MSc Project Plan

Title: *Cooperative Learning Between a Large LLM and a Small VLA*
Subtitle: *Evaluating How Linguistic Diversity Affects SmolVLA Manipulation Performance*
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Date: December 2025

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1. Project Aim

This project evaluates how **LLM-generated linguistic diversity**—including paraphrase quantity, linguistic style, persona, and reasoning-chain augmentation—affects the performance and generalisation of a **small Vision-Language-Action model (SmolVLA)** on manipulation tasks.

A large LLM (QWEN/GPT) is used to **rewrite, expand, paraphrase, stylise, and add reasoning chains** to instructions paired with demonstration episodes. The resulting datasets are used to train **multiple SmolVLA variants**, whose behaviour is compared in simulation and on a real SO100 robot.

This is a **controlled study** of how text influences robot policy learning. No prior work has directly measured this.

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2. Novelty

This project provides the **first systematic ablation study** investigating:

- how **paraphrase quantity** affects VLA performance,
- how **linguistic style** (concise, verbose, symbolic, hierarchical, reasoning) influences results,
- whether **persona-based rewriting** changes learned behaviour, and
- whether **reasoning-chain augmentation** improves grasping or planning.

The study is:

- **controlled** (only the text changes; demos & visuals stay fixed),
- **reproducible**,
- **scalable** (LLM-generated language),

- **simulation-first** (allowing statistically meaningful evaluation),
- and grounded with a **real-robot validation** using the SO100.

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3. Research Questions

1. How does **paraphrase quantity** (1, 5, 20, 100 per demonstration) affect SmolVLA's generalisation?
2. Do different **linguistic styles** (concise, verbose, symbolic, hierarchical, reasoning-based) change policy performance?
3. Does **persona-based rewriting** (terse, verbose, safety-focused, technical, optimistic) bias the learned behaviour?
4. Does adding **reasoning chains** (step-by-step or causal reasoning) improve manipulation success?
5. Do these effects seen in simulation transfer to the **real SO100 robot**?

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4. System Architecture

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                │   Real SO100 Teleoperation    │
                │   • Human-controlled demos    │
                │   • RGB camera data / actions│
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                 │   MuJoCo LeRobot-Gym        │
                 │   (github.com/DanielBryars/│
                 │    lerobot-gym)             │
                 │   • SO100 simulation env    │
                 │   • Teleop + auto-reset     │
                 │   • Calibration debugging   │
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             │ Base Dataset:                        │
             │ • Images (real + sim)                │
             │ • Actions (joint deltas / EE pose)  │
             │ • Single task description per demo  │
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               │ LLM Linguistic Augmentation       │
               │ • Paraphrase counts: 1,5,20,100   │
               │ • Styles: concise, verbose,       │
               │   symbolic, hierarchical,         │
               │   reasoning-based                 │
               │ • Persona-based rewriting         │
               │ • Reasoning-chain augmentation    │
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│   Model Variant    │ │   Model Variant      │ │   Model Variant      │
│  (1 paraphrase)    │ │ (20 hierarchical)    │ │ (100 mixed styles)   │
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│  Train SmolVLA     │ │   Train SmolVLA      │ │   Train SmolVLA      │
│    (LeRobot)       │ │                      │ │                      │
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│             Evaluation Pipeline (Simulation + Real)              │
│        • Simulation: 200 randomised trials per model             │
│        • Real-world SO100: external validity tests               │
│        • Metrics: success rate, robustness, error types          │
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Simulation provides the **main** experimental dataset.
The real SO100 robot provides a **small but meaningful external validity check**.

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5. Experimental Design

5.1 Paraphrase Count Conditions

For each demonstration:

- **1** (baseline)

- **5**
- **20**
- **100**

5.2 Linguistic Style Conditions

- **Concise**
- **Verbose/narrative**
- **Symbolic** (e.g., “MOVE A → B; VERIFY STATE = OK”)
- **Hierarchical / Stepwise**
- **Reasoning-Based** (“I should pick up the block because…”)

5.3 Persona-Based Conditions

LLM rewrites instructions using personas such as:

- terse engineer
- overly verbose assistant
- safety-focused
- optimistic motivator
- highly procedural technician

5.4 Reasoning-Chain Augmentation

Chain-of-thought–like expansions:

- step-by-step plans
- causal reasoning (“to avoid knocking the other block…”)
- decomposed subgoals

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6. Experiment Matrix

A simplified version (full matrix adjustable depending on time):

Count	Style	Persona	Reasoning	Model ID
1	baseline	none	no	M1
5	concise	none	no	M2
20	hierarchical	technician	no	M3
20	reasoning-based	none	yes	M4

Count	Style	Persona	Reasoning	Model ID
100	mixed styles	mixed	mixed	M5

These models differ **only in language**; visuals/actions remain identical.

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7. Evaluation

Simulation (Primary)

- MuJoCo SO100 gym
- 200 trials per model
- Randomised object placement
- Metrics:
  - success rate
  - robustness to unseen phrasing
  - wrong-object / wrong-goal errors
  - trajectory stability

Real SO100 Robot (External Validity)

- Test 1–2 of the strongest/weakest conditions
- 20–30 trials
- Confirm whether trends from simulation hold in real hardware

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8. Task List

- Finalise calibration in MuJoCo gym
- Collect clean baseline demonstrations
- Generate paraphrases across counts, styles, personas, and reasoning modes
- Assemble all augmented datasets
- Train each SmolVLA variant
- Evaluate all models in simulation
- Conduct real-world validation
- Analyse performance differences and error patterns
- Write the dissertation (methods, results, discussion, limitations, future work)

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9. Summary

This MSc project delivers a **rigorous, controlled, and novel** investigation into how language affects robot manipulation policies.

I will:

1. Collect demonstration data
2. Generate broad linguistic variation with a large LLM
3. Train multiple SmolVLA models
4. Evaluate them across simulation and real-world tasks
5. Identify which linguistic properties most improve performance

The study advances understanding of **how LLM-generated language shapes the behaviour of small VLA models**, providing actionable insights for future robot learning systems.

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10. Stretch Goals

RGB-D Sensing

- Add a RealSense-style RGB-D camera
- Compare RGB-only vs RGB-D training

Reinforcement Learning Integration

- Use PPO/SAC in MuJoCo to fine-tune the policy
- Explore IL+RL hybrid training
- Learn recovery behaviours

Additional Manipulation Tasks

- Occlusion (“digging”) tasks
- Multi-object tasks
- Shape/colour variation

Multi-Camera Fusion

- Wrist + overhead + side view experiments

Representation Experiments

- Joint deltas vs end-effector pose (FK/IK)
- IK remapping at inference

Generalisation & Adversarial Tests

- Distractors, lighting changes, clutter
- Zero-shot language stress-tests

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11. Repository References

- **SmolVLA / LeRobot:** https://github.com/huggingface/lerobot
- **SO100 MuJoCo Gym:** https://github.com/DanielBryars/lerobot-gym
- **QWEN Models:** https://huggingface.co/Qwen