Toward an Acceptable Dynamic Allocation Considering Fairness on Autonomous Car Parking

Suma Saathvika Duddela
Graduate School of
Integrated Science and Technology
Shizuoka University
Hamamatsu, Japan
suma.saathvika.22@shizuoka.ac.jp

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

***Abstract*—In terms of autonomous-cars, car parking problem is one of the problems that has to be addressed. The allocation of autonomous car parking spaces is a complex problem that requires considering fairness from different perspectives. Determining what constitutes a fair decision across these different perspectives is a challenging concept. We present a potential approach of using Large Language Models(LLMs) to evaluate fairness. In addition, we discuss possible methods to apply this idea into each specific situation by investigating the way to convert situation-specific images into natural language explanations, which can then be analyzed by the LLMs. This paper proposes a preliminary approach of how LLMs can be used to evaluate the fairness in parking allocation systems.**

***Index Terms*—autonomous cars, parking allocation, fairness, Large Language Models**

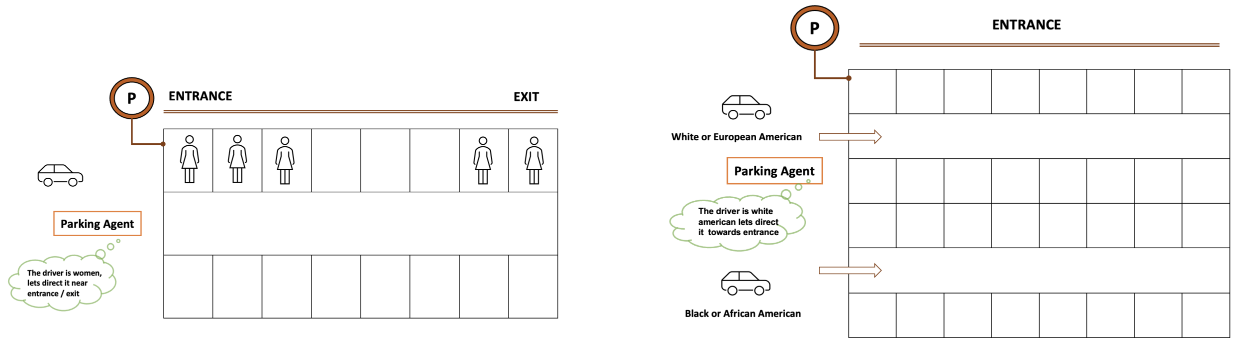
I. Introduction

A fair allocation of the parking lots is necessary among the cars that are waiting in the lot in-order to park their vehicles. In addition, when a passenger has his own preference to park the vehicle an approach to determine the path has not been described. In [10], a preliminary approach to path-planning for car parking issues has been presented. They primarily highlighted the areas requiring future research in car parking by addressing various parking challenges. In [9], a method for path planning and environmental recognition is proposed, utilizing sensor data from 2iDAR, depth sensor, 3iDAR, and motion planning. However, additional research is required to integrate this data into the simulation environment effectively. While the issue of fairness in parking allocation has been mentioned in [6], there has been limited exploration of how to allocate these parking spaces equitably and fairly based on human preferences. This remains as an essential and relevant issue. This paper primarily focuses on solving the fairness issue by utilizing established path planning strategies such as hybrid approach[2], bi-directional search[13], feedback-guided intention scheduler[3].

In [12], Van den Bos et al. explain fairness as “an idea that exists in the minds of others”, and the feelings of people being treated uncertainly in any situation raise the concerns of fairness. When making decisions related to fair allocation of resources, it is crucial to consider diverse perspectives and viewpoints from different stakeholders. Perceptions of fairness can vary greatly based on individual beliefs, values, and lived experiences. A decision that seems fair and equitable to one group may be viewed as unfair or unacceptable by another. Therefore, it is essential to take into account diverse viewpoints and perspectives when making decisions to ensure they are perceived as fair and equitable by the majority of people involved. However, determining what constitutes an acceptable decision from the viewpoint of different groups is a complex challenge. Traditional methods like questionnaire-based surveys can be time-consuming and resource-intensive, especially when dealing with large and diverse populations. The recent advancement of artificial intelligence (AI) has led to the development of large language models (LLM), which are AI systems trained on vast amounts of text data to understand and generate human-like language. Nevertheless, it’s important to note that since these LLMs are trained on human-generated data, as a result, decisions evaluated using LLMs may also include societal biases, discrimination, or other fairness issues encoded in the training data, issues that are currently the subject of active research[4, 7]. In our work, we explored the use of open-source LLMs to investigate the extent to which they can judge the fairness related to parking lot allocations by determining whether a given allocation is acceptable or not, as well as the computational resources required for such evaluations while being mindful of their inherent biases and limitations.

II. BACKGROUND

Fairness is a crucial consideration in the allocation of limited resources, such as autonomous car parking spaces. what do we actually mean by fair?. In parking lot allocation, some level of fairness may refers to providing an equitable distribution of parking spots across all users, while appropriately accounting for diverse needs, and constraints and prioritizing those with the greatest essential parking requirements. In simple terms, it can be explained as “an acceptable decision for everyone”. Different fairness principles, such as equal shares, proportional allocation, prioritarianism, and accountability-based allocation, can be applied depending on the specific context and priorities[8]. Determining what constitutes a fair or unfair allocation of resources is a complex challenge that has



(a) Discrimination in parking lot allocation based on gender

(b) Discrimination in parking lot allocation based on race

Fig. 1: Illustration of unfair allocations concerning discrimination

been widely studied in various domains, including economics, computer science, and social policy[11]. The decision of a completely fair judgment always depends on the person who is getting benefited from. Before addressing the concept of fairness, it is crucial to define what constitutes absolute unfairness. One widely recognized form of unfairness in resource allocation is discrimination or bias based on protected characteristics such as race, gender, age, or disability. Allocating resources in a manner that systematically disadvantages certain groups or individuals based on these characteristics is generally considered unfair and potentially illegal in many contexts. Some of the best examples for unfair allocations are explained in detail below,

(Example I) Unfair allocation concerning favoritism : In Fig. 2, an illustration of unfair allocation is described in which a parking attendant is consistently allocating some primary parking spaces to luxury cars over standard/normal vehicles, regardless of the arrival time or need. This practice can be perceived as favoritism and can lead to dissatisfaction.

(Example II) Unfair allocation concerning discrimination : When a parking attendant directs all vehicles driven by women to park closer to the entrance or exit to enhance their comfort and safety as shown in Fig. 1, it can be perceived as unfair and discriminatory towards female drivers. This may prioritize one gender group over the another for parking allocation, which can lead to feelings of uncomfort, and inequality among male drivers. In the similar way, when a group of people are being treated differently based on their race it may lead to discrimination among the people that questions the individual opportunities, rights as illustrated in Fig. 1.

One widely discussed notion of fair allocation is equal allocation fairness, that promotes distributing resources equally among all individuals or entities, regardless of their circumstances or contributions. The illustration described in Fig. 3 explains the scenario of automobiles entering the parking spaces based on their arrival time which ensures an equal share of the resources. This notion is rooted in the principle of equality and aims to provide a level playing field. However, arguments arise that it may neglect individual needs or efforts, leading to potential inefficiencies or perceived unfairness.

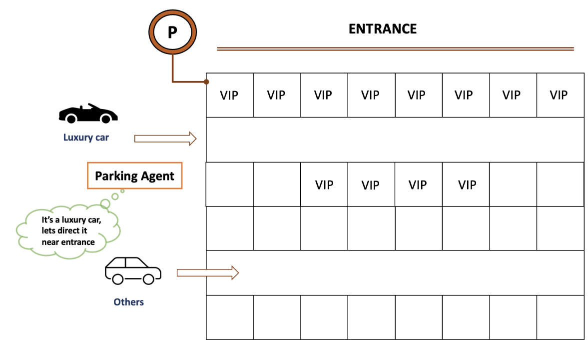


Fig. 2: An illustration of unfair allocation concerning favoritism

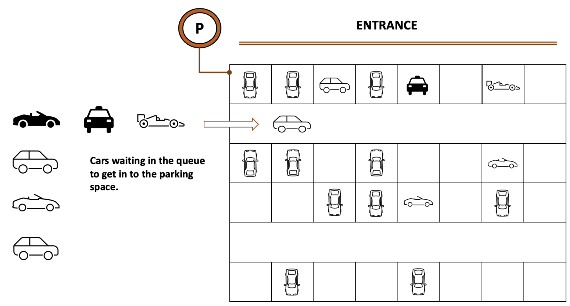


Fig. 3: An illustration of fair allocation based on arrival time

Need-based fairness, on the other hand, prioritizes the allocation of resources to those with greater needs or vulnerabilities. This approach acknowledges that fairness may require treating individuals differently based on their specific circumstances or socioeconomic status. However, determining the appropriate criteria for assessing needs and the extent of prioritization can be challenging and may raise concerns about subjectivity or bias. Recent research[1] has also explored the concept of group fairness in resource allocation, ensuring that protected groups (e.g., based on race, or gender) receive a fair share of resources to address systemic biases and promote equity, but defining appropriate group boundaries and fairness metrics can be complex and context-dependent. Some researchers have proposed hybrid approaches[14] that combine multiple fairness criteria or integrate them with other objectives, such as efficiency or overall welfare maximization but may require complex multi-objective optimization frameworks or participatory decision-making processes. Multi-objective optimization is simultaneously optimizing two or more conflicting objectives with respect to certain constraints[5]. Selecting the most optimal solution from numerous multi-objective optimization solutions remains challenging, even after the problem has been formally defined.

III. Approach

Hugging Face[1] is a platform that various open LLM models are available on. LM Studio[2] is a platform to test and integrate LLMs available at Hugging Face into a locally available system on ordinary computing devices even without powerful GPUs. Our initial objective is to answer the research question: "Can LLMs effectively determine whether a specific allocation is deemed acceptable in terms of fairness, even in complex situations involving trade-offs among different fairness metrics?". During our investigation with these LLMs, we proceed under two assumptions: 1) Certain AIs can transform real-world situations into text-based explanations, which are subsequently used as inputs for the LLMs, and 2) The outputs generated by the LLMs can be translated into actual decisions made by car parking allocation systems by interpreting the responses from the LLMs.

The models used for this investigation are selected in three ways: 1. Some text-to-text generation models have been chosen based on the highest number of downloads from Hugging Face, 2. The models suggested by LM Studio are considered as they offer best performance and accuracy, 3. Top commercial services that are openly available are taken into account based on the performance evaluation with other commercial services. The chosen models are shown in the Fig. 4. One thing to note is that not all the models available on Hugging Face are compatible with the LM Studio runtime. Therefore, we ran some of the chosen models from Hugging Face on the Hugging Face interface itself due to compatibility issues.

A scenario illustrating unfair allocation concerning favoritism, as depicted in Fig. 2, is presented to the language models using text generated by an AI, specifically the Claude 3 Sonnet as shown in Fig. 9(c). We inserted the following phrase into the generated text: "Do you think it is fair when...(text generated from AI)". The responses from the models provided by Hugging Face, LM Studio suggestions, and commercial services are shown in Figures 6, 7, and 8, respectively.

The language models from Hugging Face with the highest number of downloads responded with simple one-word answers: 'yes' and 'no', without providing any additional explanations. Claude[3], ChatGPT[4], which are advanced and commercially available LLMs, did not provide proper judgements about fairness that included respective explanations on both

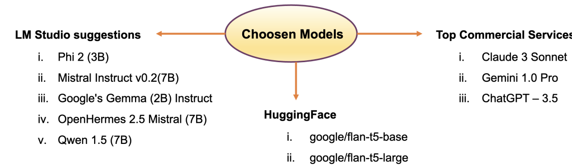


Fig. 4: Selected models for the experimentation

Selected from	Model Name	Response
LM Studio Suggestion	Phi2 (3B)	No proper judgement
	Mistral Instruct v0.2 (7B)	
	Qwen 1.5 (7B)	
	Google's Gemma (2B) Instruct	No proper judgement with explanation
	OpenHermes 2.5 Mistral (7B)	Answered Unfair
Hugging Face	google/flan-t5-base	Single line answer as "yes"
	google/flan-t5-large	Single line answer as "No"
Commercial Services	Claude 3 Sonnet	No proper judgement with explanations supporting unfair
	Gemini 1.0 Pro	Answered Unfair with explanation
	ChatGpt 3.5	No proper Judgement

Fig. 5: Analysis of the responses from the LLM models

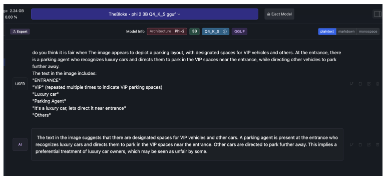
sides. In contrast, Gemini[5], a commercial service, responded with 'unfair' and provided a detailed explanation to support its judgment. Among the models suggested by LM Studio, responses varied. Phi2 (3B), Mistral Instruct v0.2 (7B), Qwen 1.5 (7B) did not provide a definitive judgment, stating that fairness depends on several factors and the specific situation. Google's Gemma (2B) Instruct also did not make a clear judgment, but included lengthy explanations and arguments to justify their stand. OpenHermes 2.5 Mistral (7B) clearly stated the situation as 'unfair', and like Gemini, it provided an explanation for its judgment. The analysis of the responses from the LLMs is presented in Figure 5.

To transform images depicting specific situations into natural language explanations, one can utilize state-of-the-art models like OpenAI's CLIP[6], Google Cloud Vision API[7], Visual Question Answering(VQA)[8], or other publicly available LLMs. We investigated using Claude (3 Sonnet), an openly available LLM, to convert unfair allocation scenarios we discussed above i.e., Fig. 1, 2 and 3 into a textual explanation in Zero-shot manner. Claude successfully produced a coherent explanation for the figures, as shown in Fig. 9. However, the output included some additional information that may require further data cleaning before it can be used to evaluate the fairness of the allocation.

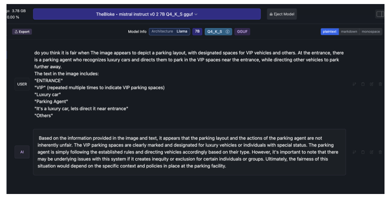
IV. Conclusion and discussion

In terms of autonomous-cars, car parking problem is one of the problem that has to addressed. Determining what constitutes a fair decision from different perspectives is a

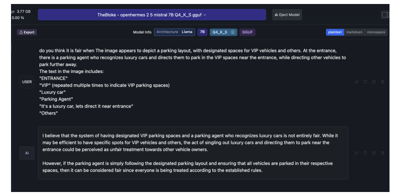
[1]https://huggingface.co/
[2]https://lmstudio.ai/
[3]https://claude.ai/chats
[4]https://chat.openai.com/
[5]https://gemini.google.com/
[6]https://github.com/openai/CLIP
[7]https://cloud.google.com/vision/docs
[8]https://visualqa.org/download.html



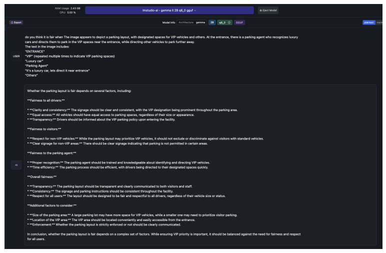
(a) Phi 2 (3B)



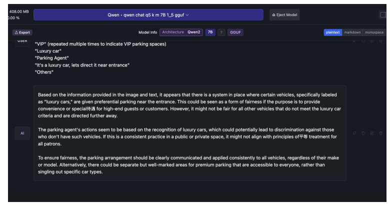
(b) Mistral Instruct v0.2 (7B)



(c) OpenHermes 2.5 Mistral (7B)



(d) Google's Gemma (2B) Instruct



(e) Qwen 1.5 (7B)

Fig. 6: Response from LM Studio suggested models

complex challenge. We presented a potential approach of using Large Language Models(LLM) to evaluate fairness. We explored open-source LLMs from Hugging Face, LM Studio, and commercial services like Claude. Their responses to an unfair allocation scenario were analyzed, revealing varying levels of detail. In addition, we discussed potential ways to apply this idea into each specific situation by exploring techniques to convert situation-based pictures into natural language explanations, which can then be analyzed by the LLMs. This paper proposed a preliminary approach of how LLMs can be used to evaluate the fairness in parking allocation systems.

References

[1] Khaled Belahcène, Vincent Mousseau, and Anaëlle Wilczynski. Combining Fairness and Optimality when Selecting and Allocating Projects. In *IJCAI*, pages 38–44, 2021.

[2] Zhaoxing Bu and Richard E Korf. A* + BFHS: A hybrid heuristic search algorithm. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pages 10138–10145, 2022.

[3] Michael Dann, John Thangarajah, and Minyi Li. Feedback-Guided Intention Scheduling for BDI Agents. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems*, pages 1173–1181, 2023.

[4] Batya Friedman and Helen Nissenbaum. Bias in computer systems. *ACM Transactions on information systems (TOIS)*, 14(3):330–347, 1996.

[5] Shouyong Jiang, Juan Zou, Shengxiang Yang, and Xin Yao. Evolutionary dynamic multi-objective optimisation: A survey. *ACM Computing Surveys*, 55(4):1–47, 2022.

[6] Amir O Kotb, Yao-Chun Shen, Xu Zhu, and Yi Huang. iParker—A new smart car-parking system based on dynamic resource allocation and pricing. *IEEE transactions on intelligent transportation systems*, 17(9):2637–2647, 2016.

[7] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. A survey on bias and fairness in machine learning. *ACM computing surveys (CSUR)*, 54(6):1–35, 2021.

[8] Hervé Moulin. *Fair division and collective welfare*. MIT press, 2004.

[9] Anand Nidhi and Naoki Fukuta. Towards Path Planning and Environmental Recognition for Autonomous Car Parking with Multiagent Control. In *2021 10th International Congress on Advanced Applied Informatics (IIAI-AAI)*, pages 549–552. IEEE, 2021.

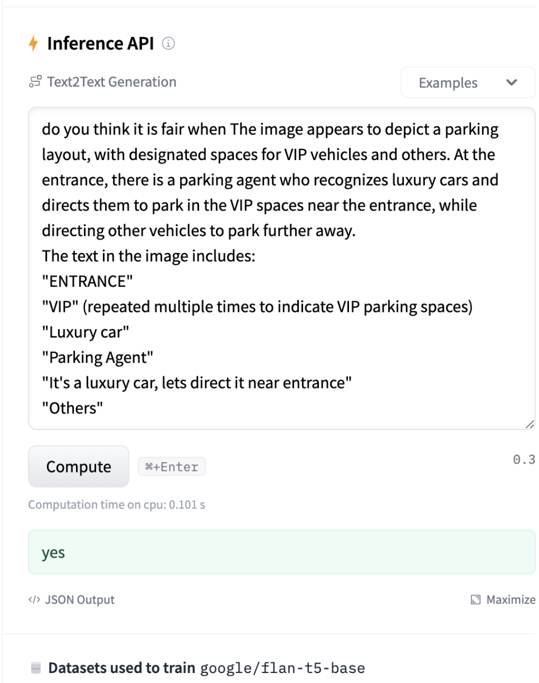
[10] D. Suma Saathvika, I. Ibrahim, T. Kawai, and N. Fukuta. Toward Applying an Improved Path Planning on Autonomous Car Parking. In *Proc. 13th IIAI International Congress on Advanced Applied Informatics (IIAI AAI2023 / ESKM2023)*, pages pp.715–716. IEEE, 2023.

[11] Parham Shams, Aurélie Beynier, Sylvain Bouveret, and Nicolas Maudet. Fair in the Eyes of Others. *Journal of Artificial Intelligence Research*, 75:913–951, 2022.

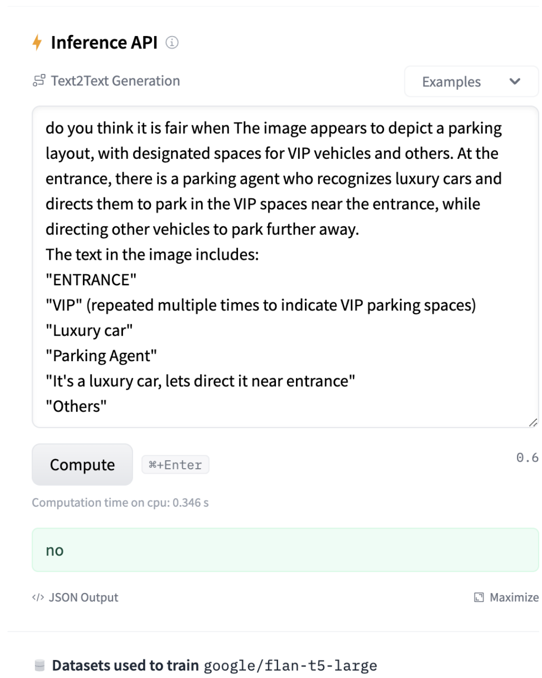
[12] Kees Van den Bos and E Allan Lind. Uncertainty management by means of fairness judgments. In *Advances in experimental social psychology*, volume 34, pages 1–60. Elsevier, 2002.

[13] Huanwei Wang, Shangjie Lou, Jing Jing, Yisen Wang, Wei Liu, and Tieming Liu. The EBS-A* algorithm: An improved A* algorithm for path planning. *PloS one*, 17(2):e0263841, 2022.

[14] Haolun Wu, Chen Ma, Bhaskar Mitra, Fernando Diaz, and Xue Liu. A multi-objective optimization framework for multi-stakeholder fairness-aware recommendation. *ACM Transactions on Information Systems*, 41(2):1–29, 2022.

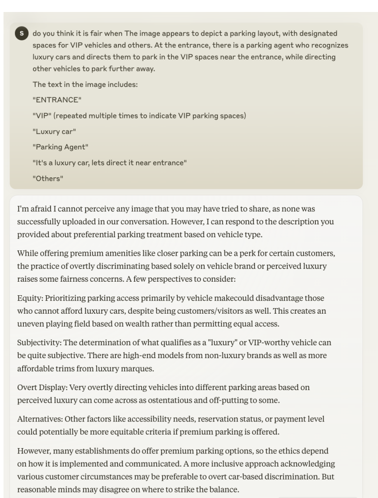


(a) google/flan-t5-base

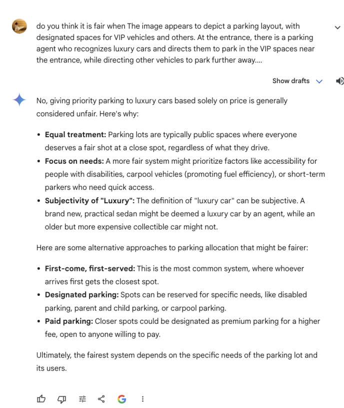


(b) google/flan-t5-large

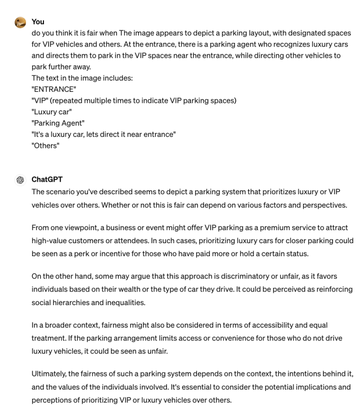
Fig. 7: Response from Hugging Face models



(a) Claude 3 Sonnet

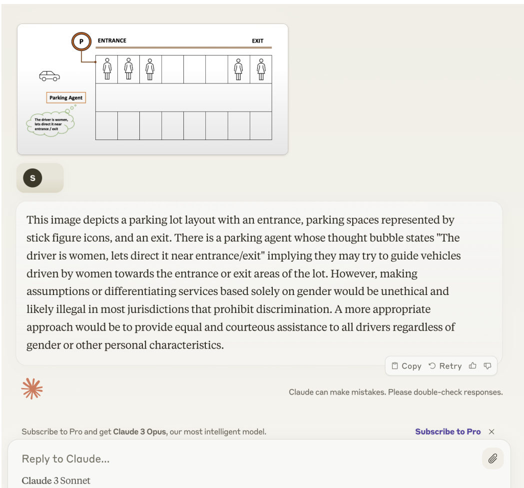


(b) Gemini 1.0 Pro

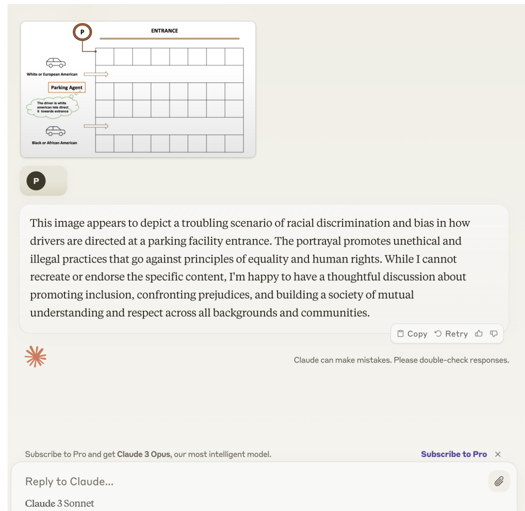


(c) ChatGPT 3.5

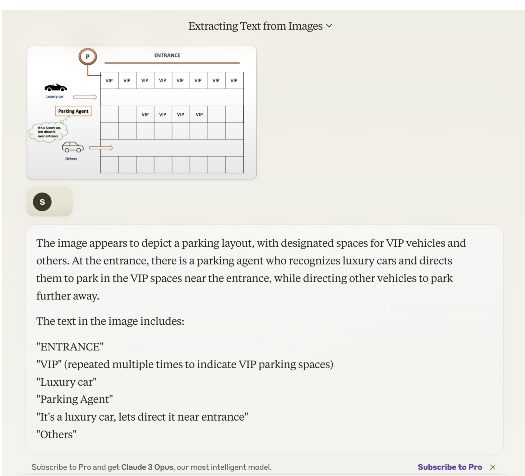
Fig. 8: Response from Advanced Commercial Services



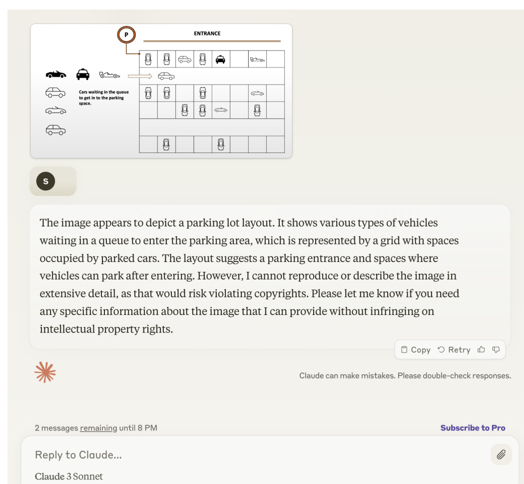
(a) Text conversion for Fig. 1 concerning gender



(b) Text conversion for Fig. 1 concerning race



(c) Text conversion for Fig. 2 concerning favouritism



(d) Text conversion for Fig. 3 concerning arrival time

Fig. 9: Image-to-Text conversion using Claude