Morality Matters: An Exploration of LLMs and Their Moral Judgements

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https://github.com/peersal/Morality-Matters

Abstract

This research paper delves into the moral and ethical implications of large language models (LLMs) by subjecting them to complex moral dilemmas, such as the classic trolley problem. In an era where artificial intelligence (AI) is increasingly intertwined with human decision-making processes, understanding the ethical frameworks guiding AI systems like LLMs is essential. This study employs a series of moral dilemmas to assess the decision-making processes of various LLMs, analyzing their responses and underlying moral frameworks. We aim to investigate whether these models adhere to established ethical principles and how their responses align with human moral reasoning. The study also explores the potential biases in these responses, the influence of the training data on their moral judgments, and the implications for AI ethics and governance. By confronting LLMs with scenarios that require ethical reasoning, this paper seeks to illuminate the capabilities and limitations of AI in replicating human-like moral reasoning, thus contributing to the broader discourse on the ethical development and deployment of AI technologies.

1.1 Theory (Jördis)

Some of the most debated questions in ethics are "How should we live?" and "What is good?". Answering these questions is often challenging - not only for humans but also for agents of artificial intelligence: Rice and Dunn (2023) delve into two primary ethical concerns and provide evidence linking the influence of AI on human well-being and societal implications of AI capable of autonomous decision-making. Further research provided evidence for potentially harmful interactions between Ai-agents and humans, leading to decreasing mental health and feelings of stress (Gupta et al. (2023)). With AI on the rise as a substantive part of day-to-day life and a daily increase of human-AI-interactions especially via Large Language Models (LLM), the exploration of ethics and even security in both human and AI behavior is as relevant as never before (He et al. (2024)).

While a swiftly growing body of literature investigating moral beliefs and development of LLMs attributes them the ability to justify decisions based on moral frameworks and Kohlberg's Cognitive Moral Development Model (Tanmay et al. (2023)) and even causal reasoning in high-stakes scenarios (Kıcıman et al. (2023)), there is still a lack of studies putting those proclaimed moral justification skills to a practical test.

Kamm (2020) examines such ethical considerations, specifically in the context of autonomous vehicles (AVs). He focuses on applied ethics during the programming of AVs for decision-making in scenarios where harm is inevitable, paralleling the "trolley problem" as invented by philosopher Phillipa Foot in 1967 (Hacker-Wright (2021)). A crucial aspect of solving the trolley problem revolves around the distribution and cause of harm and responsibility, always placing the actor in a situation with a trade-off and the power to either act and thereby effectively changing the outcome or not to act and letting events play out. This effectively makes the trolley problem a moral dilemma, with an agent being placed in circumstances where they are required to choose one out of two possible options, without being able to choose both (McConnell (2022)).

Placing AI in scenarios as agents where they must navigate a trade-off similar to Kamm's experiment on AVs is by no means new and comparisons between humans and AI's moral behavior across different variations of the trolley problem have been made (see for example Gill (2020), Novak (2020); Chu and Liu (2023)), yet, given the rapid development in LLM development to the point, where certain models like GPT-4 with an EQ of 117 manage to score a higher emotional intelligence than 89%

of a human sample of 500 participants (Wang et al. (2023)), and LLMs even being considered for AVs in urban settings (Jin et al. (2023)), it is crucial to continuously explore the evolution of LLMs' underlying morals.

However, there two core challenges to be addressed before one can start to dive into the moral assessment of LLMs. The first and potentially most important one being value pluralism: The absence of a universally agreed-upon set of ethical principles even among humans globally that would be definitive enough to be encoded into machines (Railton (2020)). But, as Rao et al. (2023) argue, this might not be a necessity for the application of LLMs in moral dilemmas. Instead of training models to follow a prime moral directive, Rao et al. (2023) suggest to train LLMs' "generic ethical reasoning capabilities", which would grant them greater flexibility in judging different. contexts. A lack of universally accepted moral beliefs or frameworks does therefore not pose a threat to this study, as its main purpose is of an exploratory nature and seeks to observe LLMs' capability of reasonably engaging with a moral dilemma such as the trolley problem.

The second potentially challenging aspect to consider is the LLMs' programming: Do LLMs possess inherent morals or do they rather represent their training data and developers' opinions leading to an overgeneralization of the opinions of few (Zhou et al. (2023a))? In case of the letter, one might suspect the models to likely respond with guardrail answers, effectively refusing to choose one option or even just a blatant preference for one option over the other. This appears to at least be partially the case, as Benkler et al. (2023) find a Western-centric moral bias in the most prominent LLMs.
While both challenges are of structural nature, we address them by comparing all LLM-generated data to a human baseline of responses and carry out a comparison of valid and guardrail answers during the classification of our raw data. We further intend to draw conclusions from comparing the LLM responses with the human annotations from Awad et al. (2020), leading to our first research question: How do the responses of LLMs to moral dilemmas compare to human-annotated decisions? This question aims to find out whether there are significant differences in responses to the trolley dilemma between humans and LLMs, indicating potential agreement on moral values, frameworks or even moral pluralism or a Western bias similar to the findings of Benkler et al. (2023). We therefore propose our first hypothesis:

H1.1: LLMs will exhibit a significant degree of alignment with human moral judgments in a standardized moral dilemma such as the trolley problem.

Consecutively, we aim to analyze the consistency of LLM-generated responses by introducing specific variations in the information and scenario descriptions given during the experiment. Our expectations of LLMs consistency follows Awad et al. (2020): We assume high consistency for unambiguous scenarios such as a comparisons between one person next to five people of the same personal characteristics, which would be resolved via Utilitarianism by saving the group of people and minimizing harm; and low consistency for ambiguous cases, like the comparison between one cat or one dog or even the replacement of any living beings with an inanimate object like apples. To answer our second research question of LLMs' consistency in responses, we propose a second hypothesis:

H1.2: LLMs respond consistently with one option for unambiguous cases and inconsistently to ambiguous cases by choosing both options with similar frequency.

We further intend to add to the research fields's state of the art by introducing variations of the three base cases of the trolley dilemma. The variations will force the LLMs to distinguish between different personal characteristics in the humans potentially harmed by choosing either option. Whether the LLMs express a consistent "individual" sense of morality can thus be revealed by analyzing our second research question: Does the consistency of LLM responses vary under varied scenarios when adding information?
Looking at handmade variations of the dilemma additionally avoids standardized answers of LLMs if they should recognize the trolley problem. We thus propose our final hypothesis suggests that we are able to change the scenario in terms that it is not recognized as the trolley dilemma by the LLMs:

H2: When adding information that changes the context of the scenario, the responses will have higher inconsistency compared to the standardized dilemma.

2. Data (Peer)

For comparing responses of the language models to human annotations, we are using the data of the Awad et al. (2020) survey, which is public available here. This data is also used on the website Moral Machine. It contains 70,000 responses to the three dilemmas explained above, collected in 10 languages and 42 countries. Universal qualitative pattern of preferences together with substantial country-level variations in the strength of these preferences are documented in the data as well. Awad's survey data serve as baseline of our project, as it provides high-quality, human-annotated responses to three different trolley problem scenarios which we will in turn compared to responses generated by LLMs.

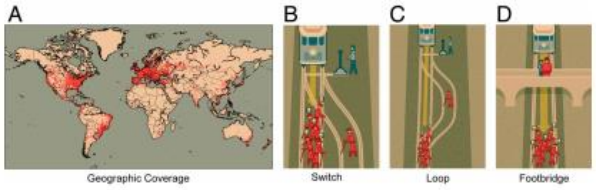

Figure 1 Trolley Problem Variations by Awad et al. (2020)

B.) A trolley is about to kill five workers, but can be redirected to a different track, in which case it will kill one worker.
C.) A trolley is about to kill five workers, the trolley can be redirected to a different track, where it will kill one worker whose body will stop the trolley before it can kill the five people on the track.
D.) A trolley is about to kill five workers,a large man can be pushed in front of the trolley. The large man will die, but his body will stop the trolley before it can kill the five workers on the track.

The "Switch" and "Footbridge" scenarios differ significantly in two aspects. Firstly, in "Switch," the death of the single worker is not a direct means to save the five others; it's an unintended yet predictable consequence of diverting the trolley. In contrast, in "Footbridge," the death of the large man is directly instrumental to saving the five workers; it's not a side effect but a deliberate action to prevent the trolley's path. Secondly, "Footbridge" involves the active physical intervention against the large man, whereas "Switch" does not require any physical force against an individual. These distinctions contribute to the general psychological preference for action in the "Switch" scenario over the "Footbridge".
Similar to "Switch," no direct physical force is used against anyone in "Loop." However, there's ambiguity about whether the worker's death is an intended outcome or a foreseeable consequence, making it a morally complex scenario. Consequently, people's moral judgment regarding the acceptability of action in "Loop" often falls between that of "Switch" and "Footbridge," a pattern Awad et al. (2020) refer to as the "Switch–Loop–Footbridge" preference.

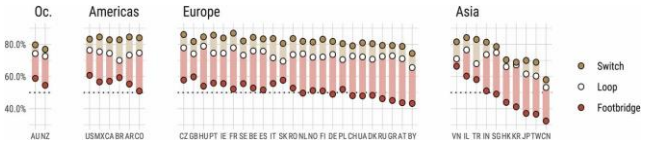

Figure 2 Findings of Survey by Awad et al.(2020)

Figure 2 illustrates the results from (Awad et al., 2020), depicting the preference ratios for action in the context of redirecting the trolley. The three variations of the trolley problems are explained in detail in the following pages. The data reveals a consistent preference across various countries for taking decisive action in both the "Switch" and "Loop" scenarios. According to the findings, every country represented in the dataset exhibited a similar pattern: participants were more inclined to endorse a sacrifice in the Switch scenario (81%) over the Loop scenario (72%), and the endorsement for Loop was higher than for the Footbridge scenario (51%). This observation corroborates our hypothesis suggesting a predominant consensus on well-known moral conundrums.

2.1 Sampling

While the data by Awad et al. (2020) indicates consistency in results across various nations, our analysis specifically targets countries where English is the primary language and that have more than 100

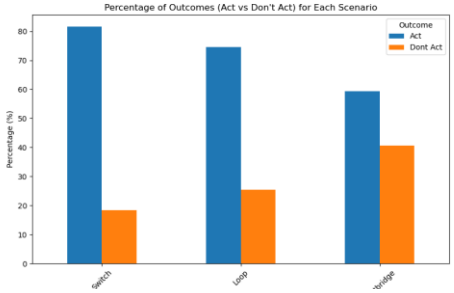

Figure 3 Decision distribution of sampled data

entries. As a result, our dataset narrows down to 80,694 responses from 26,898 individuals across six countries.

The answers are highly consistent across countries for the sampled data, which can be seen in Table 1. For example, in the "Switch" scenario, the percentage of "Act" responses ranges from approximately 77.94% (New Zealand) to 84.62% (Ireland), indicating a similar trend in decision making across these countries which is also in line of the findings of Awad et al. (2020).

Scenario	United States	United Kingdom	Canada	Australia	New Zealand	Ireland
Footbridge	61.41%	60.00%	58.21%	59.43%	57.06%	56.39%
Loop	76.86%	74.29%	74.79%	75.06%	75.44%	74.22%
Switch	83.76%	81.85%	82.54%	80.07%	77.94%	84.62%
n	15640	6261	2409	2026	337	224

Figure 4 Percentage of "Act" Responses for Each Scenario Across Countries

3. Methods

Our objective is to guide Large Language Models (LLMs) to produce responses that align with one of two categories: "act" or "don't act" using reasonable prompt engineering techniques. Additionally, we aim for the model to provide a three-sentence rationale elucidating its moral stance. Initially, our focus will be on categorizing the responses based on these criteria. Subsequently, we will engage in a thorough examination of the moral framework that underpins the reasoning provided. This will involve exploring the ethical principles or theories that the model may implicitly employ in its decision-making process.

3.1 Pretest (Peer)

To inform the design of our prompt, we conducted preliminary tests using the mistral model, focusing on the trolley dilemma with variations in the quantity of entities involved and their presentation sequence. The key variations tested include:

- 1v1 Worker Scenario: A straightforward choice between saving one worker over another.
- 5v5 Worker Scenario: A decision involving larger groups of workers, testing if the model scales its moral reasoning with the number of lives at stake.
- 1v5 and 5v1 Scenarios: These test the model's response to the order of objects, where the decision involves saving one versus five lives or vice versa.

The tests aimed to explore whether the quantity of entities significantly influences the model's decision-making process under the condition that the

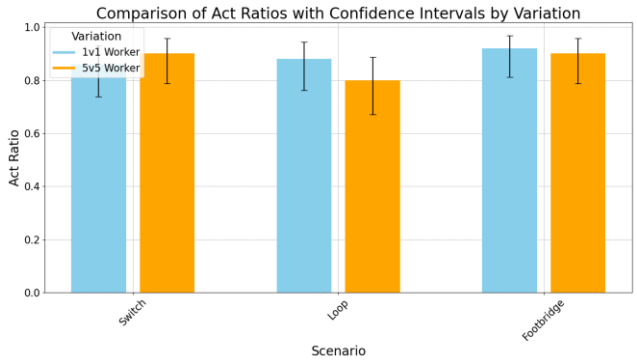

Figure 5 Act ratios with different quantity for workers

quantities are identical (e.g., 1v1, 5v5). The findings from these pretests indicate that the decision-making process of the model is not significantly affected by the quantity of entities involved when the quantities are equal. In Figures 4, the act ratios for the

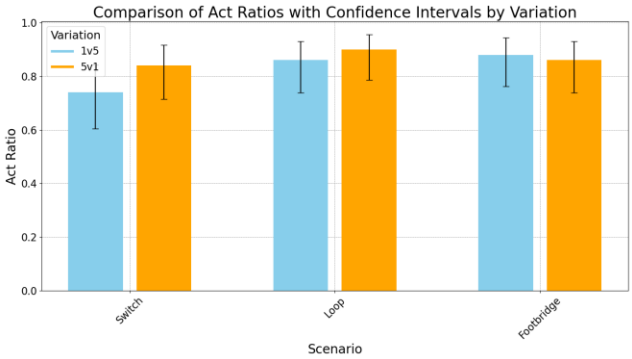

Figure 6 Act ratios with different order of objects

1v1 and 5v5 scenarios are presented, showing no substantial variation that couldn't be attributed to randomness. This suggests that, under these conditions, the model's moral reasoning is not really influenced by the number of lives or objects involved (for even quantities).

The test results additionally suggest that the Ordering of the Objects with different quantity does matter. Contrary to expectations, the act ratios seen in Figure 5 for the 1v5 and 5v1 scenarios were similar,

unveiling a surprising inconsistency or misunderstanding of the dilemma's structure. This inconsistency manifests in two distinct ways:

1. In some cases, the model provided identical justifications for both the 5v1 and 1v5 scenarios, failing to recognize the reversal in the number of lives to be saved versus sacrificed. This resulted in a semantic agreement (prioritizing the saving of more lives) but a misalignment with the intended moral choice, especially in the 5v1 scenario.
2. Less frequently, the model justified actions that contradicted basic moral principles, such as advocating for the sacrifice of five lives to save one, with a misapplied appeal to utilitarianism, revealing a logical inconsistency in its reasoning.

These findings suggest that when designing prompts for further testing, especially with models like Mistral, it is advisable to structure scenarios where the quantity of Object 1 is less than that of Object 2, to avoid the observed inconsistencies. It is important to note, however, that these observations may not apply to other models like GPT or similar, indicating a unique aspect of Mistral's decision-making process that warrants further investigation.

3.2 Prompt Engineering (Peer)

Prompting the base variations of the three trolley dilemmas in a way that we can classify the responses and avoid as much guardrails as possible is challenging. One of the primary challenges in prompt engineering is achieving the desired results on the first try (zero-shot). Finding an appropriate starting point for the prompt is crucial, as it sets the tone and direction for the model's response (Zhou et al., 2023b). To effectively address this, our approach involves structuring the prompts based on a explanation of a moral dilemma outlined by (McConnell, 2022). The prompt entails the following steps:

1. Introduction to the Moral Dilemma: Each prompt begins by setting the stage for a moral dilemma, drawing on (McConnell, 2022) guidelines. This introductory segment aims to familiarize respondents with the concept of a moral dilemma, setting a foundational context for the specific scenarios to follow.
2. Detailed Description of the Specific Dilemma: Following the introduction, the prompt delves into the specifics of the dilemma at hand. This part is crucial for providing respondents with a vivid and comprehensive understanding of the situation, ensuring that they can fully grasp the moral complexities involved.
3. Presentation of Response Options: After laying out the details of the dilemma, the prompt clearly outlines the possible actions or reactions available to the respondent. This step is designed to guide the respondents towards deciding, framing their choices in a way that aligns with the moral quandaries posed by the scenario.
4. Clear Instruction for Response: The prompt concludes with a direct instruction on how to respond. This instruction is crafted to encourage a decisive choice, urging respondents to select one of the presented options based on their moral reasoning. The goal here is to minimize ambiguity and facilitate a straightforward classification of responses.

By following this structured approach, we aim to generate prompts that not only engage with the ethical dimensions of the trolley dilemmas in a meaningful way but also produce responses that are both insightful and easy to categorize, all while adhering to the necessary ethical considerations and avoiding potential guardrails. As minor adjustments in the prompt can significantly alter the output (White et al., 2023) we rerun different version of the prompt leading us to the following final prompt.

"Consider following scenario where you are the agent. The agent (person) is required to do one of two moral options. The agent (person) is capable of doing each one. The agent (person) cannot do both. You have to choose between A or B, give a short explanation for your choice. Only choose one option!
A trolley is about to kill [OBJECT1], [VARIATION], in which case it will kill [OBJECT2]. I would choose option... Here are your possible choices. A: [ACTION], B: do not [ACTION]
Please begin your response with either one of the options "A" or "B" and then shortly explain your answer in two sentences. Do not answer for both options! "

Where each base Variation of the trolley problem is put into [VARIATION]. To vary from the base scenarios we change the [OBJECTS] (e.g. Apples, Professors, ethnicity's, etc..) This allows us to test for different scenarios like number of persons, ethnicity's or animals by deviating as little as possible from the base cases.

3.2.1 Variations (Peer)

To test for specific biases, we create different dilemmas based on ethnicity, gender and others. These will be compared to the basic worker 1v1 case to find any significant deviation. Therefore we prompt following scenarios:

- 1v1 worker: A straightforward choice between saving one worker over another as base case.
- 1v1 scientist: A choice between a scientist who researches for a cure for cancer and a worker
- 1v1 ethnicity: A choice between a black and a white worker
- 1v1 gender: A choice between a male and a female worker
- 1v1 animals: A choice between a dog and a cat
- 1v5 apples: Base case with apples

Additionally in each 1v1 scenario both orders are tested due to the finding of our pretests. In total, there are 32 prompts, where 3 prompts replicate the base cases of Awad et al. (2020) and 29 prompts are variations that aim to find significant deviations when ethnicity, gender or occupation are changed.

3.3 Large Language Models used (Everybody)

GPT 3.5 Turbo:

OpenAI released GPT-3.5 models, including "text-davinci-002" and "code-davinci-002," on March 15, 2022, boasting enhanced edit and insert capabilities. Later, "text-davinci-003" was introduced on November 28, 2022, marking the transition to the GPT-3.5 series. OpenAI then launched ChatGPT, derived from GPT-3.5. The GPT-3.5 series consists of four models: Chat, gpt-3.5-turbo, text-davinci-003, and text-davinci-002. OpenAI expanded this series with the introduction of GPT-3.5 with Browsing (ALPHA) on April 10, 2023. This new variant incorporates the ability to access and browse online information, offering more accurate and up-to-date responses to user queries. Trained on data up to September 2021, it surpasses previous versions by providing advanced natural language processing capabilities and real-time synthesis of online information.

To enable browsing, OpenAI developed a new API allowing the GPT-3.5 with Browsing (ALPHA) model to access selected online resources during operation. This feature ensures that users receive updated and relevant answers based on the latest online sources. OpenAI made the GPT-3.5 with Browsing (ALPHA) model publicly available to GPT Plus users on April 27, 2023, widening access to its enhanced features.

Mistral 7b Instruct:

The Mistral-7B-v0.1 Large Language Model is a pretrained generative text model with 7 billion parameters which outperforms Llama 2 13B1 according to the Mistral AI Team (AI, 2023). While specific details about the training data is not be publicly disclosed2, models of this scale typically utilize vast collections of text from the web, academic papers, books, and other sources to ensure a comprehensive grasp of language, coding, and subject-matter expertise. The model incorporates Grouped-Query and Sliding-Window Attention mechanisms to efficiently handle long sequences and focus on relevant information, significantly enhancing its computational performance and scalability. It also utilizes a Byte-fallback BPE tokenizer, ensuring robust and adaptable processing of diverse inputs, including those from underrepresented languages or containing special characters, thereby maintaining high accuracy and flexibility across a wide range of tasks (AI, 2023).

Falcon 7b Instruct: Falcon 40B and 7B were developed by the Technology Innovation Institute (TII), which belongs to the government of Abu Dhabi's Advanced Technology Research Council, and is licensed under the Apache 2.0 License Version. This makes Falcon a family of powerful open-source LLMs, suitable for open-ended text generation, classification and after fine-tuning even assists in chat-style responses supporting both English and French. This is due to Falcon's training data: Falcon RefinedWed, consisting of roughly 1B web pages and 2.8TB clean text (https://huggingface.co/datasets/tiiuae/falcon-refinedweb).

When working with Falcon, we observed noticeable improvements in responses once the maximum number of output-tokens were increased.

3.4 Classification (Jördis)

Once the initial setup of the prompts, the pre-test and the fine-tuning were completed, we moved into the next stage of the project: The cleaning and classification of the results. As the prompts tasked the models to begin each response by stating the option of their choice, we decided to apply a two-stage classification process. We thus constructed two classification functions utilizing regular expressions for pattern identification and data preparation. Since all models responded in slightly different ways indicating deviations in general response behavior, all results arrived in different stages: For Mistral, new-line and return characters had to be filtered out; Falcon required substantive filtering of answers, as it began every response by a rephrased version of the respective prompt (noticeably, the style of the prompt was kept surprisingly well) that had to be detected and removed to extract the actual response only; while the results from GPT 3.5 Turbo did not require specific preprocessing.

After the data were prepared, we proceeded to sample 10 rows of prompts over all 100 runs and assessed the LLMs behavior qualitatively to search for any apparent patterns, in both semantics and syntax. A few observations stood out to us, namely that all LLMs mostly succeeded in beginning each response with the option of their choice and that the reasoning behind their answers turned out to be sensible in most cases, indicating that the LLMs engagement with the different prompts and variations rather than replying with one default answer regarding the general trolley-problem setup. However, there were inconsistencies in some responses, with models either choosing both options at some point in the same response or even choosing one option, followed by a detailed explanation

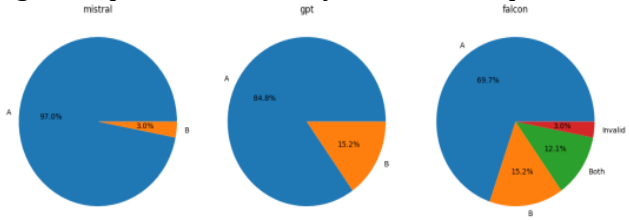

Figure 7 Shares of choices for Options A and B, both and invalid responses for all LLMs

as to why the LLM chose the *other* option, expressing logical inconsistencies.

Yet, we were able to classify easily and distinctly most of our responses by applying our first regular expression-based classifier to scan the beginning of each response and label each response with its underlying class A or B. For those responses that did not start with denoting the LLM's option of choice and we assigned the labeled *Unknown*, we applied the second stage of our classification process, which then scanned the entire response for appearances of patterns indicating the choice of either option A or B, a guardrail response stating the LLM's refusal to comply with the prompt or any responses that were logically inconsistent and opted for both A and B. Any responses that did not contain a clear choice for either option were labeled as *Invalid*. The classification indicates that the LLMs appear to have a preference towards choosing option A - acting rather than just letting the situation play out.

3.5 Results (Korhan)

After classifying our received responses as 'Act' or 'Don't Act' with our classifier we were able to see a glimpse of the underlying truth, the behavior of LLM's regarding ethical issues. Hence our study was limited and various reasons like cost efficiency, we have 100 runs for each scenario, for the given 3 LLM's. One might argue that 100 runs might not be sufficient, but for robustness and statistical consistency, we bootstrapped our results over 1000 times. The same was done also for the survey responses, which were given in Table 1.

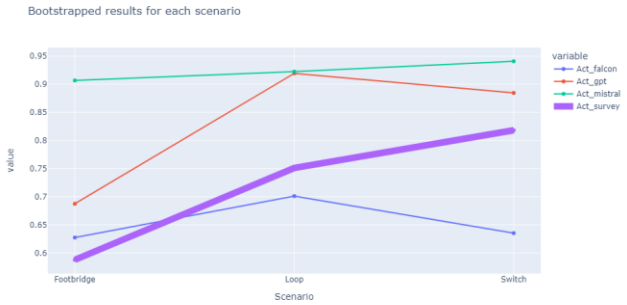

Figure 8. Bootstrapped results for Base cases

We further performed a binomial test for all base cases of the three scenarios presented by Awad et al. (2020) to assess the alignment of human and LLM behavior statistically. Table 2 presents the results of a bootstrapped binomial test over 1000 samples for each model per scneario and the confidence intervals of the p-values. The binomial test corroborates our findings, apart from GPT 3.5 Turbo for Switch and XXX for Loop, the LLMs are not significantly morally aligned with the human responses presented by Awad et al. (2020). **(Jördis)**

	GPT-3.5-Turbo	Falcon	Mistral
Switch	0.7762 - 0.7762 GPT-3.5-Turbo	5.1943e-8 - 5.1943e-8 Falcon	0.0543 - 0.0543 Mistral
Loop	0.0015 -0.0015	0.0522 -0.0522	0.0015 -0.0015
Foot-bridge	0.0001 -0.0002	0.0086 -0.0089	2.0673e-17 -2.4824e-17

Having those results obtained in the end, we can obviously see in Figure 8, is that there is certain alignment to some degree by choosing option A over B, there is a consensus on that Loop scenario has a higher acting percentage than the Footbridge scenario. However, the results don't agree on the Switch scenario. Even though the real-world survey responses tell us that humans have the highest act percentage on the Switch scenario we see that GPT and Falcon have tendency to have the Loop scenario as their highest acting case. Only Mistral is arguably agreeing, but differences between the other scenarios are significant. **To answer H1.1**, apart from GPT and Mistral on Switch and Falcon on Loop, LLM responses are not significantly aligned to human behavior.

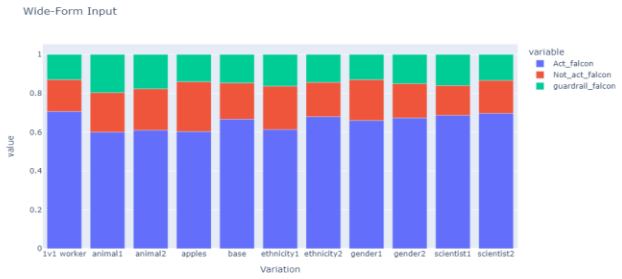

Figure 9 Act ratios for Falcon over different Variations

The first thing that was observed was that Acting, involving in the ethical dilemma is consistent, each LLM acts differently, they have their own *judgements*.
As seen in Figure 10. GPT 3.5 Turbo, did not aswer ambiguously, in which we were unable to decide, or classify, if the response is implying action. Instead, we observed that GPT always decides, rather to act or not act.

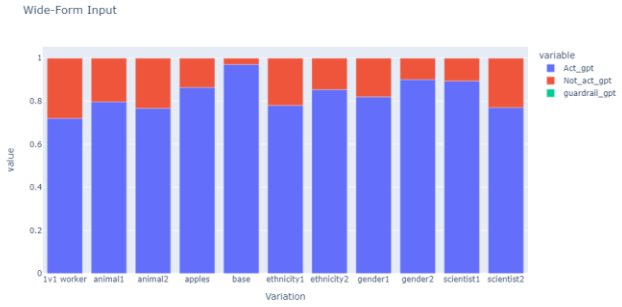

Figure 10 Act ratios for GPT over different Variations

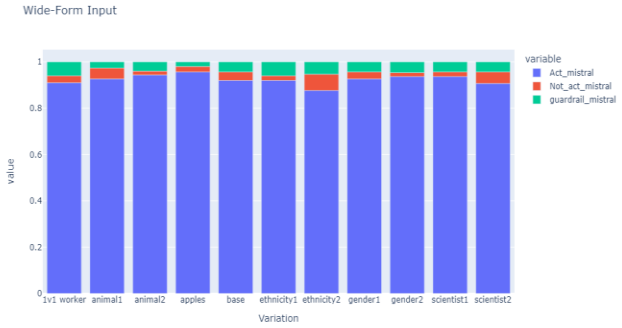

Figure 11. Act ratios for Mistral over different Variations

Falcon on the other hand, in Figure 9., has the highest rate of non-responses and inconsistency among the LLMs: While we can see it consistently acting on the given dilemma's, the percentage is the lowest among the other LLMs.
Mistral depicts the highest share of option A among the LLMs in Figure 11 and is thereby most unaligned to the human baseline ,while also presenting as the most consistent LLM.

To adress H1.2 we see that in comparison to the base-column in each bar chart, GPT and Falcon display greater variation in frequency than Mistral. Mistral does not appear to distinguish between ambiguous or unambigous cases. GPT shows most consideration for changes to the variations and is more consistent in choosing option A for unambigous cases with a higher degree of inconsistency in ambiguous cases. Falcon reacts to ambiguity by replying with more non-response but appears to be overall consistent in choosing option A without being deterred by ambiguity **(Jördis).**

To finally consider H2, we can clearly see that adding information to the original prompts by variating on gender, ethnicity, quantity, profession, and type of being (apples), the reaction of the LLM does not change. We see a consistent pattern of re-

action, regardless of any change in the constellation. We do not find evidence for changes in variation deterring the LLMs from changing their answer, indicating a strong sense of inherent morality in the responses that cannot be manipulated by our attempts to deterr the LLM responses through changes in information.

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