”ALEXANDRU-IOAN CUZA” UNIVERSITY OF IASI

FACULTY OF COMPUTER SCIENCE IASI

MASTER’S THESIS

Ethical Compliance Assessment in Autonomous Vehicle Decision-Making Using NLP and Rule-Based Evaluation

by

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Session: July, 2025

Advisor

Conf. Dr. Ignat Anca

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Conf. Dr. Ignat Anca.

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Declarație privind originalitatea conținutului lucrării de disertație

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Contents

Motivation

Software application creation serves as a fundamental building block for today's digital environment. From personal tools to large-scale enterprise systems, software drives innovation across all sectors—including healthcare, finance, education, and autonomous technologies. As the reliance on digital tools increases, so does the need for more accessible and efficient ways of developing them.

Traditionally, creating software code requires technical proficiency, domain knowledge, and an understanding of programming syntax and structure. This creates a barrier for non-technical users, limits collaborative innovation, and contributes to increasing development costs. Additionally, this complexity restricts individuals with disabilities or without formal training from participating in software creation, reinforcing the digital divide.

Recent advancements in natural language processing (NLP), automatic speech recognition (ASR), and machine learning (ML) offer promising opportunities to address these challenges. By translating spoken natural language into executable source code, intelligent systems can significantly lower the threshold for software development. This democratization of programming enables users to express logic verbally and generate syntactically correct and context-aware code through a user-friendly interface.

However, the relevance of this thesis extends beyond software accessibility and user empowerment. In parallel with the rise of intelligent systems is the growing demand for ethical transparency in autonomous decision-making, especially in areas like self-driving vehicles, healthcare diagnostics, and AI policy enforcement. A key concern is how systems interpret and respond to ethical dilemmas, particularly when they involve conflicting outcomes.

A major obstacle in studying such dilemmas lies in the diversity of ethical frameworks and contextual data used in decision-making. Therefore, a crucial part of this research is not only generating systems through speech but also building a prototype capable of fetching, comparing, and analyzing ethical data across databases—to surface consistent patterns, contradictions, or edge-case scenarios. The system is intended to support reasoned, data-informed decision-making in ethically charged contexts.

For example, when evaluating moral scenarios like those found in autonomous vehicle decision-making (e.g., the Moral Machine dataset), intelligent systems can compare real user responses and ethical choices across diverse populations and scenarios. Such systems can aid researchers, engineers, and policymakers by offering interpretable visual and logical outputs that reflect ethical trade-offs and highlight possible standards or inconsistencies.

This thesis is motivated by a convergence of goals:

- Making software creation more accessible through voice-driven systems and speech-to-code translation
- Empowering individuals with limited technical background or physical ability to participate in programming and automation
- Creating intelligent systems capable of analyzing complex ethical data, drawing insights from cross-database comparisons, and assisting in automated ethical reasoning
- Offering tools for transparency and informed decision-making in the design of autonomous systems

The research embraces a multidisciplinary vision, combining software engineering, human-computer interaction, natural language understanding, and applied ethics. By integrating these domains, the resulting platform demonstrates how intelligent systems can serve not only as productivity tools but also as facilitators of socially and morally aware automation.

In summary, this work contributes to a future where inclusive design, ethical reasoning, and intelligent automation converge—reshaping both how we program and how we confront the ethical implications of machine decisions.

Chapter 1

Introduction

1.1 Purpose and Research Question

This thesis focuses on creating and examining a system for generating code through speech commands using natural language processing (NLP) and machine learning (ML) technologies. The central research question that drives this work asks:

> What methods enable the combination of natural language processing and speech recognition to create correct and context-sensitive code from spoken commands?

The research intends to deliver a unique voice-driven programming prototype through its contributions which aim to enhance software development accessibility and efficiency.

1.2 Approach and Methodology

Natural language processing (NLP) and machine learning (ML) applications have grown to include language translation along with content generation and conversational agents among other domains. This research creates a web-based platform which uses user speech to generate pertinent source code through applied software engineering technologies.

The methodology consists of:

- Preprocessing speech input using automatic speech recognition (ASR)
- Converting spoken language into textual instructions

- Using trained NLP/ML models to interpret and convert the instructions into programming constructs
- Evaluating the generated code through testing and usability feedback

Python will be the main programming language, leveraging libraries such as TensorFlow, spaCy, and open-source speech-to-text APIs.

1.3 Scope and Limitations

To ensure the timely completion of this research, the project scope has been intentionally limited. The system will focus on generating code in a single programming language—Python—and will handle a defined subset of tasks such as function declarations, loops, and conditional statements. Complex multi-line logic, debugging suggestions, and real-time feedback will be outside the scope of this implementation.

Furthermore, the speech recognition system will be trained to understand English-language input and may not handle accents or multi-language commands effectively in its initial version. Despite these limitations, the project will provide a proof-of-concept implementation and testing environment for future expansion.

1.4 Target Group

The target group for a speech-based code generation system includes:

- Beginners and non-programmers seeking an easier way to create software
- Individuals with disabilities that make typing difficult
- Developers interested in rapid prototyping through voice commands
- Educators and students in computer science exploring assistive learning tools

By lowering the entry barrier, this system will make programming accessible to all.

1.5 Outline

The thesis will begin with a literature review of the state of the art in NLP and ML to be used in code generation tools. The review will also highlight the limitations and problems associated with these tools and outline areas of future research.

Following the literature review, the thesis will cover the methodology and deployment of the web application used as the user interface. This application allows users to record and play back verbal commands and retrieve the generated code, as well as the NLP and ML components that facilitate the speech-to-code functionality.

The implementation chapter will also cover system architecture, development process, and integration of significant technologies. The evaluation portion will cover speech-based system testing, including measures of usability as well as the quality of code generated.

The final chapters will cover the outcomes, present an extensive comparison with existing methodologies, and examine the limitations. The thesis will finalize with a summary of the conclusions, debating implications for the software industry, and recommending avenues for further research.

1.6 Research Activity

Beyond the core focus of my thesis, I have also maintained active engagement in the broader domain of Intelligent Systems, particularly with an emphasis on sustainability and renewable energy applications. This interdisciplinary exploration led to the conception and development of a project titled *"Renewable Energy Investment Calculator"* [12], which was presented at the *2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA) 2022*. This work represents a critical intersection of intelligent system design, environmental consciousness, and economic modeling.

The central objective of the project was to create a computational tool capable of simulating and evaluating the long-term financial outcomes of various renewable energy investments. The calculator provides users with an intuitive platform to input financial parameters and energy consumption data, enabling a comparison between traditional energy sources and renewable alternatives such as solar and wind energy. The system models cost-benefit projections over multiple time horizons, incorporating factors like installation costs, maintenance, government incentives, and energy prices. In doing so, it empowers individuals, policymakers, and businesses to make data-driven and environmentally responsible decisions regarding energy investments.

Our approach combined principles from artificial intelligence, economic modeling, and software engineering. From a technical standpoint, we employed intelligent algorithms to assess and forecast energy savings, ensuring the results adapt dynamically to user-provided inputs. The result was a decision-support system that contributes meaningfully to discussions around climate change mitigation, energy efficiency, and sustainable development. Furthermore, the project addresses global policy trends advocating for green transition and highlights how intelligent systems can facilitate these large-scale shifts.

Integrating this research activity into my academic portfolio demonstrates not only the practical utility of intelligent systems but also my capacity to engage with diverse and socially relevant problem domains. It highlights my ability to apply interdisciplinary knowledge—bridging technical design with societal impact—to develop tools that support real-world decision-making. Moreover, it underlines my commitment to addressing contemporary global challenges through innovation and responsible system design. This work stands as a testament to both the adaptability of intelligent systems and my ongoing pursuit of meaningful, problem-solving research.

Chapter 2

Related Work

The increasing autonomy of vehicles raises not only technical but also critical ethical challenges. As these systems gain the ability to make complex driving decisions without human intervention, the question arises: how should these decisions be evaluated from an ethical standpoint?

2.1 Theoretical Background

2.1.1 Ethical Dilemmas in Autonomous Driving

Autonomous vehicles (AVs) are rapidly becoming a key part of transportation innovation. While they promise increased safety and mobility—particularly for individuals with disabilities—they also bring forth a range of ethical and societal challenges. One widely discussed ethical scenario is the adaptation of the classical trolley problem: what should an AV do when confronted with two outcomes, both involving potential harm?

The "Moral Machine" experiment developed by MIT addressed this question by collecting millions of responses from people around the world, revealing significant cultural differences in what is considered “the right” ethical decision [11]. However, such extreme dilemmas are rare in real-life driving. More commonly, AVs must handle everyday ethical choices—such as reacting to jaywalking pedestrians, sharing the road with cyclists, or choosing safe behavior in dense traffic conditions [5].

These subtle, everyday moral decisions are now the focus of my research and are being analyzed using a combination of rule-based assessments and natural language inputs. For example:

"This vehicle does not operate fully autonomously in both urban and rural areas. It does require human intervention and the human is capable of handling all traffic conditions."

Assessment: SAE Level 0 — Human Responsibility **Conclusion:** Text complies with ethical expectations for this level.

"The autonomous vehicle is designed to prioritize the safety of its passengers, even if it means endangering pedestrians in extreme situations."

Assessment: SAE Level 5 — Full Responsibility **Conclusion:** Text may conflict with ethical expectations for this level.

2.1.2 Decision-Making Models in AV Ethics

Several ethical decision-making models have been proposed to guide AV behavior:

- **Rule-based systems:** These rely on strict adherence to traffic laws and regulations.
- **Consequentialist models:** These evaluate the outcomes of each possible action and choose the one that minimizes harm.
- **Data-driven ethical learning:** These models learn from aggregated human decisions in similar scenarios, attempting to mimic human judgment [9].

A more nuanced approach is the *Ethical Valence Theory*, which argues that AVs should consider not only the number of people involved but also social vulnerability, likelihood of injury, and contextual sensitivity [10].

2.1.3 Regulation and Legal Frameworks

Ethical programming alone is not sufficient; these vehicles must operate within a legal framework that reflects society's values. Currently, there is no globally unified legislative approach to AV ethics. However, the European Union has introduced the *Ethics Guidelines for Trustworthy AI*, while countries such as Germany and Japan have created national ethics committees to guide AV development [3].

My dissertation further analyzes these frameworks in comparison to tools like the MIT Moral Machine, assessing how effective or incomplete they are when applied in real-world ethical evaluations.

2.1.4 Complementary Technologies

To increase transparency and trust, technologies such as Natural Language Processing (NLP) and Explainable AI (XAI) play a vital role. These systems allow AVs to justify their decisions in human-understandable ways, which is crucial in scenarios involving accidents or unexpected behavior.

Moreover, ethical databases derived from real-world user inputs and public consultations are being developed to train AV systems according to cultural values and social expectations [11, 10].

Chapter 3

Literature Review

This chapter reviews the theoretical and technological foundations relevant to the ethical evaluation of autonomous vehicle decisions. It is divided into four main areas: (1) ethical dilemmas in autonomous driving, (2) the Moral Machine dataset, (3) SAE levels of automation, and (4) natural language processing (NLP) in ethical AI systems.

3.1 Ethical Dilemmas in Autonomous Vehicles

Autonomous vehicles (AVs) face complex ethical dilemmas that require decision-making beyond programmed logic. A widely recognized example is the *trolley problem*, where a vehicle must choose between two harmful outcomes. These scenarios demand ethical frameworks that align with human values and societal norms [4, **?**].

Traditional programming approaches fall short in handling such nuanced trade-offs, which has led to efforts to encode moral reasoning into AVs using decision-theoretic and rule-based methods.

3.2 The Moral Machine Experiment

The *Moral Machine* project by MIT Media Lab collected over 40 million ethical decisions from people across the world [1]. Participants were presented with variations of trolley-type dilemmas involving pedestrians and passengers, with diverse attributes (age, gender, profession, lawfulness).

This large-scale dataset provides insights into:

- Cultural and regional preferences for ethical decisions

- Patterns in human moral reasoning
- Factors influencing perceived fairness and justice

It serves as a benchmark for comparing algorithmic decisions against human judgments.

3.3 SAE Levels of Vehicle Automation

The Society of Automotive Engineers (SAE) defines six levels of driving automation, from Level 0 (no automation) to Level 5 (full automation) [6]. Each level has implications for ethical responsibility:

- **Level 0–2**: Driver retains full or partial control.
- **Level 3–4**: Shared or conditional autonomy.
- **Level 5**: Full machine decision-making without human input.

As automation increases, the ethical responsibility shifts from human to machine, necessitating advanced ethical rule systems embedded within AVs.

3.4 Ethics in Artificial Intelligence

Recent literature stresses the importance of fairness, accountability, transparency, and explainability (FATE) in AI systems [7]. In the context of AVs, this includes:

- Distributing risk equitably among all road users
- Avoiding discrimination by age, income, or status
- Logging and auditing ethical decisions made by AI

Rule-based systems and value-sensitive design are commonly used to encode ethical principles into AV logic [2].

3.5 Natural Language Processing in Ethical Analysis

Natural language processing (NLP) plays a crucial role in translating scenario descriptions into structured ethical evaluations. Tools like spaCy and transformers allow systems to extract intent, action, and moral context from text [8].

In this project, we use keyword detection, lemmatization, and scenario generation to infer the SAE level and evaluate compliance with ethical rules. This bridges unstructured data (scenario text) and structured ethical frameworks.

3.6 Summary

This review shows the growing importance of integrating NLP and ethical reasoning in autonomous systems. The Moral Machine dataset provides a rich source for testing human-aligned ethics. SAE levels offer a framework for responsibility segmentation, while NLP enables automated ethical evaluation from naturalistic input.

The next chapter details the methodology used to develop and test our ethics-checking system.

Chapter 4

Methodology

This chapter outlines the methodological framework adopted in this study. The research leverages natural language processing (NLP), structured rule-checking, and the Moral Machine dataset to evaluate the ethical integrity of autonomous vehicle decision scenarios. The following sections detail the dataset processing, scenario reconstruction, ethical rule design, and evaluation approach.

4.1 Overview of the System Architecture

The proposed system consists of five main components:

1. **Data Acquisition and Unzipping**: Extracting scenario files from compressed datasets.

2. **Scenario Reconstruction**: Converting tabular or structured input into natural language descriptions.

3. **NLP Analysis**: Using spaCy to lemmatize and extract scenario intent and features.

4. **SAE Level Detection**: Determining the appropriate automation level based on detected keywords.

5. **Ethics Rule Matching**: Comparing inferred context with ethical rules from a structured SQLite database.

Each step is designed to incrementally transform the raw data into an interpretable format that can be ethically analyzed.

4.2 Data Sources

4.2.1 The Moral Machine Dataset

The core dataset comes from the Moral Machine project [1], which includes scenarios involving autonomous vehicles choosing between groups of pedestrians or passengers. Files are provided in both CSV and pickle format, some containing human-labeled scenario types, decision actions, and character counts.

4.2.2 Scenario Structure

Each scenario includes:

- Number and type of individuals on each side
- Whether the AV must intervene
- Whether the individuals are in or outside the vehicle
- Scenario theme (e.g., gender, lawfulness, profession)

4.3 Scenario Text Generation

4.3.1 Natural Language Representation

Structured rows are converted into readable scenario descriptions using Python functions such as `row_to_scenario_text()` and `row_to_scenario_text_gpt()`:

> "The vehicle is in the car. On side 1, there are: 2x woman, 1x doctor. On side 2, there are: 1x dog, 1x elderly man. This vehicle is fully autonomous. The vehicle must decide whether to intervene."

These representations are intentionally phrased to trigger relevant ethical and automation-level keywords during analysis.

4.4 NLP and SAE Level Inference

4.4.1 Text Preprocessing

The spaCy library is used for:

- Lowercasing and tokenization
- Lemmatization
- Filtering stop words and non-alphabetic tokens

4.4.2 Keyword Matching

Each SAE level (0–5) is mapped to a keyword set (e.g., "manual control", "self-driving", "autonomous"). A regular expression match scans for these patterns. The first match assigns the inferred level to the scenario.

4.5 Ethical Rule Database

4.5.1 Database Construction

An SQLite database is created with the schema:

```
(id INTEGER, sae_level INTEGER, principle TEXT, rule_description
TEXT)
```

Each SAE level contains multiple ethical principles, such as:

- **SAE Level 2:** "Transparency" – "System must communicate its operational limits and intention to the driver."
- **SAE Level 5:** "Non-Discrimination" – "Decisions must not prioritize safety based on race, age, or economic status."

4.5.2 Rule Matching

Once a scenario's SAE level is inferred, a matching rule is selected from the database. The system checks whether any keywords from the ethical guideline appear in the scenario. If not, the system flags a potential ethical conflict.

4.6 Evaluation Procedure

4.6.1 Validation Function

The function `validate_decision(row)` checks whether a given scenario text passes the ethics check. If the scenario contradicts the expected rule (e.g., violates ”non-discrimination”), it is marked as ethically invalid.

4.6.2 Interpretation and Reporting

All results are summarized in terms of:

- Total number of evaluated scenarios
- Number of conflicts detected
- Proportion of ethically aligned decisions

This forms the basis for quantitative reporting in Chapter 5.

4.7 Tools and Libraries

- **Python 3.10+**
- **spaCy** for NLP processing
- **Pandas** for data wrangling
- **SQLite3** for rule storage
- **re (regex)** for keyword detection

4.8 Summary

This chapter described the pipeline from scenario loading to ethical rule matching. The methodology emphasizes transparency, modular design, and linguistic interpretability. The next chapter presents the results of applying this methodology to hundreds of Moral Machine scenarios.

Chapter 5

Results and Discussion

This chapter presents the outcomes of applying the proposed methodology to the Moral Machine dataset. The ethical evaluation process was applied to scenarios reconstructed in natural language, with each case assessed for compliance with predefined ethical rules based on the inferred SAE automation level.

5.1 Evaluation Metrics

To assess the performance of the ethical validation system, the following metrics were used:

- **Total Scenarios Processed (TSP):** The number of unique scenario instances evaluated.
- **Ethical Conflicts Detected (ECD):** Number of cases flagged as potentially violating the relevant ethical rule.
- **Compliance Rate (CR):** Percentage of scenarios that passed the ethics check.
- **False Positives/Negatives (FP/FN):** Cases where ethics flags did not align with human interpretations (optional).

5.2 Dataset Characteristics

The system was applied to a subset of the Moral Machine dataset consisting of several hundred decision-making scenarios. Key statistics:

Table 5.1: Summary of Ethics Evaluation

Metric	**Value**
Total Scenarios Processed (TSP)	[Insert number]
Ethical Conflicts Detected (ECD)	[Insert number]
Compliance Rate (CR)	[Insert %]
Most Frequent SAE Level	[Insert level]
Most Violated Ethical Principle	[Insert principle name]

- Number of total cases: **[Insert Value]**
- SAE levels inferred: Ranged from Level 2 to Level 5
- Ethical rules enforced: **21** distinct rules across all levels

5.3 Quantitative Results

5.3.1 Overall System Performance

Table 6.1 summarizes the performance of the system in identifying ethically aligned vs. conflicting scenarios.

5.3.2 SAE Level Distribution

5.3.3 Conflict Types Observed

Conflicts were primarily associated with the following rule types:

- **Non-Discrimination (SAE 5):** Many scenarios seemed to prioritize younger or healthier individuals.
- **Transparency (SAE 2–3):** Several cases lacked clues indicating system transparency or explainability.
- **Ethical Fail-Safe (SAE 5):** Complex or ambiguous scenarios often triggered fail-safe-related flags.

5.4 Case Study Examples

5.4.1 Example of Ethical Alignment

> *"This vehicle is fully autonomous. On side 1, there are 2x women and 1x child. On side 2, there are 1x dog and 1x criminal. The vehicle must decide whether to intervene."*

The system detected SAE level 5 and aligned the decision with principles of proportionality and risk minimization.

5.4.2 Example of Ethical Conflict

> *"The autonomous vehicle is programmed to prioritize passengers regardless of pedestrian type."*

This scenario was flagged as violating the principle of fairness and non-discrimination under SAE Level 5.

5.5 Discussion

5.5.1 Insights and Interpretation

The results suggest that many AV decision scenarios, especially those from datasets designed to highlight moral dilemmas, trigger ethical conflicts under strict rule-based evaluation. The methodology enables structured, transparent identification of such violations.

5.5.2 Strengths of the Approach

- Provides a modular, explainable framework for ethics checking
- Can be scaled to large datasets
- Incorporates both structured logic and natural language understanding

5.5.3 Limitations

- Depends heavily on keyword matching, which may miss nuanced phrases
- Ethical rules may need customization per legal/cultural region
- Contextual weighting (e.g., saving more lives vs. saving passengers) not yet implemented

5.6 Summary

This chapter presented the quantitative and qualitative results of applying the ethics-checking methodology to the Moral Machine dataset. The system was able to detect patterns of ethical alignment and conflict, demonstrating the utility of NLP combined with structured ethical logic. In the next chapter, the conclusions and recommendations for future work are presented.

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