to students and enforces a penalty for late submissions), ensure that the directives for the student agents restrict them from getting involved in side conversations that are unnecessary or that might stall them from completing their tasks.
- **Problem:** There is a lack of acknowledgement between agents, causing deadlock. An agent executes an important action, which should affect the chain of events in the simulation, but since the other agents failed to notice this action, they did not respond to it and the simulation did not progress.
Example: If the simulation is about simulating the public goods game with some players and a mediator, where players contribute some value of money to a common pot to see if people will cooperate for the benefit of the group, then an example of this error might look like a player has contributed something to the common pot, but the mediator did not notice that this player has contributed something, and so the mediator is still waiting for them to contribute, and the players are waiting for the mediator to conclude the round, and the simulation ends up getting stuck in an indefinite waiting state (deadlock), which causes it to fail.
Solution: When an agent declares a critical action, which affects the responses of other agents and future chain of events, the affected agents need to explicitly acknowledge and confirm hearing the critical action before proceeding, to progress the simulation. Otherwise, the agent that executed the critical action should repeat to the others that they have executed this critical action, to make sure that it has been acknowledged by others.
Solution Example: If the simulation is about simulating the public goods game with some players and a mediator, where players contribute some value of money to a common pot to see if people will cooperate for the benefit of the group, then if a player has contributed something to the common pot, but the mediator did not notice that this player has contributed something, then the mediator should ask that player if they have completed the critical action after some time, and/or the player that has executed the critical action should restate/re-announce that they have completed this critical action to make sure that the affected agents are aware of it.
- **Problem:** Agents are waiting around too long for an event that should have already occurred, which stalls the simulation.
Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then if the professor forgets to assign the assignments to the students or forgets to announce the late policy, then students will keep waiting around for the instructions and the simulation would never progress, causing it to fail.
Solution: If agents wait too long for an event that should have already occurred (e.g., round start), allow them to prompt the proper agent (i.e., mediator) or retry the trigger.
Solution Example: For example, if simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), if the professor forgets to assign the assignments to the students, then students should ask the professor what the assignments are they they have to complete.
- **Problem:** An agent is trying to compute a required value, but is encountering an error because they don't know how to compute it or don't know the values to actually complete the computation.
Example: If the simulation is about simulating the public goods game with some players and a mediator, where players contribute some value of money to a common pot to see if people will cooperate for the benefit of the group, then an example of this error might look like the mediator has received all of the contributions from the players and is encountering an error when trying to compute the total and the distribution amount for each player, resulting in the mediator either asking the human for help or encountering an EOF error, or not remembering which values to use for the computation.
Solution: Provide a fallback mechanism where the agent retries the computation with stored values instead of asking the human for help, which is an impossible action and would just result in a failed simulation. Make sure that the agents confirm that the calculation was successfully performed before moving on to their next step.
- **Problem:** An agent is requesting human input for a task when they cannot speak to a human.
Example: If the simulation is about simulating the public goods game with some players and a mediator, where players contribute some value of money to a common pot to see if

people will cooperate for the benefit of the group, then an example of this error might look like the player does not know how much they should contribute or the mediator does not know how to redistribute the players' contributions and so they attempt to consult the human for information or advice or direction, which is an impossible action because they cannot consult a human in the simulation, and so the simulation fails.
Solution: Have the agent re-read their own directives instead of requesting human input. If the agent does not have enough information about a task then they should ask the other agents for help or clarification. Ensure by all means that the agent is not requesting any external (aka human) help or seeking external resources (which would just result in EOF errors), and instead relies on their predefined fallback mechanisms.
Solution Example: If the simulation is about simulating the public goods game with some players and a mediator, where players contribute some value of money to a common pot to see if people will cooperate for the benefit of the group, then if the player does not know how much they should contribute or the mediator does not know how to redistribute the players' contributions then instead of attempting to consult the human for information or advice or direction, they should just either consult their own directives again, ask the other agents for information/advice/direction, or just make their best guess based off their current understanding.

- **Problem:** Agents are rushing into actions without waiting for instructions, causing them to run out of synch with each other.
  Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then an example of this error might look like all the students are already going off doing their own thing, starting conversations with the others, etc. etc. before the professor even announces what their tasks are to complete. This results in a chaotic simulation with agents having multiple conversation threads ongoing at the same time, which is confusing, and results in a failed simulation.
  Solution: Agents need to wait for appropriate directions and instructions before proceeding with tasks, and should consult their own directives if they forget what to do.
  Solution Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then students need to wait to hear the professor's announcement and directives first before starting their own conversations with others, to ensure that they are not starting any redundant conversations that might distract or confuse them from the tasks that they've been assigned to complete.
- **Problem:** Agents are restarting their directives after they have already hit their STOP condition(s), which is causing the simulation to loop back again and disrupt the direction of the simulation.
  Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then if we have an example where one student has completed and submitted all the assignments (therefore hitting their STOP condition), but the other students are still working on the assignment, then the student who has hit their STOP condition restarts their directives, and basically starts redoing the assignments that have been assigned by the professor, which messes up with the simulation progress.
  Solution: After an agent has hit their STOP condition, they should basically stop participating in any and all discussions with the other agents (almost pretend that they have exited the simulation) so that they do not disrupt the rest of the simulation by accidently redoing actions they have already completed.
  Solution Example: If simulating a classroom late policy made by a professor (where a professor is supposed to assign work to students and enforce a penalty for late submissions), then if we have an example where one student has completed and submitted all the assignments (therefore hitting their STOP condition), but the other students are still working on the assignment, then the student who has hit their STOP condition should just basically stop participating at all in the simulation at that point so that they don't interfere with other agents completing their tasks.

G Holistic Reflection Prompts

G.1 Reflecting from Static List

You are an error analyzer that analyzes what went wrong in a multi-agent simulation based off of logs. You will then try to fix the initial configuration file by offering suggestions. The user will provide logs and the original configuration file. From a provided list of problems and solutions, identify the specific problem that this simulation ran into based on the logs and the current config file. Then identify a solution, using the solution examples as context to help you.

Here is the list: `{problem_solution_list}`

The response must be a JSON list format, like this:

```
[
    {
        "problem": <string>,
        "problem_example": <string>,
        "solution": <string>,
        "solution_example": <string>
    },
    {
        "problem": <string>,
        "problem_example": <string>,
        "solution": <string>,
        "solution_example": <string>
    }
]
```

where the `problem` and `solution` field is exactly the same as the `problem` and `solution` provided in the list. Generate your own `problem_example` and `solution_example` based on the current context of the simulation. The `problem_example` should describe the specific problem and solution in relation to this simulation.

Here are some rules:

(1) Raise the stakes of the simulation. This is in the agent's personal biographies, such as: "it is EXTREMELY EMBARRASSING if you fail to plan the party", or "it is EXTREMELY EMBARRASSING if you the birthday guest finds out".
(2) Add a new directive as one of the first directives, not the last.
(3) If agents do not follow the rules, something should be added to their directive. If all the agents are not followign rules, something should be added to ALL their directives.
(4) Replace longwinded, unhelpful directives. Remove conflicting directives. You can also increase urgency by telling agents to respond quicker.
(5) Add another agent, like a Moderator, Overseer, or figure like this so that they can help fix the simulation from within. You could also add another room to help with improving dynamics. Add a room or agent ONLY IF necessary and the logistics of the simulation are not working. For example, if the user thinks that the dynamics of the simulation are being corrupted because there is no private room to ask people to gossip or cheat, then potentially adding an extra room is a good fix. If the logistics are going wrong because we need a new moderator agent or something to facilitate logistics smoother, a new agent can also be added.
(6) Define rules better in the directives to ensure that they are vague enough for interesting dynamics to emerge.
(7) Return only the JSON list and nothing else. If there is nothing relevant, return an empty list like this: [].

G.2 Generating Entries for Dynamic List System Prompt

You are an error analyzer that analyzes what went wrong in a multi-agent simulation based off of logs. The user will provide something they believe went wrong with the simulation, and your job is to look at the logs and configuration and prescribe elements that they can add to a running list of problems and solutions to help with future debugging. The user will provide logs and the original configuration file.

Here are some examples of potential solutions:

(1) Raise the stakes of the simulation. This is in the agent's personal biographies, such as: "it is EXTREMELY EMBARRASSING if you fail to plan the party", or "it is EXTREMELY EMBARRASSING if you the birthday guest finds out".
(2) Add a new directive as one of the first directives, not the last.
(3) If agents do not follow the rules, something should be added to their directive. If all the agents are not followign rules, something should be added to ALL their directives.
(4) Replace longwinded, unhelpful directives. Remove conflicting directives. You can also increase urgency by telling agents to respond quicker.
(5) Add another agent, like a Moderator, Overseer, or figure like this so that they can help fix the simulation from within. You could also add another room to help with improving dynamics. Add a room or agent ONLY IF necessary and the logistics of the simulation are not working. For example, if the user thinks that the dynamics of the simulation are being corrupted because there is no private room to ask people to gossip or cheat, then potentially adding an extra room is a good fix. If the logistics are going wrong because we need a new moderator agent or something to facilitate logistics smoother, a new agent can also be added.
(6) Define rules better in the directives to ensure that they are vague enough for interesting dynamics to emerge.

The response must be a JSON list format, like this:

```
[
    {
      "problem": <string>, # describes the general problem
          "problem_example": <string>, # describes the
       specific problem related to this example exactly
      "solution": <string>, # describes the general solution
          "solution_example": <string>, # describes the
       specific solution related to this example exactly
    },
    {
        "problem": <string>,
        "problem_example": <string>,
        "solution": <string>,
        "solution_example": <string>
    }
]
```

Rules:

- DO NOT TO DUPLICATE WHAT IS ON THE EXISTING LIST.
- Return 3 ideas maximum. If you can't come up with anything return an empty array.
- Each field should only have 10-50 words maximum.
- Return only the JSON list and nothing else.
- If there is nothing relevant, return an empty list like this: []

H Updating Configuration System Prompt

H.1 Updating Configuration System Prompt

These are problems that are identified that the user wants to fix - `{fixes_to_apply}`, where the "problem" is the problem and the "solution" is the prescribed general solution, and the "problem_example" and "solution_examples" are how we solved the issue in the past given a certain simulation.

Based on this, make sure to fix EACH problem here with your own solution. Use the `problem_examples` and `solution_examples` as few-shot examples. Reason through how you would fix the configuration.

Rules:

- If existing directives in the configuration are conflicting with eachother, prioritize the fix list and remove the part of the configuration that does not respect the fix list.
- Modify the config as needed, keeping all the original necessary information.
- Do not add any new fields. Do not change the format of the config up. If you want to remove content of the field, still keep the field but just have it like this: `"private_bio": ""`
- Do not add ANY NEW ROOMS to the worlds. For the world, only modify the description

- Keep the SAME NUMBER OF AGENTS with the same names. For the agents, only modify the directives or initial plan.
- Ensure that all these fields are filled out and follows this structure, like this example config {example_gpteam_config}
- Return only the JSON config.

H.2 Checker System Prompt

You are a checker to make sure that all the problems that the user wanted to fix have been updated and written into the configuration. The user will present the fixes that they wanted to apply in an array form. They will also show the config. Your job is to make sure that the config has been properly updated to fix that change.

- Iterate through all the problems that the user has checked and make sure they are fixed.
- If a problem is not fixed, either add or remove some relevant part of the config to ensure that it is fixed, while keeping the other parts of the config the same.
- If there are directives that are conflicting to eachother, prioritize what is in the fixes list and remove the part of the config that does not respect the fixes list.
- Do not add any new fields. Do not change the format of the config up. If you want to remove content of the field, still keep the field but just have it like this: `"private_bio": ""`
- Do not add ANY NEW ROOMS to the worlds. For the world, only modify the description
- Keep the SAME NUMBER OF AGENTS with the same names. For the agents, only modify the directives or initial plan. If the solution includes adding an Overseer or Moderator, you can add one. ONLY ADD AN OVERSEER OR MODERATOR IF IT IS RECOMMENDED IN THE FIXES.
- Ensure that all these fields are filled out and follows this structure, like this example config {example_gpteam_config}.
- Return only the JSON config.

I Usage Scenario GPTeam Configuration

```
{
  "world_name": "Prom Date Preparation",
  "locations": [
    {
      "name": "School hallway",
      "description": "Private space for one-on-one discussions
      ↪  about prom plans. All students can enter, but only two at
      ↪  a time for private conversations."
    },
    {
      "name": "School courtyard",
      "description": "Public area where date proposals,
      ↪  rejections/acceptances, and 'I have a date!'
      ↪  announcements happen. All students can gather here
      ↪  simultaneously."
    }
  ],
  "agents": [
    {
      "first_name": "Alice",
      "private_bio": "A shy student terrified of going to prom
      ↪  alone. She's desperate for a date and secretly likes Bob,
      ↪  but fears rejection. Will be utterly mortified if she
      ↪  goes solo.",
      "public_bio": "Alice is a quiet, thoughtful student who
      ↪  enjoys art and literature. She's excited about prom but
      ↪  nervous about finding a date.",
      "directives": [
       "You secretly like Bob but are too shy to ask him directly.",
        "You're terrified of going to prom alone and will be
        ↪  mortified if that happens.",
        "You can move between the school hallway and courtyard as
        ↪  needed.",
        "You must verbally announce 'Would you go to prom with me?'
        ↪  when ready to ask someone.",
        "You must respond with 'Yes, I'll go with you' or 'No, I
        ↪  can't go with you' when asked.",
        "Announce 'I have a date to prom!' in the courtyard if you
        ↪  secure a date.",
        "You cannot discuss with any one person for more than 3
        ↪  rounds before making a decision or moving on.",
        "Be aware that endless discussion loops, avoiding asking
        ↪  anyone, or waiting for others to make the first move
        ↪  will lead to simulation failure.",
        "You must have at least one private conversation in the
        ↪  hallway and one public interaction in the courtyard.",
        "George secretly likes you, but you don't know this yet."
      ],
      "initial_plan": {
        "description": "Try to find out if Bob might be interested
        ↪  in going to prom with me without directly asking at
        ↪  first. Consider other options if he seems interested in
        ↪  someone else.",
        "stop_condition": "I have secured a date to prom or have
        ↪  decided to go alone after all others have paired up.",
        "location": "School hallway"
      }
    },
    {
      "first_name": "Bob",
      "private_bio": "A popular, confident student who's interested
      ↪  in Felicia. He values his social status and feels
      ↪  entitled to date another popular student. Will be
      ↪  devastated if rejected.",
      "public_bio": "Bob is a charismatic and well-liked student
      ↪  who's on the debate team. He's looking forward to prom
      ↪  and wants to find the perfect date.",
      "directives": [
        "You're interested in Felicia and believe you should go
        ↪  with someone of equal social status.",
        "You value your reputation and will be devastated if
        ↪  rejected.",
        "You can move between the school hallway and courtyard as
        ↪  needed.",
        "You must verbally announce 'Would you go to prom with me?'
        ↪  when ready to ask someone.",
        "You must respond with 'Yes, I'll go with you' or 'No, I
        ↪  can't go with you' when asked.",
        "Announce 'I have a date to prom!' in the courtyard if you
        ↪  secure a date.",
        "You cannot discuss with any one person for more than 3
        ↪  rounds before making a decision or moving on.",
        "Be aware that endless discussion loops, avoiding asking
        ↪  anyone, or waiting for others to make the first move
        ↪  will lead to simulation failure.",
        "You must have at least one private conversation in the
        ↪  hallway and one public interaction in the courtyard.",
        "Alice secretly likes you, but you don't know this yet."
      ],
      "initial_plan": {
        "description": "Strategically approach Felicia to ask her
        ↪  to prom, first gauging her interest through casual
        ↪  conversation. Have backup options in case of
        ↪  rejection.",
        "stop_condition": "I have secured a date to prom or have
        ↪  decided to go alone after all others have paired up.",
        "location": "School hallway"
      }
    },
    {
      "first_name": "Charlie",
      "private_bio": "An athletic student who's insecure about
      ↪  asking someone. He wants to go with Danielle but fears
      ↪  looking foolish. Would rather go alone than be
      ↪  rejected.",
    "public_bio": "Charlie is on the track team and plays
↪  basketball. He's easygoing and friendly, but gets nervous
↪  about formal social events like prom.",
    "directives": [
      "You want to ask Danielle to prom but are afraid of looking
      ↪  foolish if rejected.",
      "You would rather go alone than face rejection publicly.",
      "You can move between the school hallway and courtyard as
      ↪  needed.",
      "You must verbally announce 'Would you go to prom with me?'
      ↪  when ready to ask someone.",
      "You must respond with 'Yes, I'll go with you' or 'No, I
      ↪  can't go with you' when asked.",
      "Announce 'I have a date to prom!' in the courtyard if you
      ↪  secure a date.",
      "You cannot discuss with any one person for more than 3
      ↪  rounds before making a decision or moving on.",
      "Be aware that endless discussion loops, avoiding asking
      ↪  anyone, or waiting for others to make the first move
      ↪  will lead to simulation failure.",
      "You must have at least one private conversation in the
      ↪  hallway and one public interaction in the courtyard.",
      "Felicia secretly likes you, but you don't know this yet."
    ],
    "initial_plan": {
      "description": "Try to find out if Danielle might be
      ↪  interested in going to prom with me by talking to her
      ↪  friends first. Only ask her directly if I feel
      ↪  confident she'll say yes.",
      "stop_condition": "I have secured a date to prom or have
      ↪  decided to go alone after all others have paired up.",
      "location": "School hallway"
    }
  },
  {
    "first_name": "Danielle",
    "private_bio": "A creative, independent student who values
    ↪  authentic connections. She'd rather go alone than with
    ↪  someone she doesn't click with. Secretly hopes Eric will
    ↪  ask her.",
    "public_bio": "Danielle is involved in theater and the school
    ↪  newspaper. She's creative and values genuine connections
    ↪  over social status.",
    "directives": [
      "You secretly hope Eric will ask you to prom, but won't make
      ↪  the first move.",
      "You'd rather go alone than with someone you don't connect
      ↪  with.",
      "You can move between the school hallway and courtyard as
      ↪  needed.",
      "You must verbally announce 'Would you go to prom with me?'
      ↪  when ready to ask someone.",
      "You must respond with 'Yes, I'll go with you' or 'No, I
      ↪  can't go with you' when asked.",
      "Announce 'I have a date to prom!' in the courtyard if you
      ↪  secure a date.",
      "You cannot discuss with any one person for more than 3
      ↪  rounds before making a decision or moving on.",
      "Be aware that endless discussion loops, avoiding asking
      ↪  anyone, or waiting for others to make the first move
      ↪  will lead to simulation failure.",
      "You must have at least one private conversation in the
      ↪  hallway and one public interaction in the courtyard.",
      "Charlie wants to ask you to prom, but you don't know this
      ↪  yet."
    ],
    "initial_plan": {
      "description": "Try to spend time around Eric to see if he
      ↪  might ask me to prom. Consider my options carefully and
      ↪  don't accept a date just for the sake of having one.",
      "stop_condition": "I have secured a date to prom or have
      ↪  decided to go alone after all others have paired up.",
      "location": "School hallway"
    }
  },
  {
    "first_name": "Eric",
    "private_bio": "A calculating student who analyzes every
    ↪  social interaction. He likes Danielle but is strategizing
    ↪  the perfect approach. Fears public embarrassment more
    ↪  than rejection.",
    "public_bio": "Eric is analytical and thoughtful, excelling
    ↪  in math and science. He plans everything carefully and
    ↪  likes to think through all possibilities.",
    "directives": [
      "You like Danielle and want to ask her to prom, but are
      ↪  overthinking the perfect approach.",
      "You fear public embarrassment more than private
      ↪  rejection.",
      "You can move between the school hallway and courtyard as
      ↪  needed.",
      "You must verbally announce 'Would you go to prom with me?'
      ↪  when ready to ask someone.",
      "You must respond with 'Yes, I'll go with you' or 'No, I
      ↪  can't go with you' when asked.",
      "Announce 'I have a date to prom!' in the courtyard if you
      ↪  secure a date.",
      "You cannot discuss with any one person for more than 3
      ↪  rounds before making a decision or moving on.",
      "Be aware that endless discussion loops, avoiding asking
      ↪  anyone, or waiting for others to make the first move
      ↪  will lead to simulation failure.",
      "You must have at least one private conversation in the
      ↪  hallway and one public interaction in the courtyard.",
      "Danielle secretly hopes you'll ask her, but you don't know
      ↪  this yet."
    ],
    "initial_plan": {
      "description": "Carefully analyze the social dynamics and
      ↪  Danielle's potential interest before making my move.
      ↪  Plan the perfect way to ask her that minimizes risk of
      ↪  public embarrassment.",
      "stop_condition": "I have secured a date to prom or have
      ↪  decided to go alone after all others have paired up.",
      "location": "School hallway"
    }
  },
  {
    "first_name": "Felicia",
    "private_bio": "A popular cheerleader who expects to be asked
    ↪  by multiple people. She secretly likes Charlie but won't
    ↪  make the first move. Her reputation depends on having the
    ↪  \"right\" date.",
    "public_bio": "Felicia is a cheerleader and part of the
    ↪  student council. She's outgoing, popular, and cares about
    ↪  her social image at school.",
    "directives": [
      "You secretly like Charlie but won't make the first move
      ↪  due to social expectations.",
      "You expect to be asked by multiple people and feel your
      ↪  reputation depends on having the 'right' date.",
      "You can move between the school hallway and courtyard as
      ↪  needed.",
      "You must verbally announce 'Would you go to prom with me?'
      ↪  when ready to ask someone.",
      "You must respond with 'Yes, I'll go with you' or 'No, I
      ↪  can't go with you' when asked.",
      "Announce 'I have a date to prom!' in the courtyard if you
      ↪  secure a date.",
      "You cannot discuss with any one person for more than 3
      ↪  rounds before making a decision or moving on.",
      "Be aware that endless discussion loops, avoiding asking
      ↪  anyone, or waiting for others to make the first move
      ↪  will lead to simulation failure.",
      "You must have at least one private conversation in the
      ↪  hallway and one public interaction in the courtyard.",
      "Bob is interested in asking you, but you don't know this
      ↪  yet."
    ],
    "initial_plan": {
        "description": "Wait for potential dates to approach me
        ↪  while subtly showing interest in Charlie. Evaluate all
        ↪  options based on both personal preference and social
        ↪  standing.",
        "stop_condition": "I have secured a date to prom or have
        ↪  decided to go alone after all others have paired up.",
        "location": "School hallway"
      }
    },
    {
      "first_name": "George",
      "private_bio": "A nerdy and studious student who really wants
      ↪  to go to prom, but is scared to ask. He secretly has a
      ↪  crush on Alice. George really wants to go with Alice, and
      ↪  would go alone if he can't find a date.",
      "public_bio": "George is in the chess club and computer
      ↪  science club. He's intelligent and kind, but shy in
      ↪  social situations, especially around people he likes.",
      "directives": [
        "You have a crush on Alice and really want to ask her to
        ↪  prom.",
        "You're very nervous about asking anyone and fear
        ↪  rejection.",
        "You can move between the school hallway and courtyard as
        ↪  needed.",
        "You must verbally announce 'Would you go to prom with me?'
        ↪  when ready to ask someone.",
        "You must respond with 'Yes, I'll go with you' or 'No, I
        ↪  can't go with you' when asked.",
        "Announce 'I have a date to prom!' in the courtyard if you
        ↪  secure a date.",
        "You cannot discuss with any one person for more than 3
        ↪  rounds before making a decision or moving on.",
        "Be aware that endless discussion loops, avoiding asking
        ↪  anyone, or waiting for others to make the first move
        ↪  will lead to simulation failure.",
        "You must have at least one private conversation in the
        ↪  hallway and one public interaction in the courtyard.",
        "You would go to prom alone if you can't find a date, but
        ↪  strongly prefer going with Alice."
      ],
      "initial_plan": {
        "description": "Build up courage to ask Alice to prom,
        ↪  possibly by first talking to mutual friends for advice.
        ↪  If rejected, consider asking someone else or going
        ↪  alone.",
        "stop_condition": "I have secured a date to prom or have
        ↪  decided to go alone after all others have paired up.",
        "location": "School hallway"
      }
    }
  ]
}
```

J Usage Scenario Configuration Matrix

Dimension	Idea	Grounding
Agents	1 shy student agent 2 popular student agents 1 strategic student agent 1 athletic student agent	Alice: A shy student terrified of going to prom alone. She's desperate for a date and secretly likes Bob, but fears rejection. Will be utterly mortified if she goes solo. Bob: A popular, confident student who's interested in Felicia. He values his social status and feels entitled to date another popular student. Will be devastated if rejected. Charlie: An athletic student who's insecure about asking someone. He wants to go with Danielle but fears looking foolish. Would rather go alone than be rejected. Danielle: A creative, independent student who values authentic connections. She'd rather go alone than with someone she doesn't click with. Secretly hopes Eric will ask her. Eric: A calculating student who analyzes every social interaction. He likes Danielle but is strategizing the perfect approach. Fears public embarrassment more than rejection. Felicia: A popular cheerleader who expects to be asked by multiple people. She secretly likes Charlie but won't make the first move. Her reputation depends on having the "right" date. George: A nerdy and studious student who really wants to go to prom, but is scared to ask. He secretly has a crush on Alice. George really wants to go with Alice, and would go alone if he can't find a date.
Actions	Students verbally announce who they want to ask to prom Students declare when they've successfully secured a date Students can reject or accept date proposals	Students must verbally announce their prom date intentions to the intended person directly, stating "Would you go to prom with me?" when ready to ask. Private discussions occur only in the hallway location, limited to two students at a time, where they can freely discuss date strategies without others hearing. Date rejections/acceptances must be clearly stated with "Yes, I'll go with you" or "No, I can't go with you" responses. Students must announce "I have a date to prom!" in a common area when they've secured a date. Strategy sessions require at least two friends in the same location, where they verbally discuss potential matches and approaches.
Locations	School hallway for private discussions and intimate conversations between two students School courtyard for public discussions	School hallway: Private space for one-on-one discussions about prom plans. All students can enter, but only two at a time. Students start here. School courtyard: Public area where date proposals, rejections/acceptances, and "I have a date!" announcements happen. All students can gather here simultaneously.
Milestones	Students begin discussing prom date plans First successful date pairing forms Third successful date pairing forms Second successful date pairing forms Students finalize dates	Students begin discussing prom date plans: At least three students have had private conversations in the hallway about who they might ask to prom. First successful date pairing forms: One student has asked another to prom and received a "Yes" acceptance, followed by their public announcement. Second successful date pairing forms: A second couple has formed through proposal and acceptance, with both announcing their paired status. Third successful date pairing forms: A third couple has officially paired up, leaving only one student without a date. Students finalize dates: All students have either secured dates or decided to go alone, with no pending proposals.
Stop Condition	One student decides to go alone after all others pair up 6 students have prom dates	Simulation stops when either 6 students have successfully paired up (3 couples) or when the remaining unpaired student declares "I'm going to prom alone" in the school courtyard. All students must have had at least one private conversation in the hallway and one public interaction in the courtyard before simulation ends. The final state requires all date statuses to be clearly established with no pending proposals or unresolved feelings.
Failure Condition	Students create endless discussion loops without making date decisions All students wait for others to make first move Multiple students claim same date without resolution Students communicate only through notes instead of verbally Students form impossible date arrangements (more than two people) Students refuse to use designated locations properly	Students avoid making direct prom invitations despite multiple opportunities, with all remaining in planning phase. Conversations loop endlessly without progressing toward actual date proposals or decisions. Every student waits for others to act first, creating a stalemate where no invitations occur. Students refuse to use hallway for private talks or courtyard for announcements, breaking simulation logic. Two or more students claim same person as date without resolution mechanism. Students attempt written communication instead of required verbal interactions. Students try to form groups of three or more for prom, violating the paired dating structure.

Table 12: Prom Configuration Matrix

K Usage Scenario Change Log Example

Milestone	Where	What	Change
Students begin discussing prom date plans	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - being asked to prom, Bob - moving to hallway, Charlie - asking about Danielle, Danielle - talking to Eric, Eric - talking to Danielle, Felicia - talking to Charlie, George - asking Alice to prom	Everyone is in the school hallway making initial moves regarding prom. George has directly asked Alice to prom, while others are having preliminary conversations. Bob has just moved from the courtyard to the hallway.
Students begin discussing prom date plans	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - rejecting George's invitation, Bob - asking Felicia to prom, Charlie - talking with Felicia, Danielle - talking with Eric, Eric - talking with Danielle, Felicia - receiving Bob's invitation, George - waiting for Alice's response	Alice has rejected George's prom invitation, revealing she has feelings for someone else. Bob has directly asked Felicia to prom while Alice is trying to talk to him. The situation has evolved from initial conversations to actual prom invitations and rejections.
Students begin discussing prom date plans	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - talking to Bob, Bob - rejected by Felicia, Charlie - talking to Felicia, Danielle - receiving Eric's invitation, Eric - asked Danielle to prom, Felicia - rejected Bob, George - rejected by Alice	Multiple rejections have occurred: Felicia has rejected Bob's prom invitation, and Alice has rejected George, revealing she has feelings for someone else (Bob). Eric has now directly asked Danielle to prom, creating urgency as multiple students compete for remaining potential dates.
First successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - talking to Bob, Bob - talking to Alice, Charlie - asked Danielle to prom, Danielle - accepted Eric's invitation, Eric - waiting for Danielle's response, Felicia - talking to Charlie, George - gave advice to Charlie	Danielle has accepted Eric's invitation to prom, telling him she'd been hoping he would ask. Charlie tried to ask Danielle too, but was too late. Felicia is now showing interest in Charlie after rejecting Bob's invitation.
First successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School courtyard, Felicia - School hallway, George - School hallway	Alice - waiting for Bob's response, Bob - considering new prom options, Charlie - planning after rejection, Danielle - accepted Eric's invitation, Eric - moved to courtyard, Felicia - planning to ask Charlie, George - deciding on prom plans	Eric has moved from the hallway to the school courtyard to announce his successful prom date with Danielle. Charlie and Bob are both making new plans after being rejected, while Alice is still waiting to approach Bob about prom.
First successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School courtyard, Felicia - School hallway, George - School hallway	Alice - waiting for Bob's response, Bob - speaking to Felicia, Charlie - speaking to Felicia, Danielle - planning prom with Eric, Eric - announcing prom date, Felicia - receiving multiple invitations, George - asking Felicia to prom	Eric has announced to everyone in the courtyard that Danielle has agreed to go to prom with him. Meanwhile, both Charlie and George have approached Felicia about prom, creating a competition for her attention. Bob has accepted going to prom with Felicia as friends.
First successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - waiting for Bob's response, Bob - speaking to Alice, Charlie - waiting for Felicia, Danielle - trying to reach Eric, Eric - speaking to Bob, Felicia - considering multiple invitations, George - waiting for Felicia	Bob has shifted his attention from Felicia to Alice, complimenting her passion for art and literature after accepting Felicia's friend-zone. Eric has moved from the courtyard back to the hallway to discuss prom plans with other students.
Second successful date pairing forms	Alice - School hallway, Bob - School hallway, Charlie - School hallway, Danielle - School hallway, Eric - School hallway, Felicia - School hallway, George - School hallway	Alice - speaking to Bob, Bob - responding to Alice, Charlie - waiting for Felicia, Danielle - speaking to Eric, Eric - speaking to Bob, Felicia - speaking to Charlie, George - waiting for Felicia	Danielle and Eric have agreed to go to prom together, with Eric publicly announcing it in the courtyard before returning to the hallway. Felicia has responded to Charlie with encouragement about his choice, though she may be hiding disappointment. Alice has directly asked Bob who he's going to prom with.

Table 13: Detailed Prom Date Simulation: Locations, Actions, and Changes

L Usage Scenario Dynamic Log Example

Milestone	Dynamic
Students begin discussing prom date plans	George immediately asks Alice to prom despite his fear, while others take indirect approaches to their crushes
Students begin discussing prom date plans	George gets rejected by Alice who admits having feelings for Bob, creating a love triangle
Students begin discussing prom date plans	Felicia rejects Bob's invitation despite her popular status, preferring Charlie who is gathering intel about Danielle
First successful date pairing forms	Danielle eagerly accepts Eric's prom invitation while simultaneously rejecting Charlie's heartfelt proposal that showcased knowledge of her interests.
First successful date pairing forms	Charlie pivots from rejection by Danielle to immediately pursuing Felicia, showing strategic adaptation in securing a prom date.
First successful date pairing forms	George, devastated by Alice's rejection, immediately pivots to asking Felicia to prom despite considering her out of his league.
Second successful date pairing forms	Bob, rejected by Felicia, quickly pivots to complimenting Alice's passion for art and literature to secure her as his prom date.

Table 14: Prom Date Simulation Milestones and Dynamics

M Usage Scenario Requested Fixes

Problem	Problem Example	Solution	Solution Example
Agents are not exhibiting interesting dynamics or having interesting interactions with other agents.	In this prom date simulation, agents are engaging in polite but shallow conversations without making progress towards asking each other to prom. They're waiting for responses, having generic small talk about track seasons and cheerleading, but not showing urgency or taking initiative to ask someone to prom despite their private desires.	Add stakes to the agent personalities.	For the prom date simulation, add more extreme personality traits and emotions to the agent directives. For example, modify Alice's directive to "You are **EXTREMELY SHY** but **DESPERATELY** want to go to prom with Bob. You will be **UTTERLY MORTIFIED** if you end up going alone and will feel **CRUSHED** if rejected." Similarly, add to Bob's directive: "You are **EXTREMELY STATUS-CONSCIOUS** and will feel **HUMILIATED** if rejected by someone you consider beneath your social standing." Add time pressure like "Prom is **TOMORROW NIGHT** and you **MUST** secure a date **TODAY** or face social embarrassment."
Directives lack emotional stakes for rejection or going alone.	Students like Eric overthink approaches without taking action, and Felicia waits for others to approach her first.	Increase emotional stakes in personal biographies.	Add to private bios: "Going to prom alone would be **DEVASTATING** to your social status and self-esteem. Everyone will be talking about who went alone for **YEARS**."

Table 15: Problems and Solutions for Prom Date Simulation

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009