

MASTER THESIS

**Toward a Multi Agent Approach for
LLM-Based Dynamic Vehicle
Control and Communication in
Accidental Condition**

RAFI MD ASHIFUJMAN

**STUDENT ID:
71330708**

**SUPERVISOR:
NAOKI FUKUTA**

**Department of Informatics
Graduate School of Integrated Science and
Technology
Shizuoka University**

SHIZUOKA UNIVERSITY



MASTER THESIS

Toward a Multi Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Condition

Author:

**RAFI MD
ASHIFUJJMAN**

Supervisor:

Naoki FUKUTA

MASTER OF INFORMATICS

**Department of Informatics
Graduate School of Integrated Science and
Technology
Computer Science**

July 15, 2025

Abstract

In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a critical challenge. Traditional AVs, which are based on pre-programmed rules or pre-trained models, often struggle in scenarios where human-like reasoning is required. This research examines how Large Language Models (LLMs) can act as a main decision agent for AVs, responding to text-based real-world traffic situations simulation.

We propose a multi-agent framework consisting of two key components, a Decision Agent powered by LLMs, and a Communication Agent that enables Vehicle-to-Vehicle (V2V) information exchange. The Communication Agent shares structured, real-time data such as obstacle presence, speed, and intended actions, which is then incorporated into the Decision Agent’s reasoning process.

To evaluate the proposed system, we conducted a series of text-based simulations that simulate real-world traffic conditions. These scenarios are used to test whether LLMs, when provided with scenario-specific prompts and contextual V2V data, can generate consistent and human-like decisions. Our results indicate that while LLMs show strong reasoning abilities, their precision and reliability of decision improve significantly when augmented with contextual information through V2V communication. This research presents a preliminary approach to bridge the gap between current AV capabilities and the demands of real-world accidental conditions.

Contents

Abstract	i
1 Introduction	1
1.1 Research Background	1
1.2 Research Objectives	2
1.3 Research Motivation	2
1.3.1 Motivating Example 1 : What a current AV might do in Unknown situation	2
1.3.2 Motivating Example 2 : Lack of communication between vehicles	4
1.4 Research Questions	4
1.5 Research Contribution	4
1.6 Thesis Outline	5
2 Background and Related Work	7
2.1 Autonomous Vehicle Decision-Making	7
2.2 The Challenge of Unknown-Unsafe Scenarios	8
2.3 Large Language Models (LLMs) for Reasoning	9
2.4 Multi-Agent Systems and V2V Communication	10
2.5 Related Work	10
3 A Multi-Agent Framework for LLM-Based Decision-Making	13
3.1 Conceptual Framework: A Multi Agent Approach	13
3.2 The Decision Agent	14
3.3 The Communication Agent	16
3.4 Text-Based Simulation and Scenario Design	17
3.5 Prompt Engineering	18
4 Simulation and Results	21
4.1 Simulation-based Analysis	21
4.1.1 Scenario 1: Basic Rule-Following (Green Traffic Light) . . .	21
4.1.2 Scenario 2: Common-Sense Reasoning and Obstacle Avoid- ance	22
4.1.3 Analysis of LLM Response Characteristics	22
4.2 Simulation-based Analysis	23
4.2.1 Scenario 1: Basic Rule-Following (Green Traffic Light) . . .	23

- 4.2.2 Scenario 2: Common-Sense Reasoning and Obstacle Avoidance 25
 - 4.2.3 Analysis of LLM Response Characteristics 25
 - 4.2.4 Analysis of Decision Consistency 26
 - 4.2.5 V2V-Enhanced Decision-Making in an Occluded Scenario 27
 - Decision-Making without Communication Agent 27
 - Decision-Making with Communication Agent 27
- 5 Conclusion and Future Work 29
 - 5.1 Conclusion 29
 - 5.2 Limitations and Future Work 29
- Bibliography 31
- Publications 35
- Acknowledgements 42

List of Figures

1.1	What a current AV might do in this situation	3
1.2	Lack of communication between vehicles may lead to an accident	3
3.1	Selected Models for the Experimentation	16
3.2	An illustration of Communication Agent	18
3.3	Illustration of real-life traffic scenarios tested in the LLM-based decision system.	19
4.1	Responses from various LLMs to the Green Traffic Light scenario, showing differences in correctness and verbosity.	24
4.2	Consistency analysis of OpenHermes-2.5-Mistral-7B on a simple traffic scenario over 20 trials without V2V communication. The non-zero variance indicates a degree of unreliability.	26
4.3	Comparison of an LLM's decision in an occluded stop sign scenario, with and without information from the Communication Agent.	28

List of Abbreviations

AI	Artificial Intelligence
AV	Autonomous Vehicle
ADS	Autonomous Driving System
LLM	Large Language Model
MAS	Multi-Agent System
NLP	Natural Language Processing
RL	Reinforcement Learning
V2V	Vehicle-to-Vehicle

Chapter 1

Introduction

The advancement of autonomous vehicle technology brings us closer to the long-held vision of fully automated transportation, where vehicles operate without human intervention. However, achieving this goal of complete automation remains a significant challenge, particularly in ensuring safe and reliable decision-making in complex and uncertain environments.

1.1 Research Background

Our research investigates the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision-making in autonomous vehicles (AVs), particularly in unknown-unsafe domains. Our main concern is to explore the use of an LLM as the primary decision-making agent within an autonomous driving system (ADS) [3], evaluating its ability to reason [4] and handle uncertain traffic situations. We aim to contribute to the development of safer and more reliable Level 5 (complete automation) autonomous vehicles, as defined by the Society of Automotive Engineers (SAE International) [5], [6]. Although traditional AVs can handle predictable ‘known-safe’ and ‘known-unsafe’ situations, they struggle with highly unpredictable events, such as a pedestrian unexpectedly crossing the road while the light is red for oncoming traffic representing an unknown unsafe condition. These scenarios, which are difficult to cover in training datasets, represent the primary barrier to achieving complete automation. Human drivers use common sense [7] and past experiences to navigate these unexpected events. However, current AV systems, even those use advanced reinforcement learning (RL) [8], struggle in these scenarios. This limitation is especially evident where the correct action is not immediately clear [9]. Addressing these unknown-unsafe scenarios is critical for improving an AV’s ability to handle real-world driving environments and ensuring the development of truly reliable autonomous systems.

1.2 Research Objectives

Determining how autonomous vehicles (AVs) should make decisions in complex or fully unknown traffic situations remains a major challenge in the development of fully autonomous systems. This problem has been widely explored in the fields of artificial intelligence, robotics, and autonomous system design. The ability to make safe and contextually appropriate decisions in real-time becomes especially critical when AVs encounter unknown-unsafe scenarios traffic conditions not represented in training data or handled poorly by traditional algorithms. Traditional autonomous vehicle systems used these approaches to take driving decisions,

- Rule-based system, which operates on predefined logic and hard-coded behaviors such as "if-then" conditions. These systems cannot take decisions in unfamiliar or edge-case situations that fall outside of their rule sets.
- Supervised learning or machine learning-based models, which are heavily dependent on training data. They often fail in new contexts because they cannot reason beyond the patterns they have learned.

A fundamental challenge is to prepare for truly unknown situations. Any scenario researchers create is technically 'known,' even if unfamiliar to AVs, making it difficult to test how vehicles handle genuinely unknown-unsafe situations. In addition, recreating complex real-world scenarios in simulation environments is challenging, and accurately simulating unpredictable human actions or complicated environmental conditions remains nearly impossible. In real life, it is nearly impossible to include all the uncertain situations in training datasets for traditional autonomous driving systems. Human drivers rely on common sense to navigate these situations effectively. To address this limitation, we are going to investigate whether LLMs can provide human-like reasoning [10] that traditional systems lack, such as how human drivers handle unexpected situations. The main objective of this research is to evaluate how effectively LLMs can act as decision agents in unfamiliar traffic conditions, and potentially bridging the gap between programmed responses and adaptive decision making in autonomous vehicle systems.

1.3 Research Motivation

1.3.1 Motivating Example 1 : What a current AV might do in Unknown situation

Imagine a traffic situation where a road is partially blocked by construction cones, with a 'STOP' sign placed near the cones (Figure 1.1). A traditional AV,

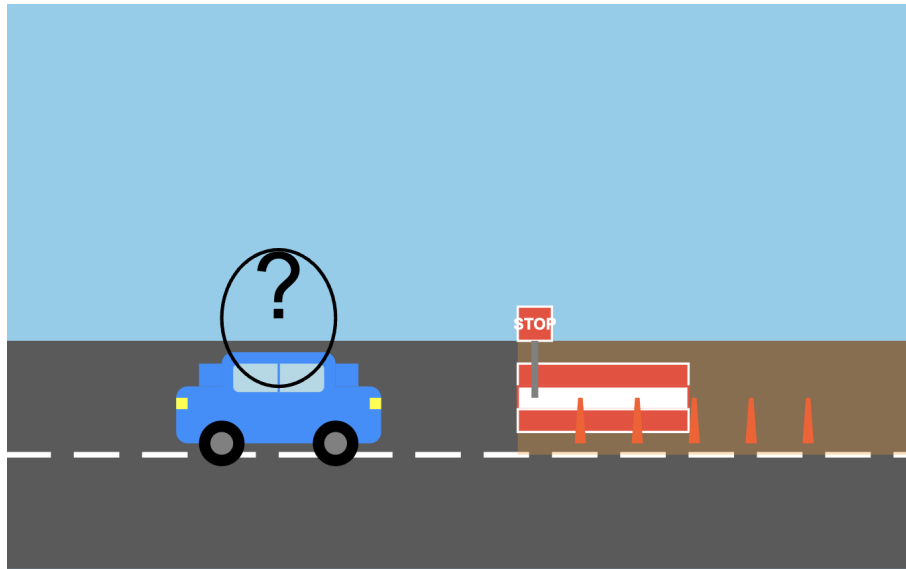


FIGURE 1.1: What a current AV might do in this situation

programmed with rigid rules, would likely interpret the 'STOP' sign literally and come to a complete halt, potentially causing a traffic obstruction. It lacks the context to understand that the sign applies only to the blocked portion of the lane. However, a human driver would use common sense to recognize that the road is only partially closed, slow down, and safely navigate through the open section. This scenario highlights the need for a reasoning system that can interpret context beyond literal rules.

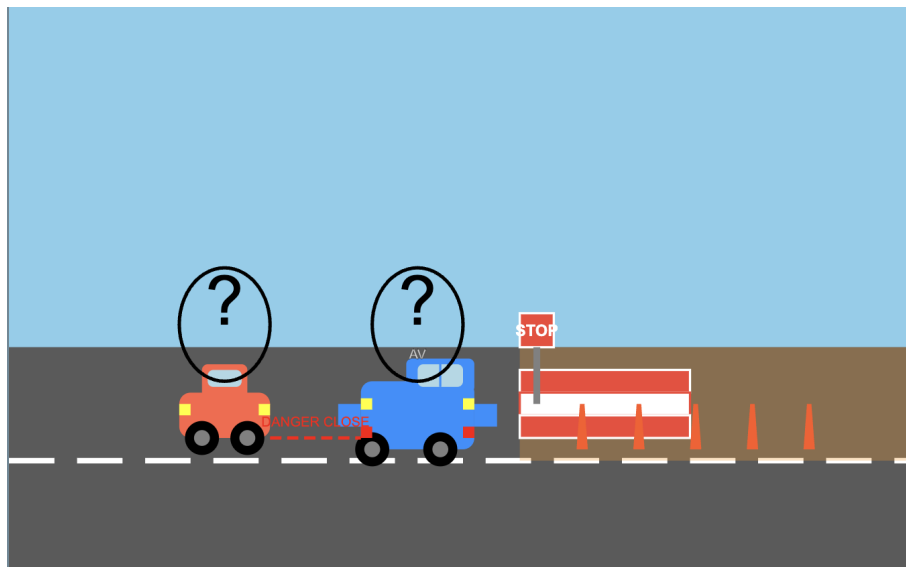


FIGURE 1.2: Lack of communication between vehicles may lead to an accident

1.3.2 Motivating Example 2 : Lack of communication between vehicles

Now, consider a more complex and realistic scenario (Figure 1.2). An autonomous truck (AV1) suddenly brakes upon detecting a partially visible ‘STOP’ sign, an action based on its own perception. Behind it, another vehicle (AV2), which could be human-driven or autonomous, is following closely. Due to AV1’s size, AV2 has no line of sight to the sign and no prior indication that AV1 is about to stop. Without any communication between the vehicles, AV2 is unaware of the hazard ahead, greatly increasing the risk of a rear-end collision. This scenario illustrates a critical limitation of single agent perception in autonomous systems. The issue is not only whether each vehicle can make the right decision for itself but also whether it can contribute to a collectively safe environment. As autonomous vehicles begin to share the road with human drivers, this limitation becomes even more pronounced, human drivers cannot anticipate AV decisions, and AVs cannot rely on human predictability. In our research, we will investigate how Large Language Models (LLMs) utilize this shared V2V information to make driving decisions. Specifically, our goal is to assess whether the inclusion of contextual data, such as obstacle positions, speed, and vehicle intentions, enables the LLM to produce safer and more accurate decisions in complex traffic scenarios.

1.4 Research Questions

One of the primary objectives of this investigation is to answer two main research questions.

- **Research Question 1:** Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation?
- **Research Question 2:** Is a single centralized decision-making agent sufficient to process all incoming Vehicle-to-Vehicle (V2V) data, or is a multi-agent system required for improved efficiency and scalability?
- **Sub-Research Question:** Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?

1.5 Research Contribution

This research introduces a novel multi-agent architecture that integrates Large Language Models (LLMs) with Vehicle-to-Vehicle (V2V) communication [11] to enhance autonomous vehicle decision-making in unknown-unsafe driving scenarios. This work demonstrates how their combined use enables emergent

reasoning capabilities, allowing autonomous vehicles to make more accurate and context-aware decisions in safety-critical scenarios. This research presents a standardized text-based simulation framework that replicates real traffic situations, used to test the LLM’s capabilities in logical reasoning, rule compliance, and dynamic decision-making domain for autonomous vehicle. Additionally, a multi-agent communication system is implemented, enabling the vehicle to share structured information such as obstacle locations, speed, and future intentions in a certain radius. This data serves as a contextual input for the LLM-based Decision Agent. The work demonstrates how contextual information sharing can transform potentially hazardous scenarios into safe outcomes. Through empirical experimentation, this research provides definitive evidence that structured V2V communication data significantly improves the accuracy of LLM-based decision making. The research develops novel approaches for quantifying the consistency and reliability of decisions in LLM-based systems, addressing one of the most critical concerns for the deployment of AI in safety-critical applications. By addressing these research areas, this work contributes to the advancement of both theoretical understanding and practical implementation of AI-enhanced autonomous driving systems, with particular emphasis on navigation through safety-critical scenarios.

1.6 Thesis Outline

This thesis is organized into six different chapters as follows:

Chapter 1 *Introduction*: This chapter describes a brief introduction to the thesis, including the research background, objectives, questions, contributions, and key motivations.

Chapter 2 *Background and Related Work*: This chapter introduces the research topics of autonomous vehicle decision-making, unknown-unsafe scenarios, Large Language Models (LLMs), and Multi-Agent Systems, defining the basic concepts and discussing related work in the field.

Chapter 3 *Approach and Example-based Analysis*: This chapter describes the problems and solving approach of this research and introduces the detailed multi-agent framework and example scenarios used for evaluation.

Chapter 4 *Simulation and results*: This chapter explains the simulation setup, implementation, approach on the codes and the analysis with limitations.

Chapter 5 Conclusion: This chapter describes the summary of the work, discusses the key findings, and outlines directions for future research as the conclusion.

Chapter 2

Background and Related Work

This chapter introduces the fundamental concepts and technologies that form the basis for this research. We examine the current state of autonomous vehicle decision-making systems, identify the critical challenges they face, and explore emerging technologies that can potentially address these limitations.

2.1 Autonomous Vehicle Decision-Making

The existing definitions of autonomous driving specified by the SAE for Levels 1 to 5 can be interpreted as, At level 1 vehicles, driving assistance systems that can sometimes help the driver complete some lateral or longitudinal driving tasks. At Level 2 vehicles can automatically provide multidimensional assistance. At level 3, vehicles can perform automatic acceleration and deceleration steering in a specific environment without the driver's intervention. At level 4, if a vehicle is currently in an autonomous driving state under limited conditions, the driver is not required to continuously control the steering wheel. At Level 5, vehicles can run automatically under any conditions and scenarios. At this level, the automatic system of a vehicle completely replaces the human driver and achieves complete automation. A complete autonomous vehicle (AV) is capable of sensing its environment and operating without human involvement. The decision-making process in autonomous vehicles follows a fundamental three-stage pipeline: perception, planning, and control.

- **Perception (See):** The vehicle uses a variety of sensors and cameras, such as LiDAR (Light Detection and Ranging), and radar systems to construct a comprehensive three-dimensional representation of its environment. This stage involves detecting and classifying objects such as other vehicles, pedestrians, traffic signs, and lane markings.
- **Planning and Decision-Making (Think):** This represents the core focus of our research. Based on the perceived environmental information, the vehicle's computational system must determine the appropriate course of action. This involves planning and taking decisions such as lane changes,

speed adjustments, and navigation through complex traffic scenarios. Traditional rule-based approaches perform well in structured and predictable traffic environments. They can only execute actions that have been explicitly predefined and encoded. When unexpected or novel situations arise that fall outside the scope of their programmed rules, these systems often do not respond appropriately [12]. Our research focuses on improving the intelligence of this decision-making component through advanced reasoning capabilities.

- **Control (Act):** Once a decision is made, the system translates the planned actions into control signals that activate the vehicle's physical components, including steering, acceleration, and braking systems. The decision-making module is particularly critical, as it is responsible for planning and performing safely.

2.2 The Challenge of Unknown-Unsafe Scenarios

The driving domain can be divided into three primary categories: known-safe, known-unsafe, and unknown-unsafe. While traditional Autonomous Vehicle (AV) systems can take proper decisions in the first two categories, which can be addressed with pre-programmed rules, their primary limitation lies in handling the complex and unpredictable nature of unknown-unsafe scenarios.

- **Known Safe Scenarios:** These are routine traffic conditions where the environment is predictable and the appropriate response is well-established. For example, driving straight on an empty highway or stopping at a red light. AVs can reliably navigate these situations using pre-defined logic.
- **Known Unsafe Scenarios:** These are situations where a clear and present danger is identifiable based on established rules. Examples include an object stationary on the road, a speeding in a school zone, or another vehicle running a red light. AVs can be trained to recognize and react to these predictable hazards.
- **Unknown-Unsafe Scenarios:** These are unexpected and unplanned situations that are not explicitly covered by pre-programmed rules and can occur without warning or precedent. Examples include a ball rolling onto the road, a pedestrian unexpectedly crossing a red light, or ambiguous hand signals from another driver. These situations require quick context-aware judgment and are difficult to cover exhaustively in training datasets.

Traditional AVs are generally capable of handling known-safe and known-unsafe scenarios effectively using pre-programmed rules, supervised learning, or reinforcement learning models. For example, they can detect and respond to traffic lights, lane markings, and other common characteristics of the driving

environment. However, they struggle when faced with new or unusual situations that are not directly covered by their programming. Human drivers, on the other hand, use common sense and past experiences to handle unexpected events, such as recognizing that traffic cones on a moving truck are not a stationary obstacle. Current AV systems, even those that use advanced reinforcement learning (RL), will struggle to make such a nuanced distinction. This limitation poses a serious safety risk in real-world driving and can lead in several critical failure modes, such as AV can incorrectly identify a safe situation as dangerous, leading to unnecessary and potentially disruptive actions like sudden braking. For example, an AV might stop for a tree shadow across the road, treating it as a solid obstacle. The AV can fail to recognize an actual danger because it does not fit a pre-programmed pattern. This is the most critical failure mode, as it can lead directly to collisions. Addressing this gap is essential for the development of fully autonomous systems that can be trusted to operate safely and reliably in the complexity of real-world environments.

2.3 Large Language Models (LLMs) for Reasoning

An important development in artificial intelligence is represented by Large Language Models (LLMs). LLMs are a type of Machine Learning (ML) model trained in vast amounts of text and code from the Internet, allowing them to comprehend and produce language similar to that of a human. LLMs represent a significant leap in natural language processing and artificial intelligence. Unlike traditional rule-based systems, these machine learning models, driven by deep learning techniques, excel at comprehending and generating extensive human-like text. Reasoning is a fundamental aspect of human intelligence, essential for problem solving, decision-making, and critical thinking. In recent years, Large Language Models (LLMs) have demonstrated emerging abilities [13], such as in-context learning [14], role play [15], and analogical reasoning [16]. These abilities allow LLMs to go beyond natural language processing problems to facilitate a wider range of tasks, such as code generation [17], robotic control [18], and autonomous agents [19]. Among these abilities, human-like reasoning has garnered significant attention from both academia and industry, since it demonstrates great potential for LLMs to generalize to complex real-world problems through abstract and logical reasoning. A notable breakthrough in this area is the ‘chain of thought’ prompting technique [20], which can obtain step-by-step human-like reasoning processes at the test time without additional training.

This research investigates the potential of LLMs to serve as the main decision makers within AV systems, assessing whether they can reason and react more like humans in complex scenarios.

2.4 Multi-Agent Systems and V2V Communication

A Multi-Agent System (MAS) is a computerized system composed of multiple interacting intelligent agents. Within an MAS, each agent has an incomplete perspective and is capable of autonomous action, but the overall goal of the system is achieved through coordination and communication between agents [21]. In the context of autonomous driving, this paradigm is highly relevant. **Vehicle-to-Vehicle (V2V) communication** is a key enabling technology for a multi-agent approach to driving. V2V allows vehicles to wirelessly exchange information about their position, speed, direction, and intended actions. This creates a collective awareness that extends far beyond the perception range of any single vehicle's onboard sensors (e.g., LiDAR, cameras). By structuring a V2V system within a multi-agent framework, we can address some of the fundamental limitations of single-agent AVs: This research proposes to integrate LLM-based decision-making within a multi-agent framework, where V2V communication provides the crucial context needed for robust reasoning in accidental conditions.

2.5 Related Work

Research in autonomous vehicle decision making has evolved through several paradigms. Traditional autonomous vehicles are based on data-driven approaches, which are categorized into modular and end-to-end frameworks [22]. Modular-based systems break the entire autonomous driving process into separate components, such as the perception module, the prediction module, and the planning module. Including tasks such as object detection [23] and object occupancy prediction. Early systems relied heavily on rule-based and finite-state machines, which are effective for predictable structured environments, but lack the flexibility to handle novel situations. The work of Fu et al. [24] established the concept of 'Drive like a human', demonstrating that LLMs can generate plausible driving behaviors in response to textual descriptions of traffic scenes. Their work primarily focused on a single agent perspective and highlighted the promise of LLMs for high-level reasoning. Our research builds directly on this foundation by investigating LLM performance in a multi-agent context. The use of Multi-Agent Systems (MAS) for traffic management and coordination is well-established. Research in this area has often focused on optimizing traffic flow, coordinating intersections, and cooperative path planning [25]. However, these works typically used simpler, more formally defined agent behaviors. This research [26] presents experiments on learning decision-making policies in multi-agent environments for autonomous systems like connected autonomous vehicles. The agents were able to learn to navigate their environment and avoid collisions even in a partially observable environment with obstacles and other moving agents. However, learning decision-making policies

is challenging due to the non-stationary nature of the environment. This research [27] explores a multi-agent system (MAS) architecture designed to facilitate cooperative control of CAVs. This hierarchical architecture enables vehicles to collaborate effectively in complex traffic environments, sharing information and making collective decisions that enhance safety and efficiency. The study emphasizes the importance of cooperation among autonomous vehicles, particularly in scenarios where rapid decision-making and coordination are critical to preventing accidents and ensuring smooth traffic flow. In this research [28], they explored how the combination of large language models (LLMs) with visual models, called Vision Foundation Models (VFMs), can make autonomous driving systems smarter and more capable [17]. Their work explains how technology evolved from basic sensors in early systems to more advanced deep learning methods that improve how self-driving cars see, plan, and make decisions. In this research [29], they introduced a method for training systems to better understand driving situations. They connected numerical driving data with GPT-3.5, a powerful LLM, which helped the system answer questions and make better driving decisions. The 'DriveMLM' research [30] created a new self-driving system that connects LLMs with vehicle planning tasks. This allowed the car to make decisions in a simulator and control the vehicle more effectively by using a standard planning module. The 'Drive As You Speak' [31] research took things a step further by allowing drivers to talk to the car using natural language. This made it possible for LLMs to understand and follow voice commands, improving the user experience and making driving more intuitive. In this research, AccidentGPT [32] introduced a model that can analyze traffic accidents. It uses different types of data (such as text and images) to recreate accident scenes and generate detailed reports. This research [33] reviews the integration of large language models (LLMs) into autonomous driving systems, highlighting their potential to improve decision-making, perception, and interaction through advanced reasoning and contextual understanding. The survey categorizes current research into planning, perception, question answering, and generation, addressing the challenges of transparency, scalability, and real world application. It underscores the need for robust datasets and interpretable models to build trust and improve system reliability in autonomous driving. This study [34] looks to explore the ability of integrating LLMs into autonomous driving (AD) structures to emulate human-like behavior. LLMs can use their memory to apply past experiences to future decision-making, improving adaptability and decision-making in AD systems. It can improve reliability and safety by enabling human-like reasoning and adaptability. Human drivers instinctively reason with common sense knowledge to predict hazards in unfamiliar scenarios and to understand the intentions of other road users. However, this essential capability is completely missing from traditional decision-making systems in autonomous driving. In response, this paper presents DriveLLM [35], a decision-making framework that integrates large language models (LLMs) with

existing autonomous driving stacks. This integration allows for the use of common sense in decision-making. DriveLLM also features a unique cyber-physical feedback system, allowing it to learn and improve from its mistakes. In real-world case studies, the proposed framework outperforms traditional decision-making methods in complex scenarios, including difficult edge cases. However, using massive amounts of human-generated data to train these models introduces potential bias issues, as the models can unintentionally reinforce the social biases found in the data [36]. Mitigating these biases is an essential and ongoing area of research [37]. This study [38] shows a potential approach of using large language models (LLMs) to evaluate fairness.

The intersection of LLMs and multi-agent communication presents a promising new direction for autonomous driving research. Existing work has shown that LLMs can replicate human-like reasoning and that MAS frameworks improve coordination and safety. However, our research uniquely combines these strengths, and using LLMs as decision agents within a cooperative V2V-enabled architecture represents a novel integration.

Chapter 3

A Multi-Agent Framework for LLM-Based Decision-Making

This chapter begins by introducing the overall approach and then provides a detailed explanation of our methodology, including how the experiments were set up, what assumptions were made, and the key factors considered when selecting models for evaluation. This is followed by illustrative example scenarios that demonstrate the system's behavior in representative traffic situations.

3.1 Conceptual Framework: A Multi Agent Approach

To contribute to the advancement of full automation in autonomous vehicles (AVs), this research proposes a conceptual framework based on a multi-agent architecture. The framework is designed to emulate human-like reasoning while enabling cooperative behavior among vehicles through structured communication. The framework focused on two primary agents: the Decision Agent and the Communication Agent, which work collaboratively to enhance decision-making capabilities in dynamic and uncertain traffic scenarios. The interaction between the Decision Agent and the Communication Agent is the core of this framework. The Decision Agent uses both its internal scenario understanding and externally shared V2V data to make informed decisions. This hybrid reasoning system provides the AV with both self-perception and extended perception capabilities with shared information.

- We investigated whether Large Language Models (LLMs) as a decision agent can replicate human-like decision-making processes in autonomous vehicle contexts.
- We also investigated how the information sharing facilitated by the communication agent impacts and potentially improves the accuracy decision in the autonomous driving system.

During this investigation with various LLMs as main decision agent, we proceed under two assumptions.

- 1) Certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs
- 2) the outputs generated by the LLMs can be translated into actual decisions made by the decision agent by interpreting the responses from the LLMs.

We have investigated the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective was to answer the research question (Research Question 1): Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation? We have also assumed that vehicle-to-vehicle (V2V) communication has already been achieved through a standardized networking protocol, such as LAN-based direct communication or a low-latency wireless system. Under this assumption, each vehicle can communicate with other vehicles within a defined radius (e.g., 10 meters). When a vehicle enters the information sharing radius of another vehicle, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we have investigated how LLMs process and utilize this information. Specifically, we have examined whether the incorporation of V2V exchanged data improves decision accuracy and enables AVs to make more precise and context-aware decisions. However, V2V communication introduces a critical question (Research Question 2): Is a single centralized decision-making agent sufficient to process all incoming V2V data and make autonomous driving decisions, or is a multi-agent system required for improved efficiency and scalability? In this research, we have investigated the answers to these two research questions. Through this multi-agent approach, the research aims to bridge the gap between current autonomous vehicle capabilities and the complex decision-making requirements of fully automated transportation systems.

To test large language models as decision agent, we have prepared a set of simple, text-based simulation scenarios of different traffic situations using Python. These scenarios are designed to cover situations that require logical reasoning or the application of common sense knowledge, such as recognizing a traffic red light and stopping accordingly. These scenarios will be used as input for various LLMs to assess how effectively they handle both types of challenges. The experiments will be conducted using the LLM selected in Fig.3.

3.2 The Decision Agent

The Decision Agent is responsible for making context-aware driving decisions. It leverages the reasoning capabilities of pre-trained Large Language Models (LLMs), such as GPT-4, Claude, and open-source alternatives. These models are

capable of processing natural language prompts that describe traffic scenarios and generate corresponding driving actions (e.g. STOP or FORWARD).

Hugging Face¹ is a platform where various open LLM models are available. LM Studio² is a platform to test and integrate LLM available on Hugging Face into a locally available system on ordinary computing devices, even without powerful GPUs. Now, **the question is what factors were considered in the selection of LLMs for this study?**

One key factor in our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [39] indicates that 8-bit quantization enables the majority of LLMs to maintain a performance level comparable to their nonquantized equivalents, regardless of model size (e.g. 7B to 70B parameters). Moreover, LLMs that are quantized to 4 bits can also up hold similar performance to their non-quantized versions across most benchmarks. This approach achieves memory reduction of 50 to 75% while preserving precision in complex tasks such as reasoning, decision making, and domain-specific applications. The models chosen for this investigation were selected using a structured approach based on three key factors, **popularity and performance in text-to-text generation, LM Studio recommendations for optimized accuracy, and comparative evaluations of the top commercial services.** More specifically,

- 1) Some models were chosen based on the highest number of downloads from Hugging Face, ensuring widespread adoption and benchmark effectiveness.
- 2) Models suggested by LM Studio were included due to their strong performance and compatibility with local inference environments.
- 3) The best commercial services were selected based on their comparative performance with open-source counterparts, prioritizing accuracy, interpretability, and real-time inference.

The selected models are shown in Figure 3.1. However, all the Hugging Face models are not fully compatible with the LM Studio runtime. As a result, some models were tested directly on the Hugging Face interface to avoid compatibility issues. Furthermore, while models such as OpenAI o1, DeepSeek R1, and Llama 3.1 405B have demonstrated strong benchmark performance, they were not included in this study due to limited quantization support, lack of local deployment feasibility, and limited open source availability.

¹<https://huggingface.co/>

²<https://lmstudio.ai/>

Recommendation	Model Name	Benchmark Performance
LM Studio Recommended Models	Mistral 7B	74.6% (MMLU), 83.5% (GSM8K)
	OpenHermes 2.5	72.1% (MMLU), 79.2% (BIG-bench)
	DeepSeek 7B	76.3% (MMLU), 85.4% (GSM8K)
Hugging Face Open-Source Models	LLaMA 2 13B	75.8% (MMLU), 80.7% (BIG-bench)
	Mixtral 8x7B	78.2% (MMLU), 88.1% (GSM8K)
Top Commercial Services	Claude 3 Sonnet	82.3% (MMLU), 90.2% (BIG-bench)
	GPT-4 Turbo	85.6% (MMLU), 92.4% (GSM8K)
	Falcon 7B/40B	73.4% (MMLU), 78.9% (BIG-bench)

FIGURE 3.1: Selected Models for the Experimentation

3.3 The Communication Agent

The **Communication Agent** facilitates structured Vehicle-to-Vehicle (V2V) information exchange, allowing autonomous vehicles (AVs) within a defined communication radius to share and receive critical environmental data. This includes information such as obstacle presence, road conditions, current speed, and the intended action of the vehicle. To ensure compatibility with Large Language Models (LLMs), the data is formatted in a simple, human-readable structure that can be seamlessly incorporated into text-based prompts. Table 3.1 defines the standardized message schema used by the Communication Agent.

The Communication Agent ensures that all AVs within the information-sharing radius can access and benefit from collective situational awareness. For example, if a vehicle cannot directly see a stop sign due to traffic or any reason to sight block, it can still receive a warning from another vehicle that has a clear line of sight. This enables more accurate and safer decisions, particularly in complex or uncertain scenarios.

The structured data format allows for seamless integration into the LLM-based Decision Agent, allowing it to reason with both local observations and external context. Figure 3.2 illustrates the information exchange process facilitated by the Communication Agent. This multi-agent communication approach significantly improves the accuracy of the AV's decision by expanding its environmental perception beyond the local perception limit.

Field	Type	Description
Vehicle_ID	String	A unique identifier for the broadcasting vehicle.
Current_Speed	Float	The vehicle's current speed in meters per second (m/s).
Obstacle_Presence	Boolean	Indicates whether the vehicle detects a critical obstacle in its immediate path.
Obstacle_Type	Enum / Null	Type of detected obstacle (e.g., 'stop_sign', 'pedestrian', 'road_block'). This is null if Obstacle_Presence is False.
Obstacle_Proximity	Float	Distance to the detected obstacle in meters.
Intended_Action	Enum	Planned action from the broadcasting vehicle Decision Agent (e.g., 'stop', 'forward')

TABLE 3.1: Structured Information Schema for V2V Communication Messages.

3.4 Text-Based Simulation and Scenario Design

The core concept is to investigate the reasoning capabilities of LLMs for AVs. In this research, we initially used a series of traffic situations and developed text-based simulation scenarios using Python to evaluate the effectiveness of LLMs as the decision agent in autonomous vehicle (AV). These scenarios were designed to test the capabilities of LLMs in these three domains, logical reasoning, rule compliance, and dynamic decision making. as shown in Figure 3.3. We did extend our experiment however, capability checking domain of LLMs was the same.

- **Scenario 1: Rule compliance** This scenario tested whether the LLM could correctly interpret a green traffic light and determine that the AV should proceed. It would assess the basic understanding of large language models of common traffic rules. This simulation is shown in figure 3.3(A)
- **Scenario 2: Common sense** In this case, a stop sign appears on a partially blocked road. The goal was to evaluate how the LLM interprets such ambiguous situations and whether it can determine an appropriate action based on partial cues. This simulation is shown in figure 3.3(B)
- **Scenario 3: Dynamic Decision Making** A more complex test involving a pedestrian suddenly crossing in front of the AV. This scenario assessed whether the LLM could dynamically adapt its decision to an unexpected and potentially hazardous situation. This simulation is shown in figure 3.3(C)


```

1  import json
2  from dataclasses import dataclass, asdict
3  from typing import Dict, List, Any
4  import random
5  import time

```

PROBLEMS

OUTPUT

PORTS

TERMINAL

Pyt

```

--- Vehicle 2 Communication Agent: Sending Own Status ---
Nearby Vehicles: ['001', '003']
Vehicle 2 Status Details:
  Vehicle ID: 002
  Obstacle Presence: True
  Obstacle Type: stop_sign
  Obstacle Proximity: 13.123529423503923 meters
  Traffic Density: heavy
  Intended Action: stop

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 001 ---
Received Status Details:
  Vehicle ID: 001
  Obstacle Presence: True
  Obstacle Type: pedestrian
  Obstacle Proximity: 14.77517543510873 meters
  Traffic Density: heavy
  Intended Action: turn_right

--- Vehicle 2 Communication Agent: Receiving Status from Vehicle 003 ---
Received Status Details:
  Vehicle ID: 003
  Obstacle Presence: False
  Obstacle Type: traffic_light
  Obstacle Proximity: 2.6441289855223764 meters
  Traffic Density: light
  Intended Action: forward

```

FIGURE 3.2: An illustration of Communication Agent

3.5 Prompt Engineering

The Natural Language Processing capabilities of Large Language Models and the growing interest in their potential applications have made prompt engineering increasingly important, as the primary method of interaction with LLMs is through prompts [40]. The design of the prompt determines LLM behavior, making prompt engineering critical, since the prompt acts as a guide and directly impacts the results. To carry out our experiment, we tested different LLM models with text-based traffic simulation scenarios using a simple prompt. Each scenario was presented to various LLM models using this simple prompt asking the models to simply respond with a single word without further explanation,

“What would the AV do? Please, just answer STOP or FORWARD.”

```

AV = Autonomous Vechiels,
S = Stop Sign of a partial road,
Other lane is open.

AV      S
-----

-----
Initial Position:
AV      S
-----

-----
Position Right Before STOP sign:
      AV S
-----

-----
Simulation ended.

```

((A)) Traffic Light

```

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:
AV      TL:green
-----

H
-----

Position Right Before TL:
      AV TL:green
-----

      H
-----

Simulation ended.

```

((B)) Stop Sign on Partial Road

```

H = Human,
AV = Autonomous Vechiels,

Initial Position:

AV
-----

-----
Position Right Before H:

      AV      H
-----

-----
Simulation ended.

```

((C)) Human Suddenly Crossing Road

FIGURE 3.3: Illustration of real-life traffic scenarios tested in the LLM-based decision system.

We are assuming that the output from the LLMs would be used as a real decision in the autonomous driving system.

Chapter 4

Simulation and Results

4.1 Simulation-based Analysis

..... This section details the responses generated by a diverse set of LLMs when presented with these foundational text-based scenarios. The scenarios were designed to test two fundamental aspects of AV intelligence: basic rule-following and common-sense reasoning. The models' outputs were analyzed for three key characteristics: Decision Correctness: Whether the model provided the logically and safely correct action. Adherence to Instructions: Whether the model's output conformed to the prompt's explicit formatting constraints (e.g., "Please just answer STOP or FORWARD"). Consistency: While not fully captured in single screenshots, the variability in response styles hints at the underlying consistency challenges explored later in this thesis.

4.1.1 Scenario 1: Basic Rule-Following (Green Traffic Light)

The first and most fundamental test was designed to evaluate if an LLM could correctly interpret a simple, unambiguous traffic rule. The scenario presented an autonomous vehicle (AV) approaching a green traffic light, with a human-driven car (H) in a parallel lane. The logically correct and safe action is to proceed. The responses, as shown in Figure 4.1, revealed significant differences in model behavior: Correct and Concise Responses: The majority of the tested models, including DeepSeek, Falcon 7B, OpenHermes-2.5-Mistral-7B, and GPT-4 Turbo, performed optimally. They correctly identified the appropriate action and responded with a single, parsable word: 'FORWARD'. This demonstrates a strong baseline capability for understanding and executing basic traffic laws from a textual description. Correct but Verbose Response: The Claude 3 Sonnet model also determined the correct action was 'FORWARD'. However, it failed to adhere to the prompt's constraint to "just answer STOP or FORWARD." Instead, it provided a full-sentence explanation for its reasoning. While the logic was sound, this verbosity represents a critical failure in the context of a machine-to-machine system. An AV's actuation layer expects a predictable, parsable command, and this unsolicited text would cause a system error. Incorrect Response: Most alarmingly, the google/flan-t5-large model responded with 'STOP'. This

represents a fundamental failure in reasoning for the simplest possible scenario. Stopping at a green light is not only incorrect but also dangerous, as it could lead to a rear-end collision. This highlights the significant reliability risk, demonstrating that not all LLMs possess even a basic grasp of driving logic.

4.1.2 Scenario 2: Common-Sense Reasoning and Obstacle Avoidance

To move beyond simple rules, a second set of scenarios was designed to test the models' common-sense reasoning. These scenarios involved an AV encountering an obstacle that requires an immediate stop. Two variations were tested: one with an explicit 'Stop Sign' and another with a 'Ball' in the road. **Explicit Obstacle ('Stop Sign')**: When presented with a stop sign, models like GPT-4 Turbo correctly and concisely responded with 'STOP'. This confirms their ability to process explicit commands present in the environment. **Implicit Hazard ('Ball in the Road')**: The scenario with a ball is more nuanced. While a ball itself is not a damaging obstacle, it strongly implies a potential, more severe hazard: a child who may run into the road to retrieve it. Human drivers react to this implicit danger instinctively. Models like GPT-4 Turbo also responded with 'STOP' in this situation. This is a significant finding, as it indicates that the model is capable of applying a layer of common-sense reasoning, associating the object (ball) with a potential, unseen threat and choosing the safest course of action.

4.1.3 Analysis of LLM Response Characteristics

The analysis of these initial simulation runs reveals several critical insights that motivate the core arguments of this thesis: **High Potential but Uneven Capability**: Advanced models like GPT-4 Turbo, Falcon, and Mistral-based variants demonstrate a strong ability to handle both rule-based and common-sense scenarios correctly. This confirms the high potential of using LLMs for driving decisions. However, the failure of other models, like *flan-t5*, on trivial tasks underscores that this capability is not universal and highlights the need for careful model selection and validation. **Parsability is a System-Critical Requirement**: The verbose nature of models like Claude, while "helpful" in a chat interface, is a functional bug in an autonomous system. The Decision Agent's output must be a clean, predictable command for the Actuation Layer to execute. This emphasizes the importance of both prompt engineering and potentially fine-tuning to ensure LLMs can operate effectively within a larger software stack. **The Need for a More Robust Framework**: These simple, single-agent scenarios represent the "easiest" tests. The fact that some models still fail or produce unusable output demonstrates that relying on an LLM in isolation is insufficient. To handle the true complexity of real-world driving—especially scenarios with incomplete or conflicting information—a more robust framework is required. This

lays the groundwork for the introduction of our multi-agent system, where V2V communication can provide the additional context needed to resolve ambiguity and improve the consistency and safety of the LLM's decisions.


4.2 Simulation-based Analysis

To investigate how Large Language Models (LLMs) assess fairness and logic in car driving scenarios, we require realistic situations that depict both simple and complex conditions. While the ultimate goal is to analyze dynamic scenarios, we began our investigation by creating a series of controlled, manual scenarios. This initial step allows for a baseline assessment of the LLMs' core reasoning capabilities, their ability to follow instructions, and their inherent biases, free from the complexities of a fully dynamic simulation. This section details the responses generated by a diverse set of LLMs when presented with these foundational text-based scenarios. The scenarios were designed to test two fundamental aspects of AV intelligence: basic rule-following and common-sense reasoning. The models' outputs were analyzed for three key characteristics: Decision Correctness: Whether the model provided the logically and safely correct action. Adherence to Instructions: Whether the model's output conformed to the prompt's explicit formatting constraints (e.g., "Please just answer STOP or FORWARD"). Consistency: While not fully captured in single screenshots, the variability in response styles hints at the underlying consistency challenges explored later in this thesis.

4.2.1 Scenario 1: Basic Rule-Following (Green Traffic Light)

The first and most fundamental test was designed to evaluate if an LLM could correctly interpret a simple, unambiguous traffic rule. The scenario presented an autonomous vehicle (AV) approaching a green traffic light, with a human-driven car (H) in a parallel lane. The logically correct and safe action is to proceed. The responses, as shown in Figure 4.1, revealed significant differences in model behavior: Correct and Concise Responses: The majority of the tested models, including DeepSeek, Falcon 7B, OpenHermes-2.5-Mistral-7B, and GPT-4 Turbo, performed optimally. They correctly identified the appropriate action and responded with a single, parsable word: 'FORWARD'. This demonstrates a strong baseline capability for understanding and executing basic traffic laws from a textual description. Correct but Verbose Response: The Claude 3 Sonnet model also determined the correct action was 'FORWARD'. However, it failed to adhere to the prompt's constraint to "just answer STOP or FORWARD." Instead, it provided a full-sentence explanation for its reasoning. While the logic was sound, this verbosity represents a critical failure in the context of a machine-to-machine system. An AV's actuation layer expects a predictable, parsable command, and this unsolicited text would cause a system error. Incorrect Response:

Most alarmingly, the google/flan-t5-large model responded with 'STOP'. This represents a fundamental failure in reasoning for the simplest possible scenario. Stopping at a green light is not only incorrect but also dangerous, as it could lead to a rear-end collision. This highlights the significant reliability risk, demonstrating that not all LLMs possess even a basic grasp of driving logic.



Figures/LLM_Responses_Combined.png

FIGURE 4.1: Responses from various LLMs to the Green Traffic Light scenario, showing differences in correctness and verbosity.

4.2.2 Scenario 2: Common-Sense Reasoning and Obstacle Avoidance


To move beyond simple rules, a second set of scenarios was designed to test the models' common-sense reasoning. These scenarios involved an AV encountering an obstacle that requires an immediate stop. Two variations were tested: one with an explicit 'Stop Sign' and another with a 'Ball' in the road. **Explicit Obstacle ('Stop Sign')**: When presented with a stop sign, models like GPT-4 Turbo correctly and concisely responded with 'STOP'. This confirms their ability to process explicit commands present in the environment. **Implicit Hazard ('Ball in the Road')**: The scenario with a ball is more nuanced. While a ball itself is not a damaging obstacle, it strongly implies a potential, more severe hazard: a child who may run into the road to retrieve it. Human drivers react to this implicit danger instinctively. Models like GPT-4 Turbo also responded with 'STOP' in this situation. This is a significant finding, as it indicates that the model is capable of applying a layer of common-sense reasoning, associating the object (ball) with a potential, unseen threat and choosing the safest course of action.

4.2.3 Analysis of LLM Response Characteristics

The analysis of these initial simulation runs reveals several critical insights that motivate the core arguments of this thesis: **High Potential but Uneven Capability**: Advanced models like GPT-4 Turbo, Falcon, and Mistral-based variants demonstrate a strong ability to handle both rule-based and common-sense scenarios correctly. This confirms the high potential of using LLMs for driving decisions. However, the failure of other models, like *flan-t5*, on trivial tasks underscores that this capability is not universal and highlights the need for careful model selection and validation. **Parsability is a System-Critical Requirement**: The verbose nature of models like Claude, while "helpful" in a chat interface, is a functional bug in an autonomous system. The Decision Agent's output must be a clean, predictable command for the Actuation Layer to execute. This emphasizes the importance of both prompt engineering and potentially fine-tuning to ensure LLMs can operate effectively within a larger software stack. **The Need for a More Robust Framework**: These simple, single-agent scenarios represent the "easiest" tests. The fact that some models still fail or produce unusable output demonstrates that relying on an LLM in isolation is insufficient. To handle the true complexity of real-world driving—especially scenarios with incomplete or conflicting information—a more robust framework is required. This lays the groundwork for the introduction of our multi-agent system, where V2V communication can provide the additional context needed to resolve ambiguity and improve the consistency and safety of the LLM's decisions.

4.2.4 Analysis of Decision Consistency

While decision correctness is crucial, it is insufficient on its own. For a safety-critical system like an AV, decisions must also be consistent. An agent that provides the correct answer only 95% To measure this, we subjected a selected LLM, OpenHermes-2.5-Mistral-7B, to repeated trials of the same scenario. For the basic rule-following scenario (approaching a green traffic light), the prompt was run 20 times. The responses were mapped numerically ('FORWARD' = 1, 'STOP' = 0) to calculate the mean and variance. The results, shown in Figure 4.2, are telling. High but Imperfect Consistency: Out of 20 trials, the model responded correctly with 'FORWARD' 19 times but incorrectly with 'STOP' 1 time. Mean Response: The mean response was 0.95, indicating a strong but not absolute tendency toward the correct answer. Variance: The variance was 0.0475. While a low number, any variance greater than zero represents an unacceptable level of unpredictability for a safety-critical function. This experiment empirically demonstrates the inherent reliability problem of using an LLM in isolation. A 5



Figures/Consistency_No_V2V.png

FIGURE 4.2: Consistency analysis of OpenHermes-2.5-Mistral-7B on a simple traffic scenario over 20 trials without V2V communication. The non-zero variance indicates a degree of unreliability.

4.2.5 V2V-Enhanced Decision-Making in an Occluded Scenario

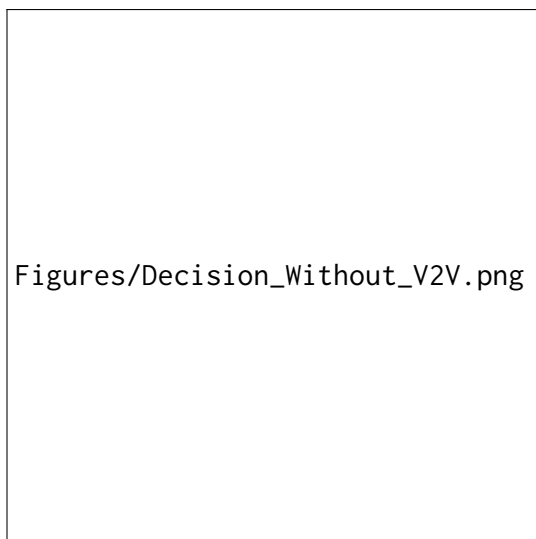
To test the core hypothesis of this thesis—that a multi-agent framework with V2V communication can improve decision-making—we designed a more complex scenario involving occluded information. In this scenario, an autonomous car (AV2) is following an autonomous truck (AV1). A stop sign (S) is positioned ahead, but AV2's line of sight is completely blocked by AV1. This setup mimics a common and dangerous real-world driving situation.

Decision-Making without Communication Agent

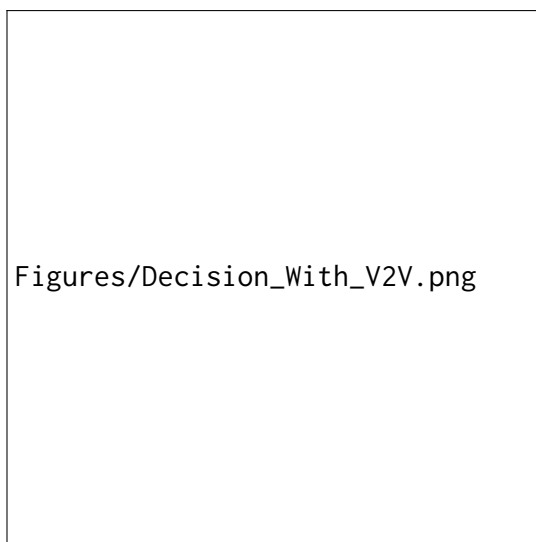
First, the scenario was presented to the Decision Agent (using GPT-4 Turbo) without any V2V data. The prompt explicitly stated, "AV2 = Autonomous Car-cant see the stop sign." As shown in Figure 4.3(a), the LLM's response was 'FORWARD'. This decision is logically sound based on the limited information available to AV2. Since it cannot see the stop sign and its only perception is the truck moving forward, continuing to follow is a reasonable, albeit dangerous, action. This result perfectly encapsulates the limitations of a single-agent perception system; the agent makes a locally optimal decision that is globally unsafe. This would inevitably lead to a rear-end collision when AV1 stops.

Decision-Making with Communication Agent

Next, the exact same scenario was run, but this time, the prompt was augmented with structured data from the Communication Agent. This data, simulating a V2V message from AV1, explicitly states AV1's perception and, critically, its Intended Action: stop. The prompt now included this new block of information: Generated code Information from communication agent: AV2 Communication Agent: Receiving Status from AV1 — Received Status Details: Vehicle ID: 001 Obstacle Presence: True Obstacle Proximity: 5 meters Intended Action: stop



((A)) Scenario without V2V data, leading to an unsafe 'FORWARD' command.



((B)) Scenario with V2V data, leading to a safe 'STOP' command.

FIGURE 4.3: Comparison of an LLM's decision in an occluded stop sign scenario, with and without information from the Communication Agent.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

We presented an approach for leveraging Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. Our results show that for RQ1, Large Language Models (LLMs) were able to make intelligent and safe decisions even in unfamiliar or novel traffic situations. They did not require specific training for each scenario and showed strong general reasoning skills, similar to how a human driver would respond to unexpected conditions. For RQ2, the use of multiple agents, such as a Decision Agent and a Communication Agent, improved the system performance compared to the single agent setup. When vehicles shared data such as speed, obstacles, and intentions through V2V communication, decisions became more accurate, consistent, and safer. This design also made the system more scalable and flexible for handling complex real-world traffic situations. These results reveal both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. By integrating contextual data derived from V2V communication with LLM reasoning, our goal is to bridge the critical gap in decision-making accuracy for autonomous vehicles.

5.2 Limitations and Future Work

- **Simulation Expansion:** Extend the simulation environment to include multilane roads and multiple vehicles, simulating more realistic traffic conditions with varying visibility and road complexity.

- **Increased the number of trails for Consistency Testing:** Run the same prompt more than 100 times per scenario per LLM to obtain a stronger statistical basis to evaluate the consistency of the decision.
- **Offline Evaluation of Local LLMs:** Test the effectiveness of local LLMs in disconnected environments to assess their viability in real-world AV applications.
- **Emergency Broadcasting via Communication Agent:**
 - Implement dynamic emergency messaging (e.g., broadcast STOP or CAUTION to nearby vehicles).
 - Evaluate radius-based alerts: Determine what warnings should be sent to the following vehicles based on proximity and shared intent.
- **Limited Scenario Diversity:** The simulation environment includes a limited range of traffic scenarios, which may restrict the system's ability to generalize to real-world driving conditions.
- **Lack of Fail-Safe Mechanisms:** The current system lacks built-in redundancy or error handling mechanisms to recover from incorrect LLM output or detect unsafe decisions in real time.
- **Unaddressed V2V Communication Constraints:** This study assumes ideal communication conditions, without evaluating real-world issues such as network congestion, signal interference, or latency, especially in dense traffic scenarios.

Bibliography

- [1] Y. Chang, X. Wang, J. Wang, *et al.*, “A survey on evaluation of large language models,” *ACM transactions on intelligent systems and technology*, vol. 15, no. 3, pp. 1–45, 2024.
- [2] Y. Wang, Z. Wu, J. Yao, and J. Su, “Tdag: A multi-agent framework based on dynamic task decomposition and agent generation,” *Neural Networks*, p. 107 200, 2025.
- [3] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, “A survey of autonomous driving: Common practices and emerging technologies,” *IEEE access*, vol. 8, pp. 58 443–58 469, 2020.
- [4] J. L. Espejel, E. H. Ettifouri, M. S. Y. Alassan, E. M. Chouham, and W. Dahhane, “Gpt-3.5, gpt-4, or bard? evaluating llms reasoning ability in zero-shot setting and performance boosting through prompts,” *Natural Language Processing Journal*, vol. 5, p. 100 032, 2023.
- [5] M. Raza, “Autonomous vehicles: Levels, technologies, impacts and concerns,” *International Journal of Applied Engineering Research*, vol. 13, no. 16, pp. 12 710–12 714, 2018.
- [6] T. Eley IV, J. L. King, K. Lyytinen, and J. V. Nickerson, *SAE J3016 as a Learning Device for the Driving Automation Community: Technical, Socio-technical, and Systemic Learning*. SAE International, 2024.
- [7] C. Geertz, “Common sense as a cultural system,” *The Antioch Review*, vol. 33, no. 1, pp. 5–26, 1975.
- [8] L. P. Kaelbling, M. L. Littman, and A. W. Moore, “Reinforcement learning: A survey,” *Journal of artificial intelligence research*, vol. 4, pp. 237–285, 1996.
- [9] D. Bogdoll, J. Breitenstein, F. Heidecker, *et al.*, “Description of corner cases in automated driving: Goals and challenges,” in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1023–1028. DOI: [10.1109/ICCVW54120.2021.00119](https://doi.org/10.1109/ICCVW54120.2021.00119).
- [10] P. N. Johnson-Laird, “Mental models and human reasoning,” *Proceedings of the National Academy of Sciences*, vol. 107, no. 43, pp. 18 243–18 250, 2010.
- [11] A. Demba and D. P. Möller, “Vehicle-to-vehicle communication technology,” in *2018 IEEE international conference on electro/information technology (EIT)*, IEEE, 2018, pp. 0459–0464.

- [12] W. Schwarting, J. Alonso-Mora, and D. Rus, "Planning and decision-making for autonomous vehicles," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 1, no. 1, pp. 187–210, 2018.
- [13] J. Wei, Y. Tay, R. Bommasani, *et al.*, "Emergent abilities of large language models," *arXiv preprint arXiv:2206.07682*, 2022.
- [14] Q. Dong, L. Li, D. Dai, *et al.*, "A survey on in-context learning," *arXiv preprint arXiv:2301.00234*, 2022.
- [15] M. Shanahan, K. McDonell, and L. Reynolds, "Role play with large language models," *Nature*, vol. 623, no. 7987, pp. 493–498, 2023.
- [16] L. H. M. Lam, R. K. Thatikonda, and E. Shareghi, "A closer look at tool-based logical reasoning with llms: The choice of tool matters," in *Australasian Language Technology Association Workshop*, 2024. [Online]. Available: <https://api.semanticscholar.org/CorpusID:270219176>.
- [17] J. Gehring, K. Zheng, J. Copet, *et al.*, "Rlef: Grounding code llms in execution feedback with reinforcement learning," *arXiv preprint arXiv:2410.02089*, 2024.
- [18] A. Brohan, Y. Chebotar, C. Finn, *et al.*, "Do as i can, not as i say: Grounding language in robotic affordances," in *Conference on robot learning*, PMLR, 2023, pp. 287–318.
- [19] X. Deng, Y. Gu, B. Zheng, *et al.*, "Mind2web: Towards a generalist agent for the web," *Advances in Neural Information Processing Systems*, vol. 36, pp. 28 091–28 114, 2023.
- [20] J. Wei, X. Wang, D. Schuurmans, *et al.*, "Chain-of-thought prompting elicits reasoning in large language models," *Advances in neural information processing systems*, vol. 35, pp. 24 824–24 837, 2022.
- [21] O. F. Rana and K. Stout, "What is scalability in multi-agent systems?" In *Proceedings of the fourth international conference on Autonomous agents*, 2000, pp. 56–63.
- [22] L. Chen, P. Wu, K. Chitta, B. Jaeger, A. Geiger, and H. Li, "End-to-end autonomous driving: Challenges and frontiers," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, pp. 10 164–10 183, 2023. [Online]. Available: <https://api.semanticscholar.org/CorpusID:259287283>.
- [23] Y. Wang, V. C. Guizilini, T. Zhang, Y. Wang, H. Zhao, and J. Solomon, "Detr3d: 3d object detection from multi-view images via 3d-to-2d queries," *ArXiv*, vol. abs/2110.06922, 2021. [Online]. Available: <https://api.semanticscholar.org/CorpusID:238744328>.
- [24] D. Fu, X. Li, L. Wen, *et al.*, "Drive like a human: Rethinking autonomous driving with large language models," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2024, pp. 910–919.

- [25] A. Iftekhhar and N. Fukuta, "Toward an efficient and resilient electric vehicle charging place allocation using multiagent approach," in *2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, 2024, pp. 663–664. DOI: [10.1109/IIAI-AAI63651.2024.00126](https://doi.org/10.1109/IIAI-AAI63651.2024.00126).
- [26] X. Wang, B. Lv, K. Wang, and R. Zhang, "Asts: Autonomous switching of task-level strategies," *ENG, International Journal of Applied Mathematics and Computer Science*, vol. 33, no. 4, pp. 553–568, 2023.
- [27] J. Liang, Y. Li, G. Yin, *et al.*, "A mas-based hierarchical architecture for the cooperation control of connected and automated vehicles," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 2, pp. 1559–1573, 2022.
- [28] C. Cui, Y. Ma, X. Cao, *et al.*, "A survey on multimodal large language models for autonomous driving," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2024, pp. 958–979.
- [29] L. Chen, O. Sinavski, J. Hünemann, *et al.*, "Driving with llms: Fusing object-level vector modality for explainable autonomous driving," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, 2024, pp. 14 093–14 100.
- [30] W. Wang, J. Xie, C. Hu, *et al.*, "Drivemlm: Aligning multi-modal large language models with behavioral planning states for autonomous driving," *arXiv preprint arXiv:2312.09245*, 2023.
- [31] C. Cui, Y. Ma, X. Cao, W. Ye, and Z. Wang, "Drive as you speak: Enabling human-like interaction with large language models in autonomous vehicles," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2024, pp. 902–909.
- [32] L. Wang, Y. Ren, H. Jiang, *et al.*, "Accidentgpt: A v2x environmental perception multi-modal large model for accident analysis and prevention," in *2024 IEEE Intelligent Vehicles Symposium (IV)*, IEEE, 2024, pp. 472–477.
- [33] M. Elhenawy, A. Abutahoun, T. I. Alhadidi, *et al.*, "Visual reasoning and multi-agent approach in multimodal large language models (mllms): Solving tsp and mtsp combinatorial challenges," *arXiv preprint arXiv:2407.00092*, 2024.
- [34] A. K. S. Sudarshan G S, and S. J U, "Llm's for autonomous driving: A new way to teach machines to drive," in *2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, 2023, pp. 1–6. DOI: [10.1109/ICMNWC60182.2023.10435998](https://doi.org/10.1109/ICMNWC60182.2023.10435998).
- [35] L. Chen, O. Sinavski, J. Hünemann, *et al.*, "Driving with llms: Fusing object-level vector modality for explainable autonomous driving," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, 2024, pp. 14 093–14 100. DOI: [10.1109/ICRA57147.2024.10611018](https://doi.org/10.1109/ICRA57147.2024.10611018).
- [36] B. Friedman and H. Nissenbaum, "Bias in computer systems," *ACM Transactions on information systems (TOIS)*, vol. 14, no. 3, pp. 330–347, 1996.

- [37] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan, "A survey on bias and fairness in machine learning," *ACM computing surveys (CSUR)*, vol. 54, no. 6, pp. 1–35, 2021.
- [38] S. S. Duddela and N. Fukuta, "Toward an acceptable dynamic allocation considering fairness on autonomous car parking," in *2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, 2024, pp. 286–291. DOI: [10.1109/IIAI-AAI63651.2024.00061](https://doi.org/10.1109/IIAI-AAI63651.2024.00061).
- [39] R. Jin, J. Du, W. Huang, *et al.*, "A comprehensive evaluation of quantization strategies for large language models," *ArXiv*, vol. abs/2402.16775, 2024. [Online]. Available: <https://api.semanticscholar.org/CorpusID:268032411>.
- [40] J. White, Q. Fu, S. Hays, *et al.*, "A prompt pattern catalog to enhance prompt engineering with chatgpt," *arXiv preprint arXiv:2302.11382*, 2023.

Publications

International Conference

Toward a Multi Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Condition

Rafi Md Ashifujman

*Graduate School of Integrated Science and Technology
Shizuoka University
Hamamatsu, Japan
rafi.md.ashifujman.23@shizuoka.ac.jp*

Naoki Fukuta

*College of Informatics, Academic Institute
Shizuoka University
Hamamatsu, Japan
fukuta@inf.shizuoka.ac.jp*

Abstract—In autonomous vehicles (AVs), making the right decision in unknown traffic situations remains a challenge. Traditional AVs rely on pre-trained models, which often struggle in such cases where human-like reasoning is required. In this paper, we examine how Large Language Models (LLMs) act as a decision agent responding to scenario-specific text prompts derived from real-world traffic situations. In addition, we propose a Communication Agent that enables vehicle-to-vehicle (V2V) information sharing, such as speed, obstacles, and future intentions, in a structured format to provide contextual support for the decision agent. This paper proposes a preliminary approach to assess whether LLMs within a multi-agent framework, when provided with structured prompts and contextual data, can support consistent and human-like decision making.

Index Terms—autonomous vehicles, large language models (LLMs), multi-agent, vehicle-to-vehicle (V2V) communication, decision making agent, communication agent.

I. INTRODUCTION

This paper explores the potential of integrating Large Language Models (LLMs) [1] into a multi-agent framework [2] to improve decision making in autonomous vehicles (AVs), particularly in unknown and unsafe traffic situations. Our main concern would be to explore the use of LLMs for autonomous driving systems (ADS) as the main decision-making agent within a multi-agent framework to evaluate its reasoning ability [3] to handle uncertain traffic situations. Our goal is to contribute to the development of safer and more reliable Level 5 [4] autonomous vehicles. We aim to contribute to Level 5 (complete automation [5]). There are numerous instances in which traditional autonomous vehicles are capable of making effective decisions in familiar scenarios using pre-trained models. However, they may have trouble facing new or unusual situations where their programmed knowledge is not directly covered in such situations. Human drivers can use common sense and past experiences to handle unexpected events, such as knowing that traffic cones on a moving truck are not dangerous. However, current AV systems, even those that use rule-based approaches or reinforcement learning (RL [6]), will struggle in these scenarios. This limitation is especially evident in what we call unknown-unsafe domain situations

where the correct action is not immediately clear [7]. During this investigation with various LLMs, we proceed under two assumptions: 1) certain AI systems can transform real-world situations into text-based explanations, which are later used as input for the LLMs, and 2) the outputs generated by the LLMs can be translated into actual decisions made by the AV's decision agent by interpreting the responses from the LLMs. We are investigating the effectiveness of various LLMs for use as decision-making agents in autonomous driving systems. Our initial objective is to answer the research question (Research Question 1): Can an agent make decisions with the help of an LLM without undergoing a specific learning process for each new situation? In our research, we will assume that vehicle-to-vehicle (V2V) communication has been achieved through a standardized networking protocol, such as LAN-based direct communication or a low-latency wireless system. Under this assumption, each vehicle can communicate with other vehicles within a defined radius (e.g., 10 meters). When a vehicle enters the information sharing radius of another vehicle, it can exchange data regarding their current status, such as obstacle detection, traffic conditions, direction, and future intended actions. To evaluate the impact of V2V communication on autonomous decision-making, we will investigate how LLMs process and utilize this information. Specifically, we will examine whether the incorporation of V2V exchanged data improves decision accuracy and enables AVs to make more precise and context-aware decisions. However, V2V communication introduces a critical question, (Research Question 2): Is a single centralized decision-making agent sufficient to process all incoming V2V data and make autonomous driving decisions, or is a multi-agent system required for improved efficiency and scalability? In this paper, we investigate the answers to these two research questions.

II. MOTIVATION AND BACKGROUND

Imagine a traffic situation, where a road is partially blocked due to construction, with traffic cones and a 'STOP' sign indicating a partial road block. A typical autonomous vehicle (AV) might see the 'STOP' sign and interpret it as a complete

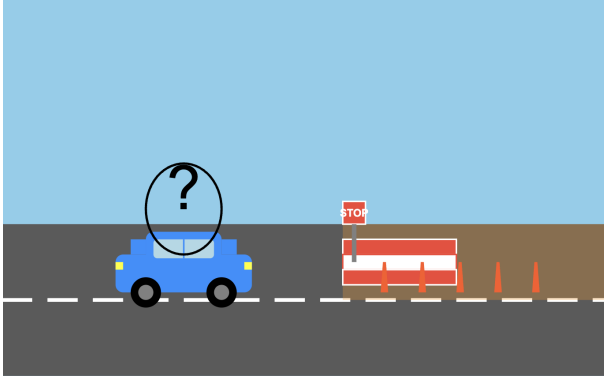


Fig. 1: What a current AV might do in this situation?

road closure, coming to a complete stop because that is what its pre-programmed data tell it to do. However, a human driver in the same situation might use common sense, realize that the road is only partially closed, and safely continue through the open section.

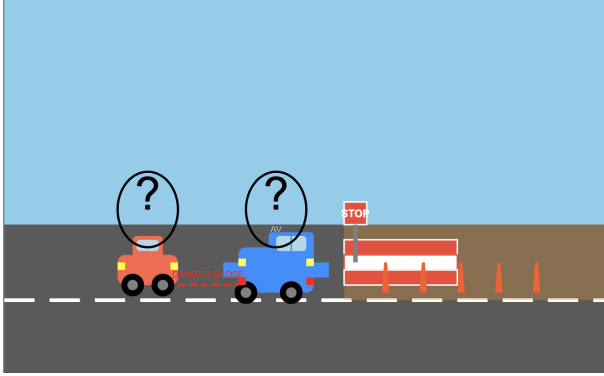


Fig. 2: Lack of communication between vehicles may lead to a potential accident.

Now imagine a more complicated situation where an autonomous truck comes to a sudden stop when it sees the ‘STOP’ sign. There is another car, driven by a human or another AV, right behind it. This sudden stop could easily cause a crash. Now imagine a human driver encountering a partially blocked road. To navigate safely, the driver would shift into the adjacent open lane, relying on instinct, experience, and situational awareness. Anticipating the possibility of an oncoming vehicle from the opposite direction or from behind, the driver would proactively slow down, assessing the risk, and would take the necessary precautions to avoid a collision. In contrast, a traditional AV, which lacks human-like reasoning and predictive thinking, may not recognize the potential danger. Without contextual understanding, it can continue at its normal speed, assuming the lane is clear, increasing the risk of a head-on collision.

However, if the AV had better reasoning abilities, it might recognize that the road is only partially closed and proceed safely through the open part. And if the AV could communicate with the vehicle behind it, it could alert the other

driver about its intended actions, particularly if the lane were to close suddenly, helping to prevent a potential accident. A fundamental challenge in traditional autonomous vehicles (AVs) is to prepare for all truly unknown situations [8]. Any scenario we create is technically ‘known’ to us, even if it feels unfamiliar to the AVs, making it difficult to test how AVs handle truly unknown-unsafe situations. In addition, it is difficult to recreate complex real-world scenarios in simulation environments. For example, it is difficult to accurately simulate unpredictable human actions or complicated environmental conditions. In real life, there could be countless unexpected situations that are nearly impossible to include in training data sets for traditional autonomous driving systems (ADS) to avoid accidents. Human drivers use common sense to deal with these situations, so through this paper we will explore whether LLMs can also show human-like reasoning to handle them effectively or not.

To address these challenges, we propose a possible approach for integrating LLMs into a multi-agent framework for autonomous driving control system. LLMs have the potential to provide common sense or reasoning ability that traditional systems lack, helping AVs better understand the context of complex real-world scenarios. Incorporating Vehicle-to-Vehicle communication using multi-agent, which will allow vehicles to exchange information with other vehicles. This capability is also essential for creating realistic and complex driving scenarios.

III. PRELIMINARY

Recommendation	Model Name	Benchmark Performance
LM Studio Recommended Models	Mistral 7B	74.6% (MMLU), 83.5% (GSM8K)
	OpenHermes 2.5	72.1% (MMLU), 79.2% (BIG-bench)
	DeepSeek 7B	76.3% (MMLU), 85.4% (GSM8K)
Hugging Face Open-Source Models	LLaMA 2 13B	75.8% (MMLU), 80.7% (BIG-bench)
	Mixtral 8x7B	78.2% (MMLU), 88.1% (GSM8K)
Top Commercial Services	Claude 3 Sonnet	82.3% (MMLU), 90.2% (BIG-bench)
	GPT-4 Turbo	85.6% (MMLU), 92.4% (GSM8K)
	Falcon 7B/40B	73.4% (MMLU), 78.9% (BIG-bench)

Fig. 3: Selected Models for the Experimentation

To investigate the use of LLMs as a decision agent in AVs, we have utilized open-source and local deployment platforms. Hugging Face¹ offers a wide range of open-source pre-trained models, while LM Studio² integrates LLM models from Hugging Face into a local system, even without powerful GPUs. Now, the question is what factors were considered in the selection of LLMs for this study? One key factor in

¹<https://huggingface.co/>

²<https://lmstudio.ai/>

```

AV = Autonomous Vechiels,
S = Stop Sign of a partial road,
Other lane is open.

AV      S
-----

Initial Position:
AV      S
-----

Position Right Before STOP sign:
      AV S
-----

Simulation ended.

```

(a) Stop sign on Partial road

```

H = Human Car,
AV = Autonomous Vechiels,
TL = traffic light.

Initial Position:
AV      TL:green
-----
H
-----

Position Right Before TL:
      AV TL:green
-----
      H
-----

Simulation ended.

```

(b) Traffic Light

```

H = Human,
AV = Autonomous Vechiels,

Initial Position:
AV
-----

Position Right Before H:
      AV      H
-----

Simulation ended.

```

(c) Human suddenly crossing road

Fig. 4: Illustration of real life traffic scenarios

our model selection was quantization, which optimizes model performance while reducing computational requirements. This research [9] indicates that 8-bit quantization enables the majority of LLMs to maintain a performance level comparable to their nonquantized equivalents, regardless of model size (e.g. 7B to 70B parameters). Moreover, LLMs that are quantized to 4 bits can also uphold similar performance to their non-quantized versions across most benchmarks. This approach achieves memory reduction of 50 to 75% while preserving precision in complex tasks such as reasoning, decision making, and domain-specific applications. The models chosen for this investigation were selected using a structured approach based on three key factors: popularity and performance in text-to-text generation, LM Studio recommendations for optimized accuracy, and comparative evaluations of the top commercial services. Specifically, 1) Some models were chosen based on the highest number of downloads from Hugging Face, ensuring widespread adoption and benchmark effectiveness. 2) Models suggested by LM Studio were included due to their strong performance and compatibility with local inference environments. 3) The best commercial services were selected based on their comparative performance with open-source counterparts, prioritizing accuracy, interpretability, and real-time inference. The selected models are shown in Fig. 3. However, not all Hugging Face models are fully compatible with the LM Studio runtime. As a result, some models were tested directly on the Hugging Face interface to avoid compatibility issues. Furthermore, while models such as OpenAI’s o1, DeepSeek R1, and Llama 3.1 405B have demonstrated strong benchmark performance, they were not included in this study due to limited quantization support, lack of local deployment feasibility, and restricted open-source availability.

To test these selected models, we have prepared a set

of simple text-based simulation scenarios using Python, as illustrated in Fig. 4. These scenarios are designed to cover situations that require logical reasoning or the application of common rules knowledge, such as recognizing a red traffic light and stopping accordingly. These scenarios will be used as input for various LLMs to assess how effectively they handle both types of challenges. The experiments will be conducted using the LLM selected in Fig.3.

IV. OUR APPROACH

The main phase of this research focuses on using the shared data of the communication agent within our proposed multi-agent framework. The Communication Agent ensures that vehicles share critical information, including obstacle detection, traffic conditions, speed, and intended actions, in a standardized format within a defined radius, the expected format is demonstrated in Fig. 5. This structured data exchange is expected to significantly improve the accuracy of Decision Agent by providing a more comprehensive contextual understanding of the driving environment. For initial testing, we selected a basic traffic scenario involving an autonomous vehicle (AV) approaching a green traffic light, as illustrated in Fig. 4(b), and presented it to various language models to evaluate their decision-making behavior. The scenario was communicated through the prompt: ‘What would the AV on the above do? Please just answer STOP or FORWARD.’ The selected models included Claude³ 3.7 Sonnet, GPT⁴-4 Turbo, Falcon⁵ 3 7B and open-source alternatives such as OpenHermes-2.5-Mistral-7B and google/flan-t5-large. The responses of these models, sourced from Hugging Face, LM

³<https://claude.ai/chats>

⁴<https://chat.openai.com/>

⁵<https://chat.falconllm.tii.ae/>

```
1 import json
2 from dataclasses import dataclass, asdict
3 from typing import Dict, List, Any
4 import random
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65
66
67
68
69
70
71
72
73
74
75
76
77
78
79
80
81
82
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97
98
99
100
101
102
103
104
105
106
107
108
109
110
111
112
113
114
115
116
117
118
119
120
121
122
123
124
125
126
127
128
129
130
131
132
133
134
135
136
137
138
139
140
141
142
143
144
145
146
147
148
149
150
151
152
153
154
155
156
157
158
159
160
161
162
163
164
165
166
167
168
169
170
171
172
173
174
175
176
177
178
179
180
181
182
183
184
185
186
187
188
189
190
191
192
193
194
195
196
197
198
199
200
201
202
203
204
205
206
207
208
209
210
211
212
213
214
215
216
217
218
219
220
221
222
223
224
225
226
227
228
229
230
231
232
233
234
235
236
237
238
239
240
241
242
243
244
245
246
247
248
249
250
251
252
253
254
255
256
257
258
259
260
261
262
263
264
265
266
267
268
269
270
271
272
273
274
275
276
277
278
279
280
281
282
283
284
285
286
287
288
289
290
291
292
293
294
295
296
297
298
299
300
301
302
303
304
305
306
307
308
309
310
311
312
313
314
315
316
317
318
319
320
321
322
323
324
325
326
327
328
329
330
331
332
333
334
335
336
337
338
339
340
341
342
343
344
345
346
347
348
349
350
351
352
353
354
355
356
357
358
359
360
361
362
363
364
365
366
367
368
369
370
371
372
373
374
375
376
377
378
379
380
381
382
383
384
385
386
387
388
389
390
391
392
393
394
395
396
397
398
399
400
401
402
403
404
405
406
407
408
409
410
411
412
413
414
415
416
417
418
419
420
421
422
423
424
425
426
427
428
429
430
431
432
433
434
435
436
437
438
439
440
441
442
443
444
445
446
447
448
449
450
451
452
453
454
455
456
457
458
459
460
461
462
463
464
465
466
467
468
469
470
471
472
473
474
475
476
477
478
479
480
481
482
483
484
485
486
487
488
489
490
491
492
493
494
495
496
497
498
499
500
501
502
503
504
505
506
507
508
509
510
511
512
513
514
515
516
517
518
519
520
521
522
523
524
525
526
527
528
529
530
531
532
533
534
535
536
537
538
539
540
541
542
543
544
545
546
547
548
549
550
551
552
553
554
555
556
557
558
559
560
561
562
563
564
565
566
567
568
569
570
571
572
573
574
575
576
577
578
579
580
581
582
583
584
585
586
587
588
589
590
591
592
593
594
595
596
597
598
599
600
601
602
603
604
605
606
607
608
609
610
611
612
613
614
615
616
617
618
619
620
621
622
623
624
625
626
627
628
629
630
631
632
633
634
635
636
637
638
639
640
641
642
643
644
645
646
647
648
649
650
651
652
653
654
655
656
657
658
659
660
661
662
663
664
665
666
667
668
669
670
671
672
673
674
675
676
677
678
679
680
681
682
683
684
685
686
687
688
689
690
691
692
693
694
695
696
697
698
699
700
701
702
703
704
705
706
707
708
709
710
711
712
713
714
715
716
717
718
719
720
721
722
723
724
725
726
727
728
729
730
731
732
733
734
735
736
737
738
739
740
741
742
743
744
745
746
747
748
749
750
751
752
753
754
755
756
757
758
759
760
761
762
763
764
765
766
767
768
769
770
771
772
773
774
775
776
777
778
779
780
781
782
783
784
785
786
787
788
789
790
791
792
793
794
795
796
797
798
799
800
801
802
803
804
805
806
807
808
809
810
811
812
813
814
815
816
817
818
819
820
821
822
823
824
825
826
827
828
829
830
831
832
833
834
835
836
837
838
839
840
841
842
843
844
845
846
847
848
849
850
851
852
853
854
855
856
857
858
859
860
861
862
863
864
865
866
867
868
869
870
871
872
873
874
875
876
877
878
879
880
881
882
883
884
885
886
887
888
889
890
891
892
893
894
895
896
897
898
899
900
901
902
903
904
905
906
907
908
909
910
911
912
913
914
915
916
917
918
919
920
921
922
923
924
925
926
927
928
929
930
931
932
933
934
935
936
937
938
939
940
941
942
943
944
945
946
947
948
949
950
951
952
953
954
955
956
957
958
959
960
961
962
963
964
965
966
967
968
969
970
971
972
973
974
975
976
977
978
979
980
981
982
983
984
985
986
987
988
989
990
991
992
993
994
995
996
997
998
999
1000
```

Fig. 5: An illustration of Communication Agent

Studio, and commercial providers, are shown in Fig. 11. GPT-4 Turbo and Falcon provided direct and expected responses ‘FORWARD’, which aligns with the logic of the situation. However, Claude deviated from the expected format by including an explanatory response, despite the prompt requesting a one-word answer. OpenHermes-2.5 responded with a clear ‘FORWARD’, demonstrating alignment with the input instructions. Surprisingly, the google/flan-t5-large output differed from all others by responding ‘STOP’, contradicting the intended logic of the scenario.

A major consideration was consistency. The subresearch question, ‘Does repeated querying of LLMs on the same scenario lead to variations in decision-making outcomes?’ will be one of such investigations of consistency. To test this, each scenario was submitted to the models multiple times for regenerating the outputs. This approach allowed us to observe whether the models produced stable and repeatable responses

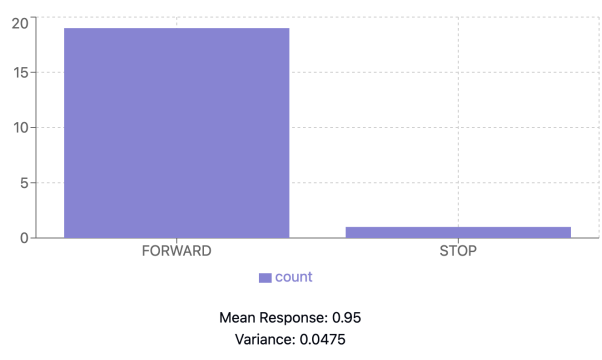


Fig. 6: LLM Model Consistency on the Tested Scenario

or if their decisions varied unpredictably. Consistency is especially critical in autonomous vehicle (AV) applications, where uncertain output can cause serious safety concerns.

For giving an example of this analysis, we ran the prompt at least 20 times on OpenHermes-2.5-Mistral-7B, and the consistency results are presented in Fig. 6. Consistency was calculated by mapping ‘FORWARD’ = 1 and ‘STOP’ = 0. ‘FORWARD’ mean is closer to 1, it indicates that the output is having greater consistency with the expected response.



Fig. 7: Extended Traffic Scenario with V2V Communication

To investigate the impact of V2V communication on autonomous decision-making, we extended our simulation to a more complex traffic scenario. In this extended scenario, AV2 (an autonomous car) follows AV1 (an autonomous truck), with a stop sign ahead that AV2 cannot see because its line of sight is blocked by AV1, as shown in Fig. 7. To investigate how LLMs process and utilize this information, this scenario was presented to the LLM with the same prompt: ‘What would the AV on the above do? Please, just answer STOP or FORWARD’. The model responded with ‘FORWARD’, as shown in Fig. 8, for the case of using GPT-4 Turbo. This decision could potentially lead to an accident. We then examine whether the incorporation of V2V exchanged data improves the accuracy of the decisions and enables AVs to make more precise and context-aware decisions. By enabling

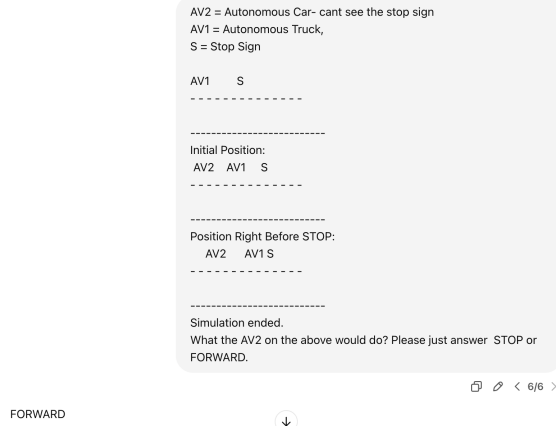


Fig. 8: LLM Model response without Communication agent's information (GPT-4 Turbo)

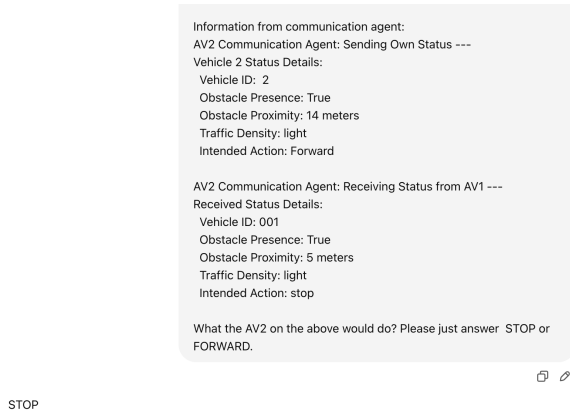


Fig. 9: LLM Model response with Communication agent's information (GPT-4 Turbo)

the Communication Agent, AV1 shares its intended action and information about the obstacle ahead with AV2. These data are structured and passed as additional input presented to the model, as shown in Fig. 9, for the case of using GPT-4 Turbo. With access to this contextual information, the model responds with 'STOP', even without direct visual confirmation of the traffic sign in the case where GPT-4 Turbo was used.

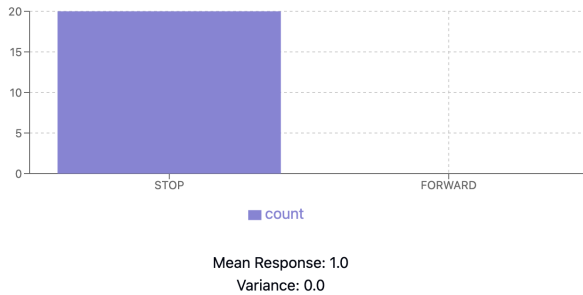


Fig. 10: LLM Model Consistency with V2V Communication support (GPT-4 Turbo)

To evaluate the consistency of the model decision, we ran the same prompt 20 times. The consistency was calculated by mapping 'FORWARD' = 1 and 'STOP' = 0. The resulting mean value of 1 for 'STOP' indicates that the output is having greater consistency with the expected response. The consistency of GPT-4 Turbo's responses with V2V support is shown in Fig. 10, which confirms that communication agent inputs help LLMs generate more accurate decisions in critical traffic environments.

V. CONCLUSION

We presented an approach for utilizing Large Language Models (LLMs) to enhance reasoning capabilities in uncertain traffic situations within a multi-agent framework for autonomous vehicles. We have investigated LLMs from Hugging Face, LM Studio, as well as major commercial services such as Claude, GPT-4 Turbo, and Falcon. Their responses to basic traffic scenarios were analyzed, revealing varying levels of consistency and accuracy. These results revealed both the promise and the current limitations of this approach, highlighting the need for improved consistency in the model responses. The proposed approach aims at the realization of adaptive autonomous systems capable of human-like reasoning in unpredictable situations. By integrating contextual data derived from V2V communication with LLM reasoning, we can have further investigations to bridge the critical gap in decision-making accuracy for autonomous vehicles.

REFERENCES

- [1] Y. Chang, X. Wang, J. Wang, Y. Wu, L. Yang, K. Zhu, H. Chen, X. Yi, C. Wang, Y. Wang, *et al.*, "A survey on evaluation of large language models," *ACM transactions on intelligent systems and technology*, vol. 15, no. 3, pp. 1–45, 2024.
- [2] A. Iftekhar and N. Fukuta, "Toward an efficient and resilient electric vehicle charging place allocation using multiagent approach," in *2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, pp. 663–664, 2024.
- [3] S. S. Duddela and N. Fukuta, "Toward an acceptable dynamic allocation considering fairness on autonomous car parking," in *2024 16th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, pp. 286–291, 2024.
- [4] J. Cho and J. Heo, "The more you know, the more you can trust: Drivers' understanding of the advanced driver assistance system," in *HCI in Mobility, Transport, and Automotive Systems. Automated Driving and In-Vehicle Experience Design: Second International Conference, MobiTAS 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, July 19–24, 2020, Proceedings, Part 1 22*, pp. 230–248, Springer, 2020.
- [5] M. Raza, "Autonomous vehicles: levels, technologies, impacts and concerns," *International Journal of Applied Engineering Research*, vol. 13, no. 16, pp. 12710–12714, 2018.
- [6] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: A survey," *Journal of artificial intelligence research*, vol. 4, pp. 237–285, 1996.
- [7] D. Fu, X. Li, L. Wen, M. Dou, P. Cai, B. Shi, and Y. Qiao, "Drive like a human: Rethinking autonomous driving with large language models," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 910–919, 2024.
- [8] T. Singh, E. van Hassel, A. Sheorey, and M. Alirezai, "A systematic approach for creation of sotif's unknown unsafe scenarios: An optimization based method," tech. rep., SAE Technical Paper, 2024.
- [9] G. Xiao, J. Lin, M. Seznec, H. Wu, J. Demouth, and S. Han, "Smoothquant: Accurate and efficient post-training quantization for large language models," in *International Conference on Machine Learning*, pp. 38087–38099, PMLR, 2023.

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do?

Please just answer STOP or FORWARD.

< 3 / 3 >

FORWARD

(a) Output from DeepSeek-V3

H = Human Car,

AV = Autonomous vehicle

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

what the AV car on the above would do? please just answer

STOP or FORWARD

FORWARD

(b) Output from GPT-4 turbo

R'

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

Edit

Based on the scenario you've presented:

FORWARD

The autonomous vehicle (AV) is approaching a traffic light that is green, and there is a human-driven car (H) in a separate lane that appears to be parallel to the AV's path. Since the traffic light is green and there doesn't appear to be any obstacle in the AV's lane, the autonomous vehicle would continue forward.

(c) Output from Claude 3.7 Sonnet

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

Compute

*+Enter

STOP

(e) Output from google/flan-t5-large

H = Human Car,

AV = Autonomous Vehicles,

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

What the AV car on the above would do? Please just answer STOP or FORWARD.

FORWARD

(d) Output from Falcon3 7B

USER

H = Human Car,

AV = Autonomous vehicle

TL = traffic light

Initial Position:

AV TL:green

H

Position Right Before TL:

AV TL:green

H

what the AV car on the above would do? please just answer STOP or FORWARD

ASSISTANT

FORWARD

(f) Output from OpenHermes-2.5-Mistral-7B

Fig. 11: Responses from different LLMs

Acknowledgements

Alhamdulillah. In the name of Allah, the Most Gracious and the Most Merciful.

First of all, I would like to express my gratitude to Almighty God ALLAH SWT for the blessing, kindness and inspiration that guided me to complete the course.

I would like to express my sincere gratitude to my supervisor **Professor FUKUTA Naoki** for his motivation and enormous contribution of knowledge. His guidance and support were invaluable to the success of this work. This study is the result of guidance from my Supervisor. I want to acknowledge and give my sincerest gratitude and heartfelt appreciation for being my Supervisor and allowing me to be a part of Fukuta lab. Our professor consistently supervised me with excellent guidance on my research, which also aided me in conducting extensive studies and learning about bunches of new topics. The encouragement, advice, support, and most importantly, the belief in us, from the initial to the final phase, helped us a lot to understand the subject. Besides my supervisors, I would like to thank my parents for their blessing, my lab members, and my friend for their support. I am incredibly grateful to all the lab members of Fukuta Laboratory and my friends at Shizuoka University for always being supportive and friendly. They are very hardworking, and I believe their academic achievement will continue to increase. Thank you for comforting me with every difficulty and suggesting the proper way to deal with it. They helped me to adopt a new culture and daily life. I am also eternally grateful to all S-port staff who lovingly and carefully advised us.

Furthermore, I want to thank my respected advisory committee and ... for giving me very helpful comments and questions at the time of the plan presentation, the mid-term presentation, and the final presentation.

I am incredibly grateful to the faculty and administrators of the **Shizuoka University's Asia Bridge Program (ABP-SU)** for the golden opportunity to be a part of it.

Finally, words are insufficient to express gratitude to my cherished family members for supporting me and encouraging me.

*Hamamatsu, Japan
July 15, 2025
Rafi Md Ashifujjman*