# Ontology-Enhanced Contextual Reasoning for Large Language Models in STEM Education

Bachelor Thesis Presentation

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# Research Problem: LLM Hallucinations in STEM Education

### The Challenge

Large Language Models (LLMs) hallucinate a lot by generating confidently plausible but factually incorrect information.

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# Research Problem: LLM Hallucinations in STEM Education

## The Challenge

Large Language Models (LLMs) hallucinate a lot by generating confidently plausible but factually incorrect information.

- LLM hallucinations occur in most technical STEM concepts
- In STEM education, accuracy is crucial for effective learning
- Traditional approaches face limitations:
  - Pure LLM-based systems risk generating misinformation
  - Rule-based systems lack natural interaction capabilities of LLMs
  - Prompt engineering is complex and requires domain Knowledge
  - Fine-tuning LLMs is resource-intensive, time-consuming, and requires domain Knowledge

# Research Question & Objectives

## Research Question

How can we make use of LLMs' natural language processing capabilities to enhance STEM education while ensuring their responses remain accurate and reliable?

## Research Objectives

- How can we integrate domain-specific knowledge with LLM reasoning?
- How can we enhance contextual understanding through structured knowledge?
- How can we create an adaptive, personalized learning system? (Future Work)

# Background: Ontologies in Knowledge Representation

## What are Ontologies?

Structured frameworks that represent knowledge within specific domains, defining concepts, properties, and relationships in a machine-readable format.

**Key Components**

- Classes (concepts)
- Properties (relationships)
- Instances (individuals)
- Axioms (rules/constraints)
- Reasoners (inference engines)

**Benefits for STEM Education**

- Fact verification
- Explicit knowledge representation
- Domain-specific constraints

# Methodology Overview

## Research Approach

Phased development approach to create an ontology-enhanced LLM system for STEM education

- **Core Functionality**
  - Environment setup and API authentication
  - System prompt structure
- **Knowledge Representation**
  - Physics ontology development (OWL/RDF)
  - Concept relationships and prerequisites structure
  - Context retrieval system implementation
  - Knowledge base integration

# System Architecture

## Integrated System Components

Our ontology-enhanced LLM system combines structured knowledge with adaptive learning capabilities

**Technical Stack**

- Quart web framework (async)
- Claude LLM API integration
- OWL/RDF ontology framework

**Information Flow**

- Bidirectional LLM-ontology integration
- Real-time fact verification
- Student model adaptation

# Ontology Design for Physics Education

## Hierarchical Knowledge Structure

Physics concepts organized in a machine-readable format with explicit relationships

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# Ontology Design for Physics Education

**Hierarchical Knowledge Structure**

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- **Educational Metadata:** Difficulty levels, learning objectives

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- **Educational Metadata:** Difficulty levels, learning objectives
- **Integration:** OWL/RDF technologies with SPARQL queries

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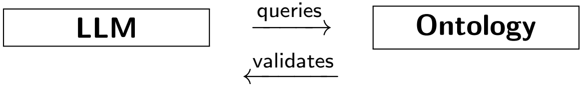


**Integration Mechanisms**

- SPARQL query generation
- Dynamic context augmentation
- Fact verification pipeline

**Prompt Engineering**

- Ontology-aware prompts
- Chain-of-thought reasoning
- Self-verification steps

# Evaluation Methodology

## Evaluation Framework

Modular implementation with statistical analysis and visualization components

**Testing Approach**

- Force Concept Inventory (FCI) dataset
- Baseline vs. ontology-enhanced model
- Multiple-choice + explanation prompts
- Hybrid hallucination detection:
  - Keyword matching
  - Expert verification

**Evaluation Metrics**

- Hallucination rate
- Trade-off analysis

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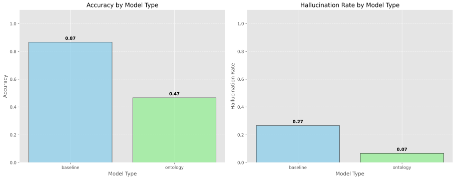
# Results: Quantitative Analysis




## Hallucination Reduction

**75%** reduction (26.67% $\rightarrow$ 6.67%)

- Key trade-off: Accuracy decreased from 86.67% to 46.67%
- Better for explanations than assessment

# Educational Impact Analysis

### Case Study: Free Fall Explanations

**Baseline (with hallucination)**
The gravitational force is proportional to the mass... heavier objects fall faster.

**Ontology-enhanced (corrected)**
All objects accelerate at the same rate regardless of mass ($g = 9.8\ m/s^2$).

**Trade-off Analysis**

- 75% reduction in physics misconceptions
- Enhanced explanation quality
- Lower accuracy in assessment tasks
- Task-dependent constraint application recommended
- Balance between factual reliability and flexibility

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# Conclusions

## Research Contributions

This thesis demonstrates how ontology-enhanced LLMs can significantly reduce hallucinations.

**Key Takeaways**

- 26.67% $\rightarrow$ 6.67% hallucination rate reduction
- Accuracy decreased from 86.67% to 46.67%
- Task-dependent performance identified
- Better for explanations than assessment

**Future Research Directions**

- Develop adaptive constraint mechanisms
- Expand statistical evaluation with larger samples
- Create an adaptive student model that adjust responses based on the student's knowledge level and learning objectives
- Create an Avatar that can interact with the student and provide personalized feedback

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