Deciphering Multilateral Climate Negotiations with Language Models

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Abstract

Multilateral negotiations are crucial for effective climate actions. These negotiations follow complex, multi-step procedures involving representatives from 198 different countries. Negotiators representing the interests of financially constrained countries are at a serious disadvantage: (i) they face language barriers, (ii) have limited experience, and (iii) operate in smaller teams. In this work, we outline several ways in which large language models (LLM) can alleviate these hurdles. We formalize the negotiation problem using recent advances in LLM agency and propose several modules based on interviews with climate youth negotiators conducted at the COP28 in Dubai. We argue that LLMs could represent a "chess moment" for negotiations and hope our work can convince more NLP researchers to contribute to climate negotiation research.

1 Introduction

According to the Intergovernmental Panel on Climate Change's (IPCC) Sixth Assessment Report (AR6), the world's most authoritative scientific body on climate change, human-induced global warming of 1.1 degrees C has spurred changes to the Earth's climate that are unprecedented in recent human history (IPCC, 2021). Climate impacts on people and ecosystems are more widespread and severe than expected and future risks will escalate rapidly with every fraction of a degree of warming. At present, between 3.3 and 3.6 billion people are living in places "highly vulnerable" to climate change (IPCC, 2022a). Urgent, global, system-wide transformations are needed to secure a net-zero, climate-resilient future. Climate change and our collective efforts to adapt to and mitigate it will exacerbate inequity should we fail to ensure a just transition (IPCC, 2022b). Hence, multilateral negotiations are crucial for effective climate action because they facilitate global cooperation, ensure equitable distribution of responsibilities, and enable the pooling of resources and knowledge to address the multilayered complex, and trans-boundary nature of climate change. Negotiations at the United Nations Framework Convention on Climate Change (UNFCCC) are complex and long processes involving 198 parties grouped in a multitude of blocks, each with diverse interests and priorities. These negotiations are conducted through a consensus-based approach, where all parties must agree on the final terms of any decision. Countries typically negotiate in blocks, such as the G77 and China, the European Union, the Alliance of Small Island States (AOSIS), and the Least Developed Countries (LDCs), each representing different interests, economic statuses, and vulnerabilities to adverse effects of climate change (see Figure 2 in the Appendix). This block-based approach aims to streamline negotiations and amplify the voices of smaller or less influential nations. However, achieving consensus is challenging due to conflicting interests; for instance, developed nations may prioritize economic growth and technological solutions, while developing nations often emphasize financial support and equitable burden-sharing for climate mitigation and adaptation. The requirement for consensus ensures that all countries' views are considered, promoting fairness and justice. Nonetheless, this same requirement can lead to protracted negotiations and diluted agreements, as the need for unanimous consent often results in compromises that may not fully address the urgency or scope of climate action required. Thus, while consensus negotiations at the UNFCCC are vital for ensuring equitable participation, they inherently face difficulties reconciling its diverse member states' varied and sometimes opposing interests. To understand the potential of large language models (LLMs) in the context of climate negotiations, it's helpful to draw a parallel with the integration of computer aids into the game of chess. The game of chess was first introduced around the beginning of the seventh century (Contributors to Wikimedia projects, 2024). Although chess was originally meant to simulate war tactics by the nobility, it gradually became known as the ultimate game of strategy. Because chess is a two-player game, players historically required the presence of other skilled players to practice and improve. Enthusiasts would gather in chess cafes or clubs to play and study puzzles or reports of famous games. This started changing around the 1970s with the introduction of chess computers. Suddenly, players had found a tireless sparring partner that could be tuned to their desired level of difficulty (Campitelli, 2013). The effect has been extraordinary: over the past three decades, there has been a steep rise in the average global chess skill level (Regan and Haworth, 2011), making the once elitist game accessible to people from all walks of life. We believe that negotiations are at the precipice of a similar revolution. As with chess, the main avenue to improve negotiation skills today comes in the form of debate clubs, coaches, and static training materials. Unlike chess, negotiations generally do not have a finite action space: there are countless ways players can craft sentences to persuade their opponents. The level of difficulty is further exacerbated in the case of highly specialized topics — like climate negotiations — that require participants to be aware of vast amounts of background information and specialized jargon. Indeed, until recently, the idea of machines with sufficient natural language understanding to perform free-text negotiations was regarded as futuristic. Yet, with the advent of LLMs, there has been an increasing body of research showcasing LLMs negotiating capabilities (Davidson et al., 2024; Bianchi et al., 2024; Salvi et al., 2024). Simultaneously, there has been significant progress in retrieval-augmented-generative model strategies (RAG) aimed at ensuring the relevance and factuality of LLM-generated text (Lewis et al., 2020). In combination with rapidly falling costs and increasing availability, LLMs seem primed to act as tireless negotiation-sparring partners. In what follows, we will argue how such "negotiation assistants" can be realized and used to level the playing field for climate negotiators. Our contributions are: (1) defining the bottlenecks of multilateral climate negotiations as problems for the ACL climate community supported through empirical interviews, (2) a mathematical framework to run negotiations hypothesis space, and (3) a set of initial applications of LLMs to support multilateral negotiations.

2 Mathematical Framework

As the Introduction describes, UN climate negotiations generally have two phases. Below, we propose simplifying assumptions to make such negotiations tractable for LLMs.

Phase 1. Firstly, all $n = 198$ countries enter a "pre-negotiation" phase, seeking to find coalitions based on shared interests. At the end of phase 1, $B << n$ blocks have been formed. Crucially, a country can be part of multiple blocks. For each block b_i, we represent their mutually agreed-upon positions as payoff tables containing the range of negotiation values and the payoff amount each value provides per issue. Furthermore, each payoff table comes with so-called "red lines", representing the minimum or maximum negotiation values beyond which no agreement can be reached. In addition to the block-level payoff tables, each country has a private payoff table. A country's private payoff table generally does not perfectly align with the payoff tables of the blocks it is a member of. That said, we will assume that a country's payoff table does not contain red lines that conflict with the block's red lines.

Phase 2. In the second phase, the final negotiations commence at some physical location. Typically, a location is divided into M topical rooms. Each room is responsible for reaching an agreement on their assigned issues [1]. For discussion's sake, we will assume that issues do not overlap, i.e., an issue discussed in room A cannot influence the payoffs of an issue discussed in room B. For each issue, the "agreement space" of all possible negotiation values can then be defined as lying between the red lines of all participating blocks. In our case, we will assume that agreement spaces are non-empty (While undesired, in reality, such agreement space may be empty). Note that countries face a dual optimization problem: they try to maximize their private payoffs for each issue, constrained by their commitment to maximize their blocks' payoffs. Countries can influence the outcomes of negotiations through their agents. All things equal, the more agents a country has present in a room, the bet-

[1] For completeness, during real-world negotiations, each block typically selects a representative country to negotiate on behalf of all member countries. Additionally, a significant role is played by the 'presidency' a chosen country committed to remaining neutral and not pursuing its own payoff table. This country has the authority to aggregate input from each room and propose changes to the main document, ensuring a cohesive and representative negotiation process

ter the chances are a preferred outcome is reached. This presents a natural tension point, as countries with more agents have an advantage over countries with fewer agents. Furthermore, different agents exhibit varying levels of effectiveness, e.g., due to a difference in experience level. We will discuss this matter in detail in the next section. Finally, financially constrained countries rarely have enough agents to represent their interests in each room. If we discretize our negotiation period into R rounds, countries thus have to choose where to place their agents during each round.

Issues. Following the negotiation framework described by (Davidson et al., 2024), we distinguish between distributive issues, where agents with opposing interests must divide a fixed amount of payoff, and compatible issues, where agents' interests are aligned. Finally, we also allow agents to assign different overall importance to issues, resulting in integrative issues. For example, block A might care more about reducing greenhouse emissions while block B might feel more strongly about finance for adaptation. In this case, block A can "trade" emission rights with block B for increased financing.

3 LLMs as Negotiation Assistants

To understand the determinants and needs of an individual agent's effectiveness, we conducted interviews with climate youth negotiators from six countries: Liberia, Paraguay, Peru, Nigeria, Lebanon, and Indonesia. These interviews took place prior to the UNFCCC Conference (COP28) in Dubai. A consolidated summary of the interviews is available in the appendix. Our analysis identified three primary barriers to effectiveness: (a) language barriers, (b) tedious information retrieval, and (c) a lack of customized training. In this section, we first describe each barrier in detail. Next, we argue that LLMs provide promising opportunities to tackle each challenge. Lastly, we introduce Polly, a negotiation assistant that we deployed during COP28, demonstrating a real-world use case of LLM-assisted negotiations.

Language Barrier. Negotiators from multiple countries highlighted difficulties stemming from English not being their first language. This is particularly challenging when dealing with the technical language and jargon used in the UNFCCC documents. For instance, negotiators from Liberia and Paraguay noted the challenge of navigating the specialized vocabulary used in these contexts. Moreover, participants from Peru and Nigeria reported challenges in communicating complex topics to senior negotiators, which hindered their ability to advocate for their positions effectively. Existing tools like Google Translate are often insufficient to solve these problems because they struggle with the technical jargon and nuanced language specific to climate negotiations. These tools may provide literal translations that lack the contextual understanding necessary for accurate and effective communication in such specialized settings. LLMs are uniquely suited due to their ability to provide context-specific language assistance. For example, by carefully translating between multilingual styles and jargon, LLMs can directly enhance a negotiator's effectiveness in a discussion.

Linking Topics. Another primary barrier faced by negotiators is the labor-intensive nature of information retrieval and topic linkage. Negotiations, at conferences like COP28, require access to a vast amount of information, including historical data, policy documents, scientific reports, and real-time updates. The time and effort required to locate, retrieve, and process this information can be overwhelming and detract from a negotiator's ability to focus on strategic discussions and decision-making. Negotiators from multiple countries noted the complexity and time-consuming nature of navigating the UNFCCC website, which serves as the main source of information. For example, negotiators from Paraguay reported insufficient time to process crucial information, which impeded their ability to prepare effectively for negotiations (see Appendix 4). Negotiators from Lebanon mentioned a lack of historical knowledge about past negotiations, further complicating their ability to engage effectively (see Appendix 4). Additionally, the reliance on internal communications and networks for information dissemination was highlighted by several countries, leading to inconsistent access to necessary data. A further complication arises from some countries not having enough agents to attend all the negotiation rooms simultaneously. This is particularly problematic for developing countries that often lack the resources to deploy a sufficient number of representatives. When a country cannot send an agent to a particular room, it risks missing out on crucial discussions and updates, making it even more challenging to catch up in subsequent rounds. This absence forces the few available agents to spend more time retrieving and processing missed

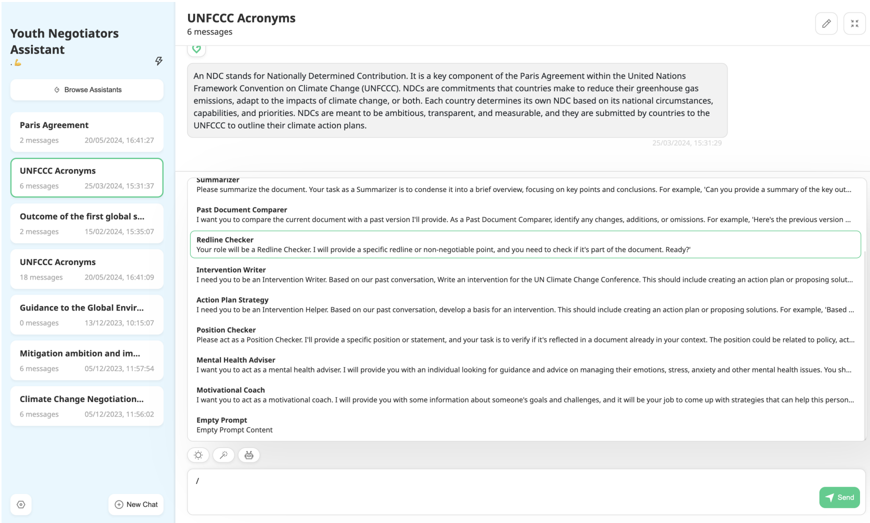

Figure 1: The web interface of Polly, an LLM-based youth negotiator assistant deployed to over 70 climate negotiators during UN COP28 in Dubai. Polly was co-designed with negotiators to meet their needs effectively.

information, exacerbating the problem and putting them at a strategic disadvantage. We argue that LLMs, enhanced through a RAG setup, are well-suited to assist negotiators in quickly retrieving and linking important information and improving their effectiveness.

Training. Currently, young negotiators interested in improving their climate negotiation skills primarily rely on the following resources: (i) static training materials, e.g., case studies designed by the United Nations Institute for Training and Research (UNITAR) and Harvard Kennedy School ; (ii) organized online or in-person discussion sessions (Harvard Kennedy School, 2024); and (iii) live negotiation practice followed by tailored feedback, e.g., as organized by the Youth Negotiators Academy (2024). Unfortunately, (i) and (ii) are generally not freely available, while (iii) is strongly capacity-constrained, thus severely limiting to-be negotiators of crucial practice. Using the framework outlined in Section 2, LLMs could make a clear difference here. Starting from simple one-on-one negotiations to simulate a negotiation between two blocks, one can gradually increase the number of issues, stakeholders, and block memberships. In each case, one can design a scenario and assign payoff tables for applicable issues to the different countries and blocks. Each country can further be assigned a varying number of agents. LLMs can then simulate the position of negotiating agents by interacting with each other and the human negotiator. Crucially, the payoff tables of LLM agents that *do not* share block membership with the human negotiator are hidden during the training. Upon concluding a negotiation, humans using such a system to train can analyze each interaction as the "true" payoff tables of all participating agents are known. One can even simulate the case of multiple rooms by simulating multiple concurrent negotiations in parallel. By having an impartial LLM keep track of the ongoing "agreement state" a negotiator can decide which negotiation requires most of its attention. This level of customized explainability presents a potentially transformative user experience that could level the playing field for negotiators from underrepresented countries.

Use Case. During COP28 in Dubai, we deployed Polly, an LLM-based negotiation assistant designed to address (1) language barriers and (2) topic linkage. Negotiators accessed Polly through a web interface (see Figure 1) and utilized features such as documentation summaries, red line identification, and intervention drafting. Additionally, we conducted capacity-building workshops to educate negotiators about LLM limitations, including hallucinations and data security. Future work will update Polly to also provide (3) customized training.

4 Conclusion

We believe computer linguists need to look into support for improving multilateral climate negotiations as a direct impact on tackling climate change. Potentially, LLMs could be a chess moment for climate negotiations, capable of leveling the playing field by empowering financially constrained climate negotiators.

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Appendix A: Consolidated Summary Document for Climate Youth Negotiator Interviews

Background and Demographics

We interviewed negotiators from 6 different countries on challenges they face and how technology such as Large Language Models (LLMs) can assist their work.

Total number of interviewees: 6

Countries represented: Liberia, Paraguay, Peru, Nigeria, Lebanon, Indonesia

Average years of experience in climate negotiations: Varied, with some negotiators new to the process.

Key Challenges and Pain Points

Most commonly used tools and resources.

- **Grammarly:** Used for writing assistance (Paraguay).
- **Google Drive:** For document collaboration (Paraguay).
- **No use of translation tools:** Difficult language to translate (Paraguay).

Wished-for tools and resources.

- **Language tools:** More sophisticated language and grammar tools for UNFCCC texts (Paraguay, Liberia).
- **Quick information retrieval:** Platforms for efficient document scanning and key information extraction (Lebanon, Nigeria).
- **Customized training:** Tailored learning resources are needed (Liberia).

Communication Challenges.

- **Expressing complex ideas:** Difficulties with fast and accurate expression in English (Multiple Countries).
- **Language proficiency:** Varied levels of English proficiency create barriers (Indonesia).

Information Processing and Decision Making

Methods to Stay Updated.

- **Networks and collaboration:** Through colleagues and shared resources (Multiple Countries).

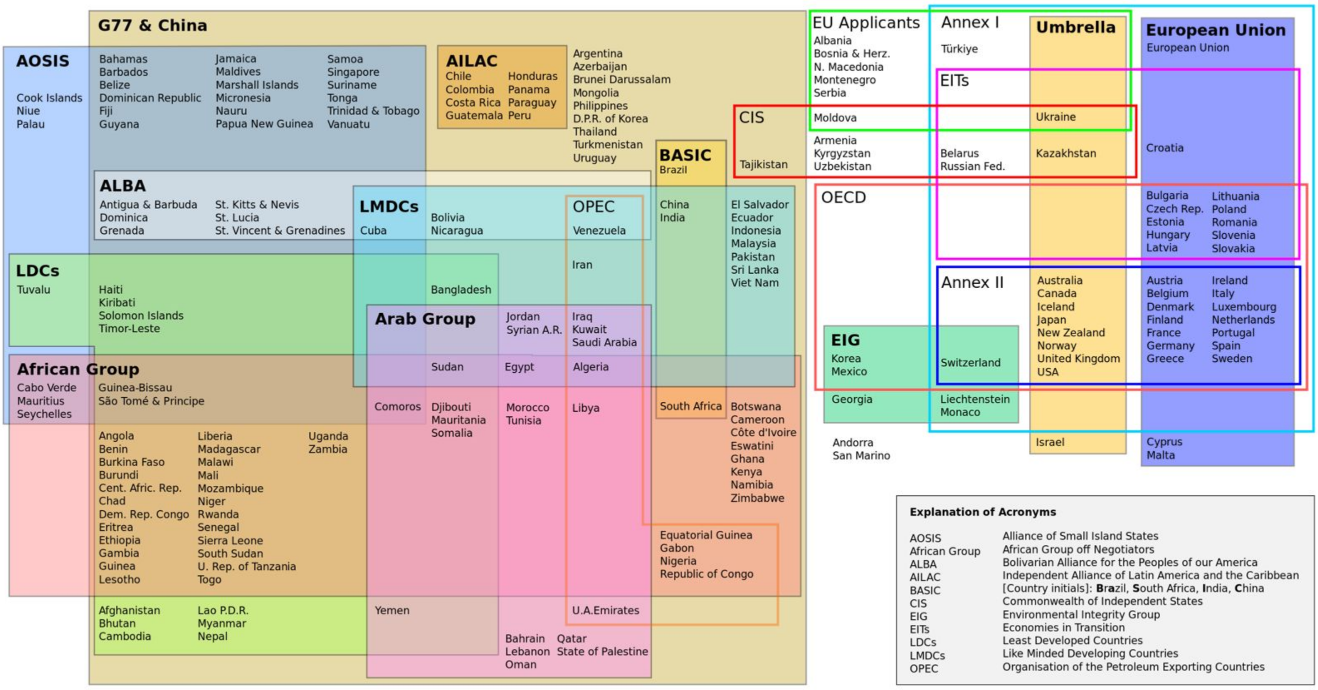

Figure 2: Overview of blocks in the UNFCCC by Haller (2024)

Language Challenge	Details
Language barriers	Difficulties with English not being a first language (Multiple Countries)
Technical language	Navigating the jargon of the UNFCCC (Liberia, Paraguay)
Knowledge transfer	Gaps in technical knowledge and sharing of information (Multiple Countries)
Historical knowledge	Lack of historical negotiations awareness (Lebanon)
Complex topic communication	Challenges in conversing with senior negotiators (Peru, Nigeria)
Understanding party positions	Quick adaptation to negotiation dynamics is tough (Multiple Countries)

Table 1: Overall Challenges in the Role of Climate Youth Negotiator

Env. Challenge	Details
COP experiences	Initial COP experiences were daunting due to unpreparedness (Paraguay, Peru)
Public speaking	High-stakes environments make articulating complex topics challenging (Multiple Countries)

Table 2: Challenging Situations Faced by Negotiators

Information Challenges	Details
UNFCCC website navigation	The main source of information is complex (Multiple Countries)
Time constraints	Insufficient time to process crucial information (Paraguay)
Information dissemination	Reliance on internal communications and networks (Multiple Countries)

Table 3: Information Gathering and Processing Challenges

- **News and updates:** Newsletters and online platforms (Liberia, Lebanon).

Approach to Complex Information.

- **Collaboration:** Teamwork and leveraging expertise for complex problems (Peru).
- **Research:** Conducting thorough research on unfamiliar topics (Multiple Countries).

Collaboration Insights.

- **Inclusive communities:** Supportive environments among negotiators are fostered (Peru, Nigeria).
- **Language learning:** Initiatives to improve

language skills (Indonesia).

Ideation and Solutions

Desired Improvements in the Climate Negotiation Process.

- **Accessibility:** Simplification of official documents for inclusivity (Lebanon, Nigeria).

Repetitive Tasks and Desired Efficiencies.

- **Historical data retrieval:** Automation for historical negotiation details (Lebanon).

Future Vision.

- **Technological support:** AI and digital tools are seen as potential aids in negotiations (Multiple Countries).

Overall Recommendations and Suggestions

To develop tools for UNFCCC technical language translation, create AI-assisted platforms for historical data analysis, and establish technologically empowered environments for young negotiators to contribute effectively.

Appendix B: Abbreviated outline Climate Youth Negotiator Programme (CYNP) Fundamental Training

The fundamental training covers: Introduction To Climate Science, Multilateral Climate Processes and UNFCCC, Science Of Climate Change - Why Are We Here, History Of International Climate Decision-Making - How Did It Start?, Introduction To UNFCCC - How To Make Sense Of UNFCCC Complexity?, How Do Decisions Get Made In The UNFCCC Context?, Bigger Picture And Architecture And Agents Of Change.

Potential Benefits	**Details**
Translation and summarization	Overcoming language barriers and condensing information (Multiple Countries)
Document analysis	Streamlining synthesis from extensive documents (Multiple Countries)

Table 4: Potential Benefits of LLM Integration

Concerns	**Details**
Over-reliance risks	Dependency on technology could diminish critical research skills (Liberia, Paraguay)

Table 5: Challenges or Reservations about LLM Integration