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SCENARIO PLANNING WITH AGENTIC AI FOR REINFORCEMENT LEARNING AND RISK MITIGATION IN DEVELOPING ECONOMIES BUSINESS EDUCATION

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ABSTRACT

Problem: Business leaders in developing economies face significant challenges due to volatile environments, supply chain shocks, and institutional voids, leading to suboptimal decision-making and a critical need for adaptive pedagogical tools.

Approach: This study employs a Design-Based Research approach, utilizing the "Captains of Industry" simulation, an AI-augmented experiential learning framework that integrates Product Service System theory and Design Thinking. The simulation generates bespoke scenarios and provides AI-driven feedback for reinforcement learning.

Objectives: To analyze the impact of AI-driven simulations on cognitive problem-solving skills, risk appetite, and standardized decision-making; evaluate the AI agent's effectiveness in enhancing student performance; detail the simulation's design and implementation; and elaborate on the role of bespoke scenario design and localized data.

Findings: The simulation effectively enhances decision-making capabilities and risk mitigation strategies. Analysis of 125 students revealed a mean performance of 59.3% and significant heterogeneity in learning trajectories (4.7-4.8% mean growth rate, but varied individual improvements/declines). Diffusion Maps identified non-linear geometric patterns and "micro-clusters" in student performance, while Kernel Two-Sample Tests statistically confirmed "separable achievement profiles" between top and bottom performers.

Implications: The framework provides a dynamic laboratory for developing adaptive decision-making and risk mitigation skills in complex environments. It offers a scalable solution for in-company training, addresses data scarcity in developing regions, and frees human instructors for higher-level mentorship.

KEYWORDS: Agentic AI Simulation, Scenario Planning, Reinforcement Learning, Risk Mitigation, Developing Economies.

1.0 INTRODUCTION

The dynamic and often unpredictable nature of business environments, particularly in developing economies, necessitates robust decision-making frameworks that can adapt to rapid change and mitigate unforeseen risks (Mthethwa, 2024). This is particularly salient given the "liability of newness" experienced by businesses in these regions, where high switching costs and technological lags create persistent uncertainty (Agrawal & Syan, 2025). This paper explores the application of agentic AI within a scenario planning framework to enhance reinforcement learning and improve risk mitigation strategies for business leaders in such volatile contexts. Specifically, it addresses the cognitive bottlenecks and bounded rationality often encountered by decision-makers in developing economies, proposing a method to leverage AI-driven simulations to improve adaptability under constraints. This multifaceted challenge aligns with the concept of a 'wicked problem' in design thinking, underscoring the necessity for innovative, AI-driven solutions to achieve positive impact and leverage competitive advantages. To address this, we have developed and approach which aims to challenge traditional decision-making paradigms by simulating diverse scenarios, thereby enhancing the decision-makers' cognitive problem-solving skills and refining their risk appetite with standardized decision-making probabilities.

This study will investigate how agentic AI can generate bespoke scenarios, allowing decision-makers to explore a wider range of potential futures and refine their strategic responses in a controlled, simulated environment, thereby overcoming the limitations of traditional problem-solving approaches that often rely on mimicry of solutions from dissimilar contexts (Csaszar et al., 2024). By explicitly challenging decision-makers with simulated scenarios, this research aims to improve their adaptability and preparedness for the unique challenges prevalent in developing economies. Central to this investigation is the "Captains of Industry" simulation, an AI-assisted, scenario-based assessment designed to cultivate these critical decision-making faculties within an Operations Management curriculum. This educational tool leverages generative AI to create adaptive and personalized learning experiences, addressing the gap between theoretical knowledge and practical application in complex business environments (Mollick et al., 2024) as students learn how to manage contemporary businesses within developing regions.

1.1 Problem Statement

The escalating uncertainty in global business environments, particularly in developing economies, exposes decision-makers to significant challenges, including supply chain shocks, institutional voids, and information asymmetry. These conditions often lead to satisfying behaviors and suboptimal outcomes due to cognitive bottlenecks and bounded rationality (Biloslavo et al., 2024). Traditional problem-solving approaches, frequently mimicking solutions from dissimilar contexts, fail to adequately address the unique complexities and technological lags prevalent in these emerging regions. Consequently, there is a critical need for innovative pedagogical tools that can cultivate adaptive decision-making skills and robust risk mitigation strategies.

This paper addresses this gap by pursuing the following objectives:

- Analyze the impact of AI-driven simulations on cognitive problem-solving skills, risk appetite, and the probability of standardized decision-making among students operating within simulated developing economy contexts.
- Evaluate the effectiveness of the AI agent's role in enhancing student performance within the "Captains of Industry" simulation, serving as a proxy for improved management performance.
- Detail the design and implementation of the "Captains of Industry" simulation as an innovative experiential learning framework that overcomes the limitations of conventional case-based problem-solving by providing a dynamic and interactive environment.
- Elaborate on the critical role of bespoke scenario design and localized data in ensuring the efficacy of AI-driven simulations, highlighting the imperative for cultivating rich data ecosystems in developing regions (Pacheco-Velázquez et al., 2024).

By achieving these objectives, this research aims to demonstrate how AI-augmented scenario planning can prepare future business leaders to navigate and mitigate risks effectively in dynamic and unpredictable environments.

2.0 LITERATURE REVIEW

Scholarship establishes generative AI's pivotal role in business education by enabling scalable simulations that promote experiential learning that bridge theory-practice gaps (Mollick et al., 2024). Multi-agent AI systems deliver personalized feedback, role-playing, and rubric-aligned assessments, fostering higher-order skills amid uncertainty (Meincke & Carton, 2024; Zhang et al., 2025). The "Captains of Industry" simulation exemplifies this by integrating AI evaluation with longitudinal metrics to cultivate judgment and adaptability in operations management.

Given the prevalence of uncertainty in resource constrained emerging markets, agentic AI systems can be employed to positively impact business decision making, where supply chain shocks, institutional voids, and asymmetric information provoke satisfying behaviors rather than optimization (Rehman et al., 2020). Managers confront exogenous hazards and complex interdependencies, often misframing deep uncertainty as manageable risk, which perpetuates vulnerabilities in operations and logistics (Kumar & Sharma, 2021).

These challenges amplify cognitive biases and bounded rationality, as heuristics like overconfidence, anchoring, and availability distort probabilistic reasoning and risk perception (dar et al., 2021; Tversky & Kahneman, 1974). In high-stakes contexts, such deviations lead to planning fallacies, herding, and suboptimal resource allocation, particularly among SMEs and in emerging markets where cultural factors like uncertainty avoidance moderate effects (Capolupo et al., 2024; Deshpande, 2025). The application of agentic AI within the "Captains of Industry" simulation directly addresses these cognitive limitations by exposing decision-makers to a spectrum of meticulously crafted scenarios, thereby enhancing their capacity for robust strategic formulation and risk mitigation.

Agentic AI counters these limitations through reinforcement learning frameworks that simulate real-time interactions, self-critique, and iterative fine-tuning, as demonstrated in Wharton's educational simulations where LLMs provide instructor-comparable feedback superior to traditional NLP (Meincke & Carton, 2024). Such systems scale formative critiques via teacher-student LLM loops, enhancing met cognition and bias mitigation without extensive human grading (Zhang et al., 2025).

Scenario planning via serious games further mitigates risks by immersing learners in multi-stage narratives that reveal decision trade-offs, coordination dynamics, and growth trajectories (Kavota et al., 2024). Flexible simulations like the FSCMG adapt parameters for supply chain intricacies, outperforming lectures in skill development and foresight (Kavota et al., 2024; Shovityakool et al., 2019). If lectures are based on experienced of lecturers then their efficacy is limited by subjective interpretations and the inability to dynamically adapt to evolving student responses, unlike AI agents that can provide consistent and objective feedback while personalizing the learning experience (Mollick et al., 2024). This does not diminish the value of human instructors but rather augments their capabilities by offloading repetitive tasks and enabling a focus on higher-level mentorship. This augmentation allows educators to concentrate on facilitating deeper understanding and strategic thinking, fostering an environment where students can explore complex problem-solving scenarios with robust AI-driven analytical support (Trindade et al., 2024).

Recognizing the compounded issues of "liability of newness," data scarcity, and regulatory gaps that often stifle innovation and amplify vulnerabilities in developing economies, localized AI simulations emerge as a critical intervention for proactive risk management (Arévalo et al., 2025).. By generating highly context-relevant scenarios, these platforms enable decision-makers to confront and strategize against the specific, localized risks previously discussed, such as supply chain shocks, institutional voids, and market volatility. This approach not only democratizes access to sophisticated training tools but fundamentally empowers local leaders to cultivate the resilience and strategic foresight essential for effective risk identification, assessment, and mitigation. Through agentic AI-driven scenario planning and continuous reinforcement learning, decision-makers iteratively refine their responses to unforeseen challenges, transforming theoretical knowledge into practical, adaptive risk mitigation strategies. This paper thus firmly posits that this framework significantly enhances decision-making capabilities, preparing business leaders to navigate and actively mitigate risks within the dynamic and often unpredictable landscapes characteristic of developing economies.

3.0 METHODOLOGY

This study employs a Design-Based Research approach, specifically focusing on a pedagogical intervention study, to investigate how an AI-augmented simulation can enhance decision-making capabilities, foster reinforcement learning, and improve risk mitigation strategies within the context of developing economies (Collective, 2003). DBR is particularly suited for this research as it involves the iterative design, implementation, and refinement of educational interventions in authentic settings, bridging the gap between theory and practice. This approach allows for continuous refinement of the "Captains of Industry" simulation while generating empirical insights into its effectiveness in cultivating adaptive leadership skills.

3.1 Units under Investigation

The participants in this study consisted of a cohort of 125 university students. These students were engaged in an Operations Management curriculum and were exposed to both the platform's capabilities and the socioeconomic conditions prevalent in developing economies, specifically targeting Latin America and the Caribbean. Their involvement aimed to promote the adoption of technology and AI across various industry sectors, serving as future business leaders in these regions. The analysis focuses on their decision-making patterns, risk appetite, and the impact of AI feedback on their performance within simulated companies.

3.2 Design and Implementation of the Pedagogical Intervention

The core of this methodology is the "Captains of Industry" simulation, an AI-assisted scenario planning framework designed to facilitate experiential learning and skill development. Its design and implementation are meticulously crafted to provide a dynamic and interactive learning environment that overcomes the limitations of conventional case-based problem-solving.

3.3 Simulation Design and Company Structure

A standardized approach was implemented for company creation within the simulation to ensure consistency and comparability across participants. A fundamental design principle drawing from Product Service System and design thinking theory guides the simulation, enabling innovation despite inherent constraints prevalent in emerging markets. Each simulated company is comprehensively structured with a unique name, background narrative, available resources, and a specific business challenge. Initial business insights are provided for a six-month period, encompassing an income statement, sales data, procurement data, and six customer reviews. This foundational data set establishes the initial conditions for AI-generated outcomes based on subsequent management decisions.

The simulation features 27 distinct companies, strategically organized with three companies per sector or industry. This configuration fosters both complementary and competitive dynamics within regional supply chains, reflecting real-world business ecosystems (Romagnoli et al., 2022). The iterative nature of the simulation is crucial; updated business insights are generated by the AI after each simulated week, directly informing management decisions for the subsequent week. The system approach to this development is detailed in the flowing section.

Application Development and Technical Architecture

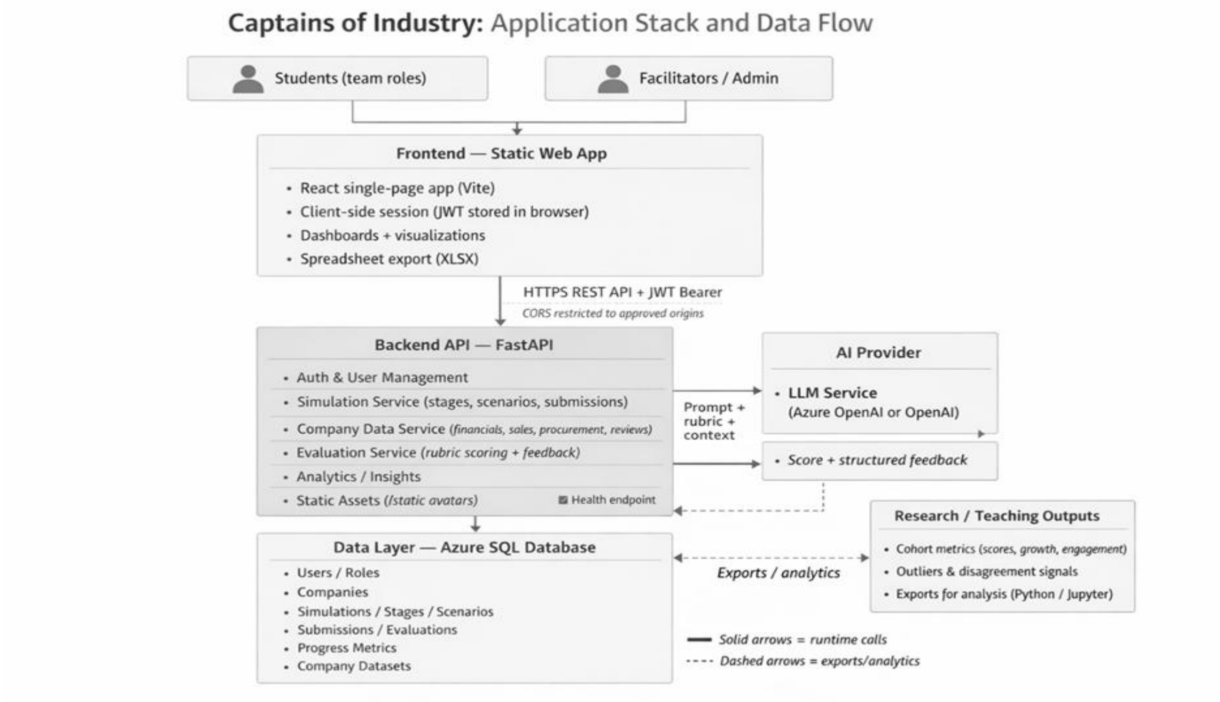

Diagram 1 Application Stack and Data Flow

The "Captains of Industry" simulation stands as a paradigm of educational innovation, its technical architecture meticulously engineered not just to support, but to *drive* sophisticated scenario planning, facilitate dynamic reinforcement learning, and cultivate superior risk mitigation strategies. This advanced platform transcends traditional monolithic educational software, embracing a modular, service-oriented design that is both agile and academically rigorous.

3.4 An Architecture for Dynamic Learning and Risk Management

The platform's service-oriented design strategically separates core functionalities—learner interaction, simulation state management, AI-mediated assessment, and cohort-level analytics. This foundational separation is paramount for delivering precise scenario perturbations, enabling adaptive AI feedback loops crucial for reinforcement learning, and validating risk-response analytics. This ensures an environment flexible enough for continuous pedagogical experimentation, traceable for robust research, and reproducible for consistent learning outcomes across diverse cohorts and institutions.

3.5 Backend Precision: Fueling Scenarios and Reinforcement

At its core, the platform's server-side, built on a modern Python web framework, establishes a robust and consistent domain model. A meticulously specified relational schema ensures construct validity and measurement consistency, vital for tracking the nuanced progression of decision-making. Core entities including dynamic scenarios with "curveballs" to inject exogenous shocks, learner submissions, and longitudinal progress records are precisely captured. Each simulated firm's structured business datasets are dynamically updated, emulating the volatile conditions characteristic of developing economies, thereby providing realistic contexts for scenario planning and risk assessment. The strict enforcement of referential integrity through Object-Relational

Mapping formalizes state transitions, ensuring that every decision and every simulated outcome is traceable and consistent, forming the high-fidelity data backbone for iterative reinforcement learning and analytical validation of risk mitigation strategies.

3.6 AI Integration: The Engine of Reinforcement Learning

Generative AI is not merely a "black-box grader," but an integral intelligence driving the reinforcement learning process. It transparently evaluates submissions against predefined rubrics, delivering both scalar performance scores and structured qualitative feedback. This dual output fuels reinforcement learning at two critical levels:

- **Learner/Team Level:** Providing immediate, actionable guidance for learners to refine strategies in subsequent decision cycles, directly impacting their ability to respond to unfolding scenarios.
- **Research/Teaching Level:** Generating stable, quantifiable features for profound longitudinal analysis of learning trajectories and risk adaptation, offering insights into the efficacy of various strategic responses.

This flexible system supports various enterprise-grade or direct LLM deployments, ensuring adaptability to institutional governance while maintaining its core function of delivering intelligent, context-aware feedback for continuous improvement in scenario-driven decision-making.

3.7 Secure Frontend: Immersive Scenario Exploration

The platform's integrity is secured by token-based authentication and externalized configuration, vital for protecting sensitive simulation data and ensuring consistent, reliable operational prerequisite for valid scenario-based analysis and risk assessment.

The intuitive single-page web interface, powered by React, precisely mirrors the intended learning cycle. It immerses learners in their firm's status, dynamic scenario prompts, and supporting data, enabling them to draft and submit decisions, and crucially, to immediately review AI-generated evaluations and historical feedback. This direct interaction with simulated scenarios and personalized feedback loops is fundamental to enabling rapid reinforcement learning and practical risk strategy refinement. Integrated visualization and data export capabilities further empower instructors and researchers to extract profound insights from the simulated risk environments, converting participant actions into actionable data for understanding complex decision-making under uncertainty.

Ultimately, the "Captains of Industry" architecture is a testament to purposeful design, where every technical choice directly reinforces the pedagogical goals of fostering adaptable leaders capable of navigating the unpredictable landscapes of developing economies through advanced scenario planning, continuous reinforcement learning, and robust risk mitigation.

3.8 Team Organization and Decision-Making Process

Each simulated company is managed by a team comprising five distinct management positions: Chief Executive Officer, Chief Financial Officer, Chief Procurement Officer, Chief Information Officer, and Chief Operations Officer. Students occupying these roles analyze all available data, subsequently formulating individual functional recommendations. These recommendations are then subjected to peer review, where other managers within the team can accept or reject them, promoting collaborative decision-making and negotiation (Tiwari et al., 2014).

The team's final collective decision is submitted for AI-guided grading, which leverages a predefined rubric. This AI-driven assessment provides weekly feedback (text base response of rubric guided gap analysis and recommendations for improvement) and a performance score to each company, along with new company performance data (updated weekly sales, income, procurement and customer reviews) (Deepshikha, 2025; Durak & Onan, 2025). This continuous feedback loop is integral to the reinforcement learning process, allowing students to assess their group's performance, understand the impact of their decisions, and adapt their strategies for the upcoming week (Dick & Akbulut, 2020). Decisions are typically submitted by Tuesday 4 PM each week over a four-week simulated period, ensuring a consistent operational tempo.

Here is a simplified table summarizing the "Design-Driven PSS Experiential Learning Cycle with AI Augmentation" framework:

Table 1 Iterative learning cycle, augmented by AI.

Stage of Experiential Learning	Integration of PSS Theory	Integration of Design Thinking	AI Augmentation
Concrete Experience	Students engage with business scenarios structured around Product Service System principles, requiring integrated product-service solutions within developing economy constraints (Keskin et al., 2017).	Business challenges presented are "wicked problems" requiring creative solutions, exposing students to real-world trade-offs (Dorland, 2024; The Impact of Artificial Intelligence on Innovation Management: A Literature Review, 2021).	AI sets up initial business insights and dynamic scenarios, providing the foundation for decisions and subsequent outcomes.
Reflective Observation	AI provides feedback on operational decisions within the PSS context, highlighting systemic implications of choices.	Peer review ("take-rates") encourages critical evaluation of diverse PSS solutions and Design Thinking iterations among students (Dorland, 2024).	AI generates consistent, rubric-aligned feedback and scores, aiding in objective reflection on decisions and their impact (Zhang et al., 2025).
Abstract Conceptualization	Students analyze AI feedback and new insights to understand PSS dynamics, market needs, and systemic impacts, moving from	Students use Design Thinking to reframe problems, ideate novel PSS solutions, and develop improved strategies,	AI-generated feedback helps students form abstract concepts about effective PSS management and

	observation to abstract understanding.	fostering an iterative approach to problem-solving (Sreenivasan & Suresh, 2024).	decision-making under uncertainty.
Active Experimentation	Students apply newly conceptualized PSS strategies, testing hypotheses and observing outcomes in subsequent simulation rounds.	Revised Design Thinking iterations are implemented as students actively experiment with refined operational decisions and problem-solving approaches.	AI dynamically updates business insights and simulates outcomes based on new decisions, allowing for continuous testing and adaptation of strategies.

Table 1 This iterative learning cycle, augmented by AI, provides a robust framework for developing adaptive decision-making skills within complex, uncertain business environments. The simulation thus functions as a dynamic laboratory where theoretical constructs from PSS and design thinking are empirically tested and refined in a controlled, yet complex, environment, preparing decision-makers for the volatile realities of developing markets.

4.0 DATA ANALYSIS

The study involves a cohort of 125 participants, generating a rich dataset comprising performance data points and AI-generated information. This data was captured and analyzed using machine learning and advanced analytics techniques. The analysis aims to understand decision-making patterns, risk appetite, and the impact of AI feedback on student performance within the simulated companies (Ersozlu et al., 2024; Jensen et al., 2023).

For the required analysis, Python extensions with Jupyter notebooks were employed. Specifically, Diffusion Maps (via scikit-learn/diffusion map libraries) was utilized for dimensionality reduction and understanding the underlying structure of high-dimensional decision-making data (Barroso et al., 2023; Sonday et al., 2010). Kernel Two-Sample Tests (via hypothesis or sklearn libraries) was applied to compare distributions of student performance or decision outcomes, allowing for robust statistical comparisons without strong assumptions about data distribution (Song & Chen, 2023). These techniques support a comprehensive evaluation of the simulation's effectiveness and the students' evolving capabilities in navigating complex business challenges (Echeverría et al., 2025; Hernández-Lara et al., 2018). Specifically, these analytical approaches will illuminate how cognitive problem-solving skills evolve, track risk appetite shifts, and quantify the probability of standardized decision-making among participants.

5.0 ETHICAL CONSIDERATIONS

The integration of AI for evaluative purposes and the handling of sensitive student data within the "Captains of Industry" simulation necessitated a robust framework of ethical considerations. To safeguard participant rights and uphold data integrity, comprehensive measures were meticulously adopted. These included securing informed consent from all student participants, guaranteeing the anonymization and privacy of their data, and establishing transparent protocols for the AI's function in delivering feedback and assessments. A central tenet was to ensure that the AI's role did not compromise fairness or diminish essential human oversight. This ethical approach aligns with broader international principles for responsible AI outlined in documents such as the UN General Assembly Resolution Global Digital Compact Untitled (United Nations, 2024). Throughout the study, human oversight remained paramount, manifested through faculty calibration of assessment rubrics and continuous review of analytics. This ongoing faculty engagement allowed for timely interventions and adjustments, ensuring strong pedagogical alignment and proactively mitigating any potential for algorithmic bias.

6.0 LIMITATIONS

While the simulation strives to replicate the "liability of newness" experienced by businesses in developing economies, the complete fidelity of this replication is challenging due to the inherent complexities of real-world technological lags and high switching costs. Students' decision-making processes are also influenced by cognitive bottlenecks and resource constraints, which, while challenged by the simulation, cannot be entirely eliminated within a controlled environment. From a broader systemic perspective, the nascent state of ecosystems for nurturing AI-driven design thinking solutions in many developing regions can limit the real-world scalability and transferability of findings from this simulated environment. These factors present methodological considerations regarding the generalizability and comprehensive capture of student responses and learning outcomes. From a systemic perspective, underdeveloped ecosystems for nurturing AI-driven design thinking solutions can limit the real-world application and scalability of such approaches.

7.0 RESULTS

This section presents the empirical findings derived from these analytical methods, elucidating the correlation between AI-augmented experiential learning and the development of robust decision-making frameworks under conditions of uncertainty. The primary goal is to determine if the AI agent's intervention and the structured experiential learning cycle significantly influenced the growth trajectory and performance metrics of the simulated businesses (Stenard et al., 2024). The analysis will specifically address how the AI agent's role influenced student performance by tracking growth rates, scores per scenario, and overall progress, as well as by identifying patterns in decision-making behaviors such as approval rates and engagement. It will further investigate the faculty analytics dashboard to identify outliers and teams with high internal disagreement and summarize cohort-level patterns to understand overall trends and areas for intervention. Overall, the cohort demonstrated solid, yet not uniformly outstanding, performance, with analytics highlighting distinct achievement profiles and learning dynamics.

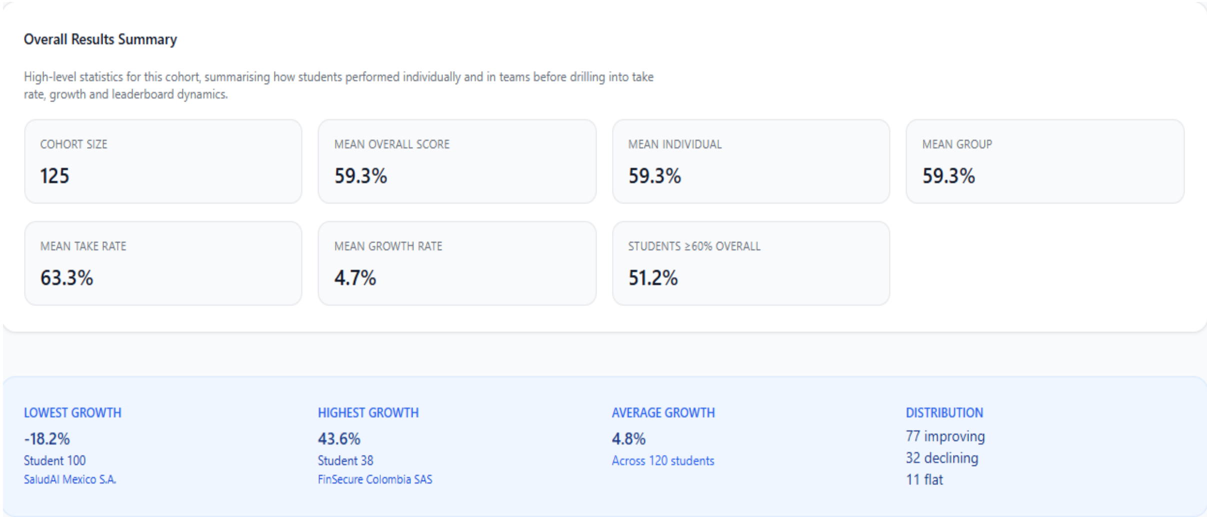

Diagram 2 Overall Results Summary

7.1 Cohort Performance and Achievement

The cohort of 125 students exhibited a mean overall score, mean individual score, and mean group score of 59.3%. This indicates that, on average, students and teams were performing at or just below a 60% proficiency benchmark, rather than exhibiting performance skewed by outliers. A total of 51.2% of students achieved a score of 60% or higher, suggesting that slightly more than half of the participants met a defined proficiency threshold, while a substantial minority may require targeted educational support.

7.2 Growth and Learning Trajectories

The mean growth rate observed across the cohort was approximately 4.7% to 4.8%. Analysis of individual performance trajectories showed that 77 students demonstrated improvement, 32 experienced a decline, and 11 remained flat. This indicates that while the simulation generally fostered an upward trend in performance, the growth was heterogeneous. For instance, the highest individual growth was recorded at 43.6% (Student 38 at Fin Secure Colombia SAS), contrasting sharply with the lowest, a decline of -18.2% (Student 100 at Salud AI Mexico S.A.). Such varied trajectories are consistent with the concept of "separable achievement profiles," underscoring diverse learning outcomes within the experiential framework (Tetzlaff et al., 2023). Previous research also highlights the importance of analyzing individual learning processes beyond group-level data to understand student success and inform personalized interventions (Saqr, 2023) which is elaborated on later with a diffusion map.

7.3 Engagement and Participation

The mean take rate of 63.3% suggests a significant level of engagement, with students actively participating in and responding to a substantial portion of the available decision opportunities or activities within the simulation. This metric indicates a generally high level of interaction, though it also implies room for further deepening student participation. Effective engagement with AI-powered feedback in simulations is critical for improving learning outcomes (Chen et al., 2022; Louie et al., 2025).

Diagram 3 Diffusion Map and Kernel Two Sample Test

Diffusion Maps and Kernel Two-Sample Tests work together to provide a robust and comprehensive understanding of student performance. Individually, each technique offers distinct advantages; however, their combined application yields deeper insights into the complex dynamics of learning within the simulation. Diffusions Maps are a powerful non-linear dimensionality reduction technique, designed to preserve the inherent geometric structure of high-dimensional data, such as the multitude of performance metrics and AI-generated information from the cohort. In this study, the textual description indicates that the Diffusion Map of the student feature space, derived from the spectral embedding of z-scored metrics, revealed intricate non-linear geometric patterns. These patterns highlighted latent learning trajectories and distinct "micro-clusters" of students, indicating that performance and learning behaviors are complex and multi-dimensional, extending beyond simple linear correlations. This capability allows for a deeper exploration of how students progress and adapt over time, potentially revealing various learning paths and strategic approaches taken during the simulation, which can be further visualized (e.g., through plots of these embeddings).

Complementing the exploratory nature of Diffusion Maps, the Kernel Two-Sample Test provided crucial statistical validation for the observed differences in student performance. This non-parametric test is particularly robust as it can determine whether two samples of data originate from the same underlying distribution without making restrictive assumptions about data normality. The Kernel Two-Sample Test was applied to compare the feature distributions of the top and bottom quartiles of overall performers. The results, a Mean Maximum Discrepancy of 0.722 and an approximate p-value of 0.012, statistically confirm that the two groups possess significantly different feature distributions. This signifies that the observed performance disparities are not merely random variations but reflect genuine differences in learning processes or strategic methodologies adopted by students (Shen et al., 2024). Together, these advanced analytics methods allowed the study to move beyond aggregate statistics, providing both a visual and statistical foundation for concluding that the simulation effectively differentiates between various levels of proficiency and adaptive capacity.

Micro-clusters imply that students adopt various effective (and ineffective) strategies, respond differently to AI feedback, and develop diverse adaptive capacities. This heterogeneity is further substantiated by the "Growth Rate Learning Trajectories", which visually confirms that while a mean growth rate of 4.7-4.8% was observed, individual growth varied drastically, with 77 students improving, 32 declining, and 11 flat, showcasing "separable achievement profiles".

Diagram 4 Growth Rate Learning Trajectories

8.0 DISCUSSION AND CONCLUSION

This study demonstrates that the "Captains of Industry" simulation, an AI-augmented experiential learning framework integrating Product Service System theory and Design Thinking, effectively enhances decision-making capabilities and risk mitigation strategies, particularly for business leaders in developing economies. The cohort of 125 participants showed a solid, though not uniformly outstanding, mean performance of 59.3% across overall, individual, and group scores. While a majority (77 students) demonstrated improvement with a mean growth rate of 4.7-4.8%, the analysis unveiled significant heterogeneity in learning trajectories, with 32 students declining and 11 remaining flat. Advanced analytics, employing Diffusion Maps, revealed intricate non-linear geometric patterns and "micro-clusters" within the student feature space, underscoring the multi-dimensional nature of performance and distinct latent learning trajectories.

The Kernel Two-Sample Test further corroborated these findings by statistically confirming "separable achievement profiles" between top and bottom performers (Mean Maximum Discrepancy of 0.722, p-value of 0.012), indicating that performance disparities are not random but reflect genuine differences in learning processes and strategic adaptation. The rich data insights derived from the Diffusion Maps and Kernel Two-Sample Tests underscored the critical role played by the bespoke scenario design and the integration of localized data in creating a truly effective and discerning simulation environment. This comprehensive approach underscores the simulation's capacity to differentiate between various levels of proficiency and adaptive capacity, providing rich data for understanding student development. The observed enhancements in decision-making and risk mitigation are a testament to the innovative design and rigorous implementation of the 'Captains of Industry' simulation as an experiential learning framework, meticulously detailed in the methodology.

9.0 IMPLICATIONS FOR PRACTICE

The findings have significant implications for both student education and in-company training programs. For students, the simulation provides a dynamic laboratory to cultivate adaptability under constraints, refine risk appetite, and develop critical cognitive problem-solving skills, bridging the gap between theoretical knowledge and practical application in complex business environments (Csaszar et al., 2024). The continuous AI-driven feedback loop fosters reinforcement learning and helps students to adapt their strategies, preparing them for the dynamic and often unpredictable landscapes of developing economies. For in-company training, this framework offers a scalable solution to empower local decision-makers to cultivate resilience and strategic foresight (Elenurm, 2024). Localized AI simulations can address challenges like data scarcity, regulatory gaps, and network effects prevalent in developing regions (Moharrak et al., 2024), by democratizing access to sophisticated training tools and fostering the adoption of technology and AI across various industry sectors. Furthermore, AI augmentation frees human instructors from repetitive grading tasks, allowing them to focus on higher-level mentorship and facilitating deeper strategic thinking (Trindade et al., 2024) as previously mentioned.

10.0 FUTURE RESEARCH

Future research should explore the potential for AI to identify emerging "micro-clusters" in real-time, enabling highly personalized interventions and tailoring feedback or challenges indicative of high internal disagreement to optimize each student's specific learning trajectory. This would move beyond a one-size-fits-all approach, catering to individual differences in strategy, adaptive capacity, and response to AI feedback. Further investigation into the faculty analytics dashboard could pinpoint specific outliers and teams with high internal disagreement, providing targeted insights for educational intervention. Additionally, continued analysis of how cognitive problem-solving skills evolve, how risk appetite shifts, and the quantification of standardized decision-making probabilities among participants will offer deeper insights into the long-term impacts of such experiential learning frameworks.

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