Exploring Learner Engagement in an LLM-Supported Simulation Environment for Complex Systems Understanding

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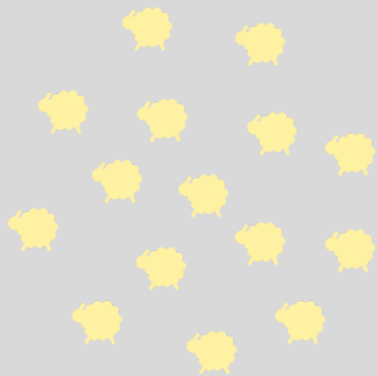
Introduction

Micro-Level

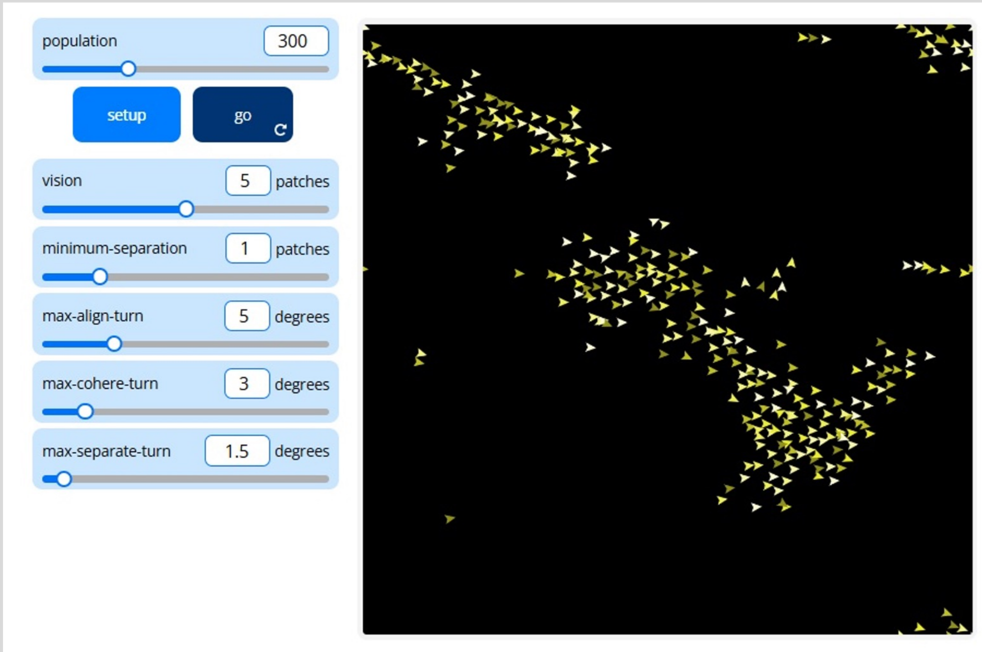


Macro-Level

Understanding complex systems is challenging as it requires reasoning across multiple levels

Introduction

- Agent-based models (ABMs) are widely used to support complex systems learning
- Learning through parameter manipulation of simulations alone can cause learners to form inaccurate interpretations



- Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. of Science, Education and Technology, 8(1), 3–19.

Introduction

- Conceptual frameworks such as PAIR-C serve to make these relationships explicit
- Despite advances in theory, it is challenging to integrate such frameworks into the design of interactive learning environments
- Prior approaches to validating PAIR-C lacked an exploratory phase during instruction

PAIR-C

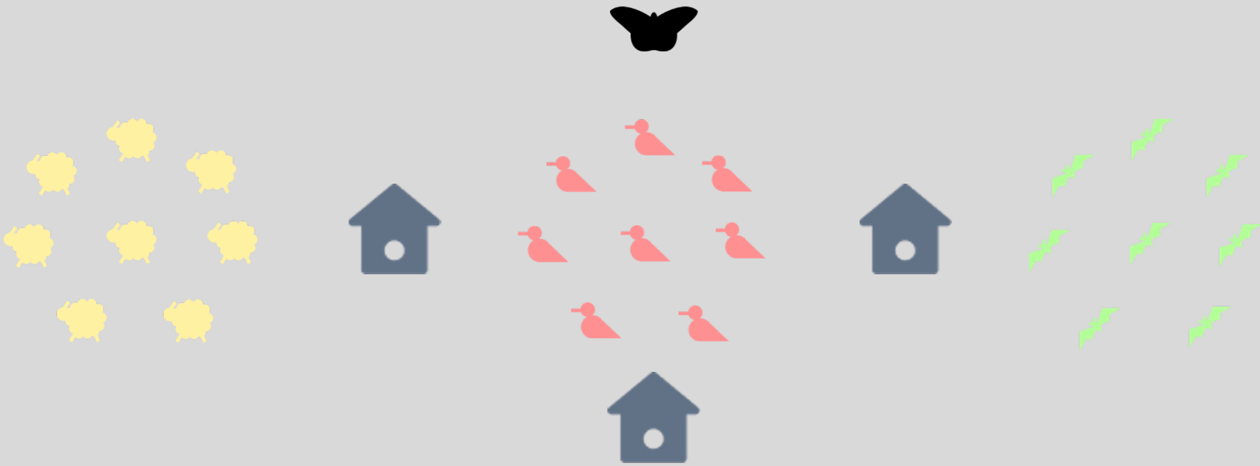
- Michelene T. H. Chi. 2023. Individualistic and collective causal knowledge structures for understanding sequential and emergent processes. Frontiers in Education 8.

Introduction

- Large language models (LLMs) have enabled context-aware conversational tutoring to be integrated in agent-based learning environments
- When integrated as pedagogical supplements, LLMs have been shown effective at enhancing academic performance

- Peer-Benedikt Degen, Igor Asanov. 2025. Beyond Automation: Socratic AI, Epistemic Agency, and the Implications of the Emergence of Orchestrated Multi-Agent Learning Architectures

Introduction



An LLM-supported open-world learning environment structured using the PAIR-C framework emphasizing exploration

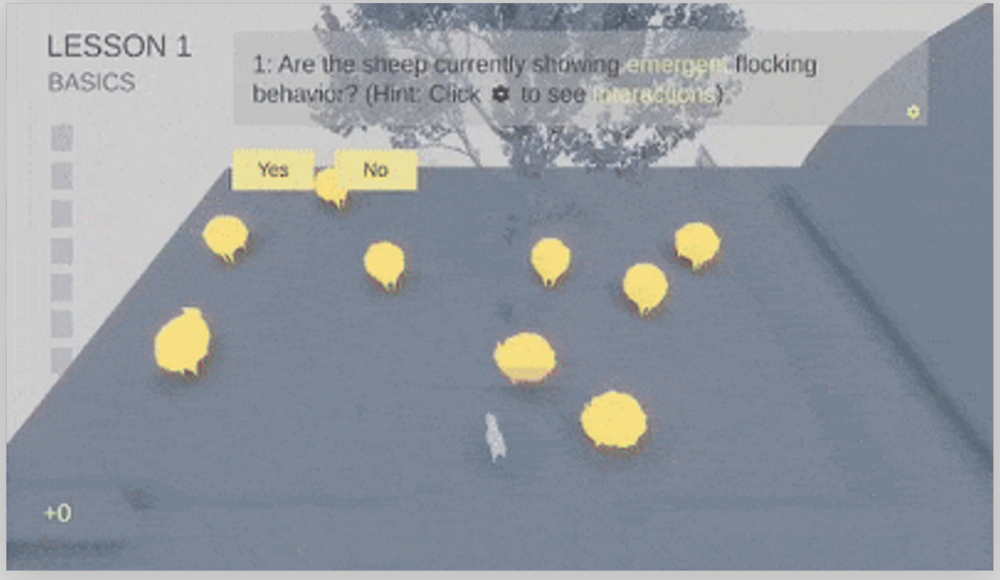
Research Question

RQ1: How does learner engagement within an open-world, self-paced LLM-supported learning environment relate to measurable learning outcomes?

H1: Learner engagement with the LLM-based tutor will predict positive learning outcomes

H2: Learner engagement with the exploratory instructional regions will predict positive learning outcomes

The Flocking Simulator

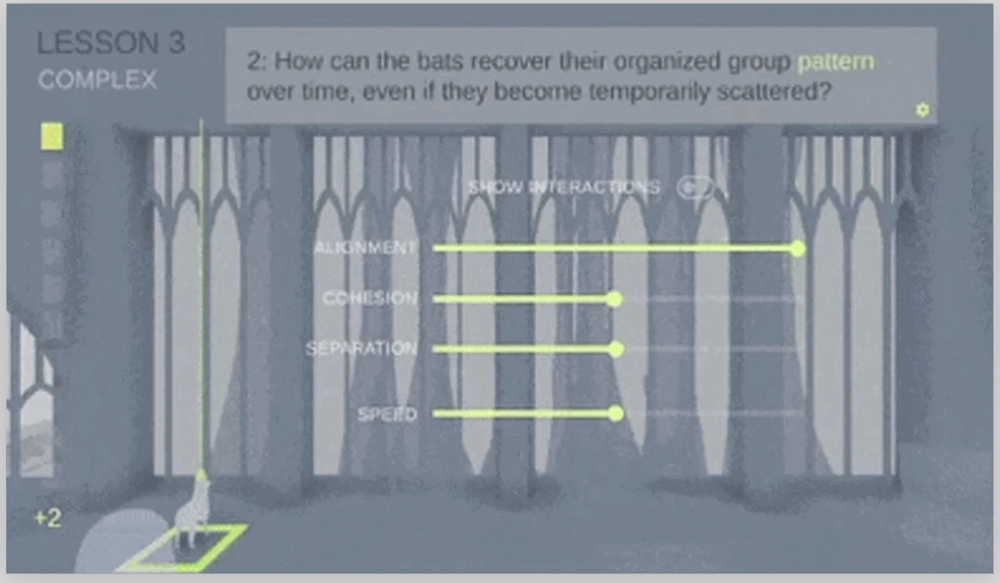


We developed: An agent-based open-world learning environment structured using the PAIR-C framework for teaching complex systems

The Flocking Simulator

Exploration mode: Learners freely engage with instructional material presented through Exhibit Areas and Hidden Systems

The Flocking Simulator



Evaluation mode: Learners manipulate flock simulations and answer 10 questions designed based on the PAIR-C framework

The Flocking Simulator

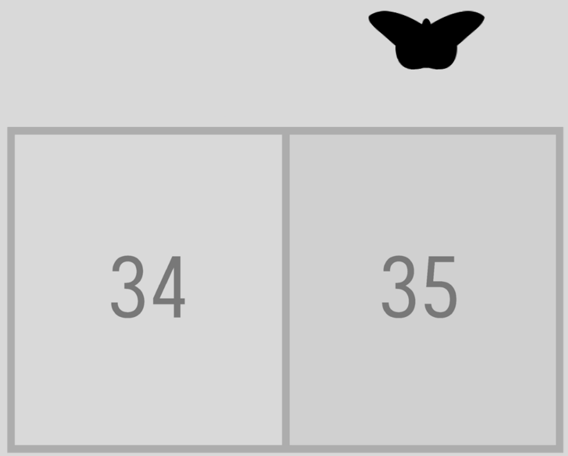
Butterfly Tutor: Provides adaptive, context-aware support grounding its responses in the PAIR-C framework

Methods

- A total of 75 graduate and undergraduate students participated with 69 completing all phases
- Participants took pretests, worked with the learning environment independently for 40-60 minutes, and took posttests
- Measures analyzed included: Number of questions received, time on-conversation with the butterfly, word count, duration to assess engagement, etc

Methods

- The study used a between-subjects 2 × 2 factorial design where participants were randomly assigned to one of four conditions
- The present study focuses on one factor: Conditions with and without access to an LLM-based tutor



Tutor Absent Tutor Present

Results (LLM tutor)

Input Type	Proportion	Example
Content-focused	35.7%	“What is flocking?”
Meta	28.5%	“Can I redo tests?”
Peripheral	26.8%	“You are a true friend”
Greeting	7.7%	“Goodbye”
Unrelated	1.3%	“I have exams soon”

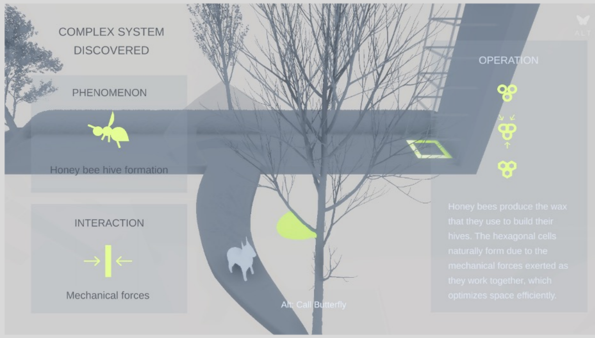
Results (LLM tutor)

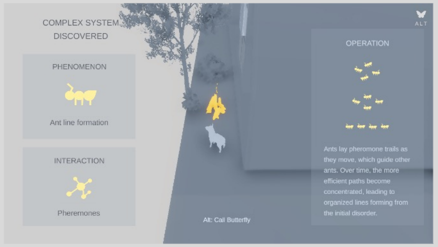
- Higher interaction frequency within the tutor positively predicted posttest outcomes
  $b = 0.14$, $p = .038$, Adj. $R^2 = .129$
- Content-focused inputs positively predicted posttest outcomes, as did greeting inputs
  $b = 0.21$, $p = .048$, Adj. $R^2 = .062$
  $b = 1.94$, $p = .025$, Adj. $R^2 = .094$
- Total word count positively predicted posttest outcomes
  $b = 0.02$, $p = .028$, Adj. $R^2 = .090$

Results (Exploratory Instruction)

- Time spent within **Hidden System 3** had a marginally significant trend with posttest performance
  $b = 0.676$, $p = .067$, Adj. $R^2 = .323$

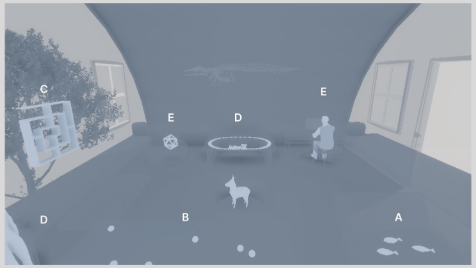
- **Hidden Systems 1 and 2** were found to be more difficult to locate, encountered by only **14.5%** (n = 10) and **10.1%** (n = 7) of participants respectively

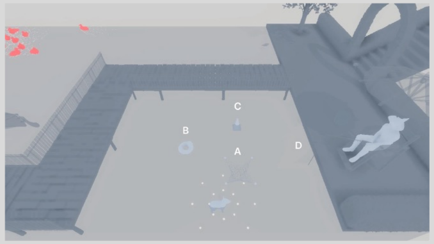




Results (Exploratory Instruction)

- Time spent within **Exhibit Area 1** was a significant positive predictor of posttest performance, while time spent within Exhibit Area 3 showed a small but non-significant positive trend
  b = 1.09, p = .004, Adj. R^2 = .323





- Exhibit Area 2 (focused on flocking) alone was not associated with gains

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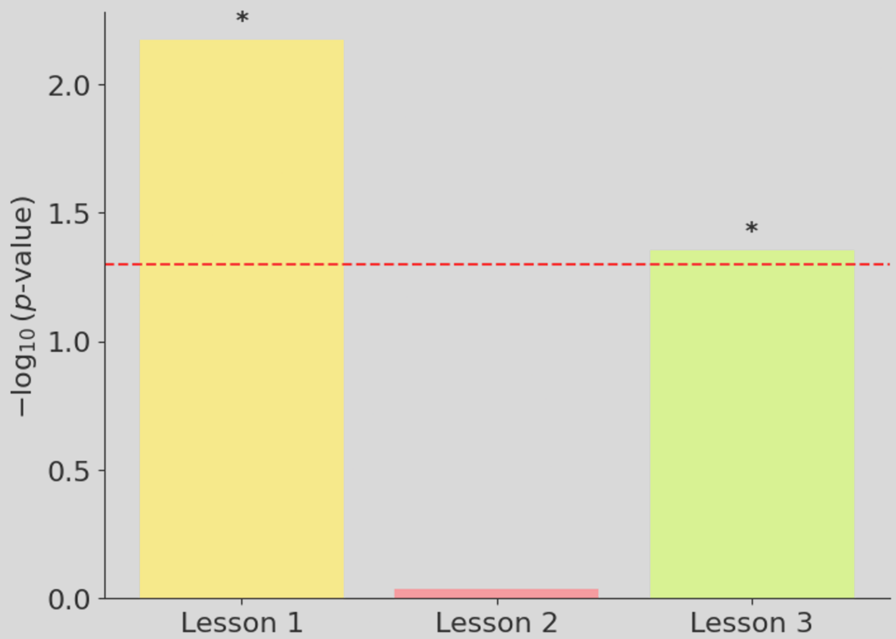

Key Takeaways

➔ Learning environments supported by LLM agents that take advantage of conceptual frameworks can support targeted, high-quality engagement

➔ Self-paced learner engagement with exploratory instructional regions can meaningfully support conceptual understanding of complex systems within open-world learning environments

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Acknowledgements

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