DIAM: Discourse Interaction and Addressee Modeling for Malaysia Hansard

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Abstract

Parliamentary debates are vital records of democratic processes, yet official transcripts such as the Hansard provide only a sequential account of speeches, omitting the underlying interactional structure. Although conducted in a formal setting, debates can become highly dynamic, making it difficult to determine who addresses whom and how utterances relate within the broader discussion. To address these gaps, we introduce DIAM, the first manually annotated discourse resource for the Malaysian Parliament, and the first dataset to jointly support Dialogue Discourse Parsing (DDP) and multi-addressee Addressee Recognition (AR) over long, formal, multi-party debate. Unlike existing DDP datasets, DIAM provides substantially longer conversations and explicit multi-addressee labels. Our benchmark experiments validate that DIAM supports both DDP and AR, while showing that existing discourse parsing methods cannot be directly applied without adaptations such as context-window strategies, and that addressee recognition is challenging due to the large number of participants per sitting. We release DIAM and our code to facilitate future research on formal discourse parsing and addressee modeling: https://anonymous.4open.science/r/DIAM-0D0E

1 Introduction

Parliamentary debates are central to democracy. Official records of these debates, known as Hansard, document how political decisions are made, party positions evolve, and politicians debate laws and policies while representing their constituents interests (Sousa and Lopes Cardoso, 2024; Vladu et al., 2024). Parliamentary debate follows strict procedural norms, including formal honorifics and constituency-based references, with each utterance serving a specific role such as questioning, explaining, or clarifying. However, debates remain highly dynamic, with interruptions, rebuttals, and rapid exchanges that make it difficult to track interactions and the relationship between utterances.

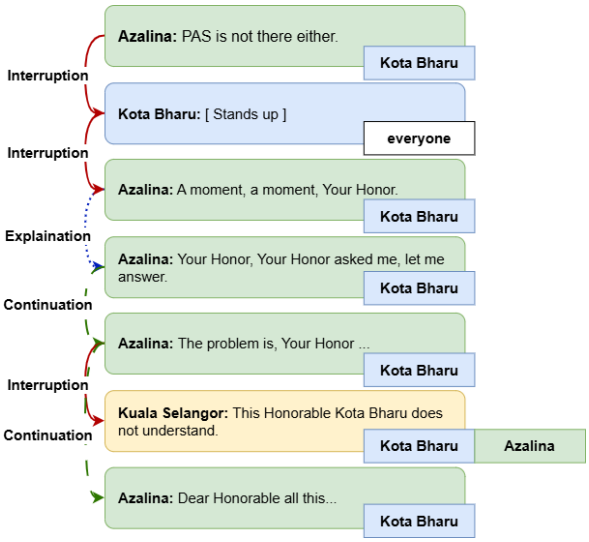

Figure 1: Sample DIAM dialogue excerpt with three participants, showing EUs, their addressees, and discourse relations. Frequent interruptions are visible. Participant names are abbreviated for clarity.

Despite capturing every utterance verbatim, the official Hansard presents parliamentary proceedings as a sequential record of speeches and actions. It does not explicitly encode the interactional structure of debates, such as the contextual function of individual **Elementary Units (EUs)** (speech segments and non-verbal events) or their intended addressees. Consequently, two critical aspects of parliamentary discourse remain implicit and must be inferred computationally:

1. Dialogue Discourse Parsing (DDP): Identifying relationships between EUs, such as question–answer, clarification, and elaboration, to capture how Members of Parliament (MPs) interact during debates.

2. Addressee Recognition (AR): Identifying the intended recipient(s) of each **EU**. Speakers

may address an individual MP, a group of MPs, or the entire House, often without explicit references, making multi-addressee interactions difficult to detect.

To address this gap, we present **DIAM**, a dataset for **D**iscourse **I**nteraction and **A**ddressee Modeling for **M**alaysia Hansard, derived from the Malaysian Parliament Hansard. In Malay, the word *diam* means "be quiet" a fitting reference to the primary language of the Malaysian Parliament and a playful nod to the occasional heated debates that take place within it. To the best of our knowledge, this is the first dataset for the Malaysian Parliament that provides manual annotations for both discourse relations and addressees. The dataset comprises 40 agendas from 31 sittings from 19/12/2022 to 30/11/2023, containing a total of 9,792 elementary units (EUs), where each EU is either an Elementary Discourse Unit (EDU, a verbal segment) or an Elementary Event Unit (EEU, a non-verbal action), all annotated with addressees, and 10,494 discourse relations between the EUs. Through this work, we provide baseline models for DDP and AR, establishing a benchmark for future research on the computational modeling of interactions within the Malaysian Parliament. An excerpt of the DIAM dataset is visualized in Figure 1. The dataset and baseline are available in: `https://anonymous.4open.science/r/DIAM-0D0E/README.md`

2 Related Work

In this section, we review the existing landscape of datasets for Dialogue Discourse Parsing (DDP) (Section 2.1) and Addressee Recognition (AR) (Section 2.2). Our review analyzes these datasets in terms of their theory frameworks, structure and conversation context that helps to plan and build DIAM within the current research landscape."

2.1 Existing Dialogue Discourse Parsing Dataset

Several datasets exist for dialogue discourse parsing, varying in their environmental grounding and theoretical framework. The STAC corpus (Asher et al., 2016) is derived from an online version of the board game *The Settlers of Catan* and consists of strategic, multiparty dialogues involving two to six speakers. Grounded in Segmented Discourse Representation Theory (SDRT), STAC represents dialogue at the level of Elementary Discourse Units (EDUs) and models non-linguistic game actions as Elementary Event Units (EEUs). It supports complex discourse units (CDUs) and non-tree discourse graphs, and its set of 16 discourse relations has laid the foundation for subsequent research (Asher et al., 2012).

Building on this foundation, Molweni (Li et al., 2020) was constructed from the Ubuntu Chat Corpus to provide a larger-scale resource for multiparty Internet Relay Chat (IRC) conversations. Unlike STAC, Molweni targets non-situated dialogue and thus omits EEUs. While it retains the 16 relations from STAC, it employs a simplified, dependency-style version of SDRT that removes CDUs to improve parsing tractability. Similarly, the Minecraft Situated Dialogue Corpus (MSDC) (Thompson et al., 2024) explores situated interaction but focuses on dyadic, task-oriented dialogue where an Architect instructs a Builder. In MSDC, EEUs correspond to Builder actions, and CDUs are used strictly to compress action sequences rather than linguistic material.

Several discourse parsing datasets are related to our work but adopt different theoretical frameworks. The GUM Corpus (Zeldes, 2017) follows Rhetorical Structure Theory (RST) (Mann and Thompson, 1988) and covers a broad range of genres, including interviews from Wikinews. Similarly, the LUNA Corpus (Tonelli et al., 2010) and DiscoGeM (Scholman et al., 2022) adopt a Penn Discourse Treebank (PDTB)-style annotation scheme (Webber et al., 2019). Additionally, many datasets are either limited to a subset of a broader collection (such as GUM and DiscoGeM) or are built in different languages, like LUNA in Italian. Notably, DiscoGeM includes parliamentary speeches from Europarl, including English texts and translations from other European languages, making it thematically related to our work. However, it does not model structured multi-party parliamentary interaction under an SDRT framework.

In summary, existing SDRT-based corpora (STAC, Molweni) target informal online settings, while broader corpora (GUM, DiscoGeM) lack deep multiparty interactional modeling. DIAM extends SDRT-style annotation to situated, formal, face-to-face parliamentary interaction with explicit addressee structure and non-linguistic events.

2.2 Existing Addressee Recognition Dataset

In multi-party conversations, knowing who a speaker is talking to is much harder than in two-person chats. While this is a key task, very few

datasets actually provide labels for group or subgroup targets that simply assume there is only one addressee.

Early research focused on physical meetings. For example, the AMI Meeting Corpus provides manual labels for individuals, subgroups, the whole group, or unknown targets (Jovanovic et al., 2005). These labels were created using extra clues like where the speaker was looking (gaze) and their body language. Similarly, the STAC corpus provides group and individual labels for an online board game setting, but without the extra clues as it is of online interaction (Asher et al., 2012).

Other researchers have used large-scale technical chats, like the Ubuntu-based corpora. However, these datasets are more limited. The Ubuntu Multiparty Conversation Corpus uses a simple rule to guess the addressee based on name mentions in the text (Ouchi and Tsuboi, 2016). Another version, used in the Graph-Structured Network (GSN) model, builds a conversation graph using "@" mentions but does not have explicit human made labels for group addressing (Hu et al., 2019).

In summary, while AMI and STAC offer the best labels for group addressing, they are limited to small meetings or games. This leaves a gap for a dataset like DIAM, which must handle formal parliamentary addressing where there are no "gaze" clues or "@" mentions, and speakers often address specific constituencies or the entire house.

3 The DIAM Dataset

This section describes the development of the DIAM corpus. We detail our data collection and processing approach in Section 3.1, while Section 3.2 outlines the annotation of addressees and discourse relations. Finally, Section 3.3 provides a quantitative overview of the resulting resource.

3.1 Data Collection and Preparation

We collected 40 agendas from 31 sittings of the Malaysian Parliament, covering proceedings from December 2022 to November 2023. The data, comprising verbatim reports of Dewan Rakyat proceedings, is publicly available on the official Parliament of Malaysia website[1] . Unlike DiscoGeM (Scholman et al., 2022), which uses professionally translated Europarl proceedings (Koehn, 2005; Cartoni and Meyer, 2012), our source texts require machine translation into English. We first translated the raw Malay transcripts to English at the passage level using a Mesolitica T5-based translation model (Raffel et al., 2020), prior to any segmentation. Translating before segmentation preserves full sentential context for the translation model and avoids propagating Malay–English structural divergences into unit boundaries. We selected this open, reproducible model because it handles Malay and code-mixed regional varieties while preserving source structure, and produced qualitatively better translations of our parliamentary data than alternative services without relying on proprietary APIs. Only after translation were non-verbal events (e.g., applause or laughter) extracted as standalone EEUs, and the remaining English text split into sentences and segmented into EDUs using SegBot (Li et al., 2018), which identifies minimal coherent units of dialogue conveying a single proposition or communicative function. Each agenda was treated as a self-contained dialogue, resulting in 40 agenda-level documents ready for annotation.

3.2 Data Annotation Process

We hired three Malaysian annotators who are fluent in both English and Malay. We chose local annotators because they are familiar with the Malaysian context and the topics discussed in Parliament. The annotators were selected after an interview assessing their linguistic background and familiarity with parliamentary discourse, followed by a two-hour training phase covering the annotation guidelines with worked examples. Two were assigned as main annotators, while the third served as an adjudicator. Annotators were compensated at RM 60 (Malaysian Ringgit; approximately USD 13) per agenda (document). All annotators provided informed consent prior to the start of the study. They were fully briefed on the annotation guidelines, the intended use of the data, and the public release of the final dataset for research purposes. The main annotators independently annotated all dialogues and cross-checked the translated EUs against the original Malay Hansard to ensure accuracy. The adjudicator resolved disagreements between the main annotators and verified the overall completeness and integrity of the annotations, including ensuring the absence of orphaned nodes or clusters, the absence of backward relations, and that every EU was assigned at least one addressee.

[1] https://www.parlimen.gov.my

3.2.1 Discourse Relation Annotation

Discourse relation annotation follows the Segmented Discourse Representation Theory (SDRT) framework, as adopted in the STAC corpus and subsequent dialogue discourse parsing datasets. As a form of situated dialogue, our dataset consists of both EDUs and EEUs. EEUs correspond to non-verbal actions such as laughter, audience reactions, or technical events (e.g., microphone being turned off). Following standard practice in dialogue discourse parsing, we do not annotate Complex Discourse Units (CDUs).

The main annotators were tasked with identifying and labeling discourse relations between pairs of EUs. For each pair, annotators identified the presence of a discourse relation and assigned the appropriate label from our predefined taxonomy. If no meaningful relation exists, no link is annotated. We extend the standard relation set by introducing an "Interruption" relation, motivated by the frequent occurrence of interruptions in parliamentary proceedings. This relation captures abrupt breaks in discourse flow and is necessary to maintain connectivity in the resulting discourse structure. Detailed definitions for all 17 relations are provided in Table 10 (Appendix A).

Consistent with SDRT, we allow EUs to have multiple parents and multiple children, but disallow self-referential links. The resulting annotations form a directed acyclic discourse graph, where nodes correspond to EUs and edges correspond to labeled discourse relations.

3.2.2 Addressee Annotation

In addition to discourse relations, annotators labeled the intended addressee for each EU. For every EU produced by a speaker, annotators identified the participant(s) to whom the EU was directed. Addressees were selected from the set of active participants in the conversation, defined as speakers who produced at least one verbal or non-verbal contribution within the agenda. An EU could not designate its own speaker as the addressee. This annotation captures interaction structure in multi-party parliamentary dialogue and complements discourse relation labeling.

3.2.3 Inter-Annotator Agreement Results

To assess the reliability of our annotations, we calculated the Inter-Annotator Agreement (IAA) using two standard metrics. For discourse relation links and labels, we report Cohen's Kappa (κ) (Cohen, 1960). For addressee recognition, we utilize Krippendorff's Alpha (α) (Krippendorff, 2011) to better accommodate the potential for multiple annotators and overlapping labels.

Table 2 summarizes IAA over 39 dialogue documents. One document was excluded because it was annotated by a subject expert to serve as the gold standard for annotator reference, rather than independently double-annotated, and therefore is not suitable for inter-annotator agreement computation. For both the Kappa and Alpha metrics, values range from 0 to 1, where higher scores indicate stronger consensus. For addressee annotation, the high α score indicates strong consistency among annotators in identifying the intended recipients of utterances and non-verbal events. Meanwhile, for discourse relation annotation, agreement is high for link detection and moderately high for relation labeling, reflecting the complexity of fine-grained discourse relations.

To contextualise our IAA scores, we compare them with previously reported results where available. For discourse relation annotation, link-level agreement in DIAM ($\kappa \approx 0.77$) is comparable to STAC ($\kappa \approx 0.72$) while falling behind Molweni ($\kappa \approx 0.91$); label-level agreement ($\kappa \approx 0.59$) is similarly comparable to STAC ($\kappa \approx 0.58$) and Molweni ($\kappa \approx 0.56$). When both annotators agreed a link existed, label disagreements centred on Continuation being used as a default relation, with the most frequent conflicts being Continuation vs. Elaboration (n=229) and Acknowledgment vs. Continuation (n=228). The latter typically involved floor-management moves across speaker turns, where one annotator marked a social receipt and the other a structural continuation.

For addressee annotation, we obtain Krippendorff's $\alpha = 0.80$, consistent with prior work reporting Cohen's κ of 0.68–0.81 (Jovanovic et al., 2005), though direct comparison is limited by differences in metric. Disagreements concentrated on non-verbal events (*[Applause]*, *[Laughs]*) and formal parliamentary motions, where annotators differed on whether the Speaker or the whole chamber was the intended recipient, reflecting both domain regularities and the inherent complexity of multi-party dialogue.

3.3 Dataset Statistics

This section provides a quantitative analysis of the DIAM corpus. Section 3.3.1 provides a Dataset Overview, including a comparison with existing

Category	Statistic	DIAM	STAC†	Molweni	MSDC
Corpus Size	Number of Dialogues	40	1,137	**10,000**	540
Speaker Statistics	Mean # Speakers per Dialogue	**9.88**	2.93	3.52	2.00
	Min # Speakers	**3**	2	2	2
	Max # Speakers	**18**	6	9	2
Dialogue-Level Statistics	Avg. # EUs per Dialogue	**244.80**	11.07	8.83	53.14
	Avg. # Relations per Dialogue	**262.35**	10.79	7.82	63.94
	Avg. # EEUs per Dialogue	7.78	0.00	0.00	**21.57**
EU Length (# Characters)	Mean Length	**58.07**	16.49	51.70	23.47
	Min Length	3	1	**8**	1
	Max Length	**554**	100	223	384
Relation Distance	Mean Distance	1.88	**2.02**	1.61	1.88
	Min Distance	1	1	1	1
	Max Distance	**234**	60	12	63

† Linguistic-only version. Situated STAC is omitted.

Table 1: Comprehensive comparison of DIAM against existing DDP dataset.

Annotation	Metric	Mean Score
Discourse Relation	κ_{link}	0.773
	κ_{label}	0.594
Addressee	$\alpha_{\text{addressee}}$	0.803

Table 2: Mean inter-annotator agreement scores over 39 documents, grouped by annotation task, where κ denotes Cohen's Kappa and α denotes Krippendorff's Alpha.

datasets (Section 3.3.2). This is followed by an analysis of Relation Label Distributions (Section 3.3.3), the Number of Addressees (Section 3.3.4), and Relation Distance Statistics (Section 3.3.5). We further examine Non-Tree Structural Properties, Relation-Specific Distance Analysis, and Speaker-Role Discourse Patterns in Appendix B, C, and D, respectively.

3.3.1 Overview

	Total	Train	Val	Test
# Dialogues	40	28	6	6
# EUs	9,792	6,792	1,535	1,465
# Relations	10,494	7,271	1,647	1,576

Table 3: Key statistics of the DIAM dataset, showing the distribution of dialogues, Elementary Units (EUs), and relations across experimental splits.

The DIAM dataset statistics are summarized in Table 3, consisting of 40 agendas with a total of 9,792 EDUs and 10,494 discourse relations. We randomly split the corpus into experimental sets, allocating 28 agendas for training and 6 agendas each for the development and test sets. Although we have a much smaller number of dialogues, the number of EUs and relations are comparable to dataset like STAC. This is because parliamentary debates are usually much longer than online chats, as speakers must follow a formal structure.

3.3.2 Dataset Comparison and Statistics

As shown in Table 1, although DIAM contains only 40 dialogues, each dialogue comprises an average of 244.8 elementary units (EUs) and 262.35 discourse relations, which is several times higher than in other widely used datasets. DIAM also provides a comparable number of EEUs per dialogue to other situated dialogue datasets that include EEU annotations. In fact, 3.18% of EUs in DIAM are actually EEUs.

Moving from volume to linguistic depth, Table 1 shows that EUs in DIAM are generally longer than in most other datasets, with a mean length of 58.07 characters per EDU and a maximum of 554 characters. This is likely due to DIAM being derived from formal, face-to-face dialogues, where utterances are more elaborate and contain more information per EDU compared to online chats or forum discussions. In contrast, datasets such as STAC and MSDC, which include in-game online conversation, exhibit shorter EUs on average, reflecting their concise nature.

Beyond the length of individual units, Table 1 summarizes the relation distance and number of speakers across DIAM and other comparison datasets. DIAM exhibits a higher maximum relation distance (234) compared to other datasets,

reflecting longer-range discourse dependencies within dialogues. It also involves more participants on average, with a mean of 9.88 speakers per dialogue, whereas STAC and Molweni typically include fewer participants, while MSDC is strictly a two-party dialogue. These statistics highlight the multiparty nature and structural complexity of DIAM dialogues relative to other datasets.

3.3.3 Distribution of Relation Labels

Label	%	Label	%
Continuation	30.33	Elaboration	17.51
Acknowledgement	9.90	Result	7.19
Interruption	7.14	Contrast	4.71
Explanation	4.60	Comment	3.32
Question	3.02	Conditional	2.66
Parallel	2.46	Background	2.04
Clarification Q.	1.91	Narration	1.78
Correction	0.70	Alternation	0.46
Q-Elab	0.29		

Table 4: Distribution of discourse relation labels in DIAM.

Table 4 presents the distribution of discourse relation types in DIAM. The most frequent relation is *Continuation* (30.33%), followed by *Elaboration* (17.51%) and *Acknowledgement* (9.90%). *Interruption* accounts for around 7% of the corpus, indicating its notable presence in parliamentary discourse. Overall, the distribution reflects a dominance of *Continuation* and *Elaboration*, which frequently occur during long speeches or extended explanations by MPs. *Acknowledgement*, on the other hand, highlights the turn-taking nature of our corpus, as MPs request permission to speak and the Speaker grants it, producing repeated short signals of understanding or acceptance.

3.3.4 Number of Addressees

# Addressees	Count	Percentage
1	7,947	81.2%
2	436	4.5%
>2	6	0.1%
Everyone†	1,403	14.3%
Total	9,792	100%

Table 5: Distribution of the number of addressees per EU in DIAM. Everyone† refers to EUs directed at the entire assembly.

Table 5 shows the distribution of the number of addressees per EU in the DIAM corpus. Most EUs are directed to a single participant (81.2%), and 4.5% of the EUs are directed to two specific addressees, while a smaller fraction addresses the entire Parliament (14.3%). EUs targeting multiple specific addressees (>2) are extremely rare (0.1%). Despite their rarity, predicting addressees is challenging in DIAM because each session involves a large pool of potential targets (averaging about 10 speakers per session, and up to 18), meaning even single-addressee EUs must be correctly assigned from many candidates. This makes multi-addressee resolution more complex than in most other dialogue corpora.

3.3.5 Relation Distance Statistics

Distance	Count	Percentage
1	8,350	79.57%
2	1,126	10.73%
3	370	3.53%
4	159	1.52%
5	98	0.93%
6–10	206	1.96%
11–99	174	1.66%
$\geq$100	11	0.10%

Table 6: Distribution of relation distances in the DIAM corpus. Distance is defined as the numerical gap between the indices of the source and target units.

Table 6 shows the distribution of discourse relation distances in the DIAM corpus. Most relations (79.57%) connect to adjacent EUs (distance 1), indicating that discourse relations are predominantly local. Relations spanning two EUs account for about 10.73%, while longer-distance relations are relatively rare. Only a small fraction of relations (0.10%) connect EUs separated by 100 or more positions, reflecting the largely sequential and locally connected nature of parliamentary discourse. More detailed analysis of the distances for each relation label is provided in Appendix C.

4 Benchmarking

4.1 Dialogue Discourse Parsing

4.1.1 Experimental Setup

We benchmark DIAM using three approaches: (1) SDDP (Chi and Rudnicky, 2022), a task-specialized, fully supervised structured parser (non-LLM) predicting links and labels over 20-EU windows (stride 10); (2) GPTforDDA (Fan et al., 2024), a prompt-based LLM (ChatGPT-3.5-Turbo) using the full dialogue; and (3) Seq2Seq-DDP (Li

et al., 2024), an open, fully fine-tuned T0-3B encoder–decoder over 8-EU windows, evaluated in end-to-end and transition modes. These baselines span the three dominant DDP paradigms: a task-specialized supervised structured parser (SDDP), an open fine-tuned generative model (Seq2Seq-DDP/T0-3B), and a prompted closed LLM (GPTforDDA). Two of the three are fully open and reproducible. For SDDP and Seq2Seq-DDP, windowing is necessary because DIAM dialogues are lengthier, containing more EUs per dialogue than typical datasets, which poses a unique challenge for fitting the input into GPU memory. Full model configurations, data splits, and evaluation scripts are released for reproducibility (Appendix E).

4.1.2 Result and Analysis

Method	Window	*F1 (Link)	*F1 (L+L)
SDDP	20 (stride=10)	**0.7859**	**0.5212**
GPTforDDA	Full	0.6754	0.1268
Seq2Seq-DDP (end-to-end)	8	0.6352	0.4332
Seq2Seq-DDP (transition)	8	0.0205	0.0145

Table 7: Dialogue discourse parsing baseline performance on the DIAM dataset. *F1 refers to F1-Score. L+L denotes Link and Label agreement.

Table 7 reports overall performance. SDDP achieves the highest link F1-Score, confirming the effectiveness of structured modeling. Seq2Seq-DDP (end-to-end) remains competitive on joint link+label prediction, benefiting from access to gold labels of prior EUs within the 8-EU window, while GPTforDDA performs worst, and Seq2Seq-DDP (transition) collapses due to error propagation.

Link detection versus relation labeling. To explain the large gap between link-only and joint link+label performance, we examine per-relation scores. GPTforDDA attains competitive link-level F1 on frequent relations (Interruption 0.90, Acknowledgement 0.80, Continuation 0.73) but collapses once labels are required (0.09, 0.17, and 0.23 respectively), accounting for its low overall L+L score. SDDP, by contrast, retains most of its link performance after labeling (e.g., Interruption $0.85 \rightarrow 0.64$). This indicates that the prompted LLM baseline can often detect *that* two units are related but cannot reliably identify *which* discourse relation holds in the formal parliamentary register. Across models, *Comment* and *Question-answer_pair* remain the hardest relations (best L+L F1 of 0.22 and 0.34, respectively), consistent with their comparatively non-local nature (19.5% and 51.4% of instances spanning $d \geq 4$).

Distance analysis shows SDDP excels on local links (d=1), whereas Seq2Seq-DDP surprisingly predicts some long-distance links (d=4–8, d $\geq$ 9) despite its 8-EU window (see Table 13 in Appendix F). Appendix G illustrates an example where distant parent EDUs outside the context window are correctly predicted. This highlights a trade-off: structured models provide stable local modeling, while generative models can capture long-range dependencies but are sensitive to accumulated errors.

Setting	*F1 (Link)	*F1 (L+L)
Full-context	0.7048	0.1321
Windowed (20, stride=10)	0.7415	0.2364

Table 8: Vanilla Llama-3.1-8B (no fine-tuning) on the test set, varying only the context regime. The link-F1 difference is within variance (it reverses on the development split); only relation labeling (L+L) improves consistently, across all 12 documents.

Full-context versus windowed parsing. To assess whether DIAM's dialogue length affects LLM-based parsing, we evaluate a vanilla Llama-3.1-8B-Instruct (no fine-tuning) under two regimes: the full dialogue in a single pass versus 20-EU windows (stride 10), with a generation budget large enough to emit a relation for every EU in either regime (Table 8). Link detection is essentially regime-independent: the small test-set gap is within variance and reverses on the development split. Relation labeling, however, improves robustly under windowing, with link+label F1 roughly doubling and windowed parsing outperforming full-context on every one of the 12 development and test documents. Thus, even without task-specific fine-tuning, focused windows do not reliably aid link identification but substantially help a model assign the correct relation label, though absolute labeling quality remains low. For DIAM users, windowing is therefore a useful strategy for relation labeling on these long dialogues, complementing the structural observation that 0.88% of relations (and 9% of Question-answer_pairs) connect EUs farther apart than a 20-EU window.

4.2 Addressee Recognition

4.2.1 Experimental Setup

To benchmark addressee recognition on DIAM, we aim to predict the addressee set for each EU given the dialogue and candidate participants. As a baseline, we adopt a simple prompt-based approach using ChatGPT (gpt-5.2) (OpenAI, 2026). The full dialogue and participant list are provided as input, and the model is instructed to output addressee predictions in a structured JSON format. No task-specific fine-tuning is performed. This design is motivated by the lack of prior work on explicit multi-addressee prediction, as most previous studies focus on single-addressee only (Ouchi and Tsuboi, 2016; Zhang et al., 2018; Le et al., 2019; Gu et al., 2021, 2023); we therefore use a strong general-purpose LLM as a reference baseline rather than a task-specific model. The prompt template is provided in Appendix H.

4.2.2 Result and Analysis

Table 9 shows the result of our simple addressee recognition baseline. The ChatGPT baseline achieves moderate overall performance (F1-Score = 0.37), indicating that addressee recognition in DIAM is non-trivial even with full dialogue access. Performance is high when the addressee is everyone, but drops substantially for single- and multi-addressee cases. Results also degrade as the candidate pool size increases, suggesting sensitivity to search space complexity. These findings highlight the structural difficulty of multi-party addressee modeling in DIAM.

Category	Count	EM	F1-Score
Overall			
Total EUs	1465	0.3611	0.3679
By Addressee Scenario			
everyone	229	0.7904	0.7904
single	1196	0.2910	0.2943
multi	40	0.0000	0.1492
By Candidate Pool Size			
4	141	0.8582	0.8582
7	111	0.5676	0.5676
10	276	0.3587	0.3732
12	262	0.1641	0.1667
16	313	0.4888	0.4909
19	362	0.1381	0.1509

Table 9: Addressee recognition performance on DIAM, reported overall, by addressee scenario, and by candidate pool size.

5 Conclusion

We introduced DIAM, the first manually annotated discourse resource for the Malaysian Parliament and, to our knowledge, the first dataset to jointly support dialogue discourse parsing and multi-addressee recognition over long, formal, agenda-driven multi-party debate. Its novelty lies in pairing substantially longer dialogues than existing DDP corpora with explicit multi-addressee labels, enabling detailed analysis of speaker-target interactions in formal proceedings. Our benchmark experiments validate that DIAM is usable for both tasks, while revealing that existing discourse parsing methods cannot directly handle it without strategies such as context windows, and that addressee recognition remains non-trivial due to the large number of participants. For practitioners building on DIAM, our analysis indicates that windowing aids relation labeling on these long dialogues and that addressee difficulty grows with the candidate pool, pointing to clear directions for future modeling. We hope DIAM serves as a foundation for future research on formal discourse parsing and addressee modeling.

Limitations

Despite its contributions, DIAM has several limitations. First, the data is restricted to Hansard sessions from December 2022 to November 2023, limiting temporal coverage from earlier or more recent sessions. Second, while the Malay-to-English translations were carefully cross-checked and manually corrected by annotators, translation imperfections may still persist. Finally, the baseline experiments are not comprehensive, we evaluate only a selected set of representative methods, and broader benchmarking with additional models may provide a more comprehensive understanding of task performance.

Ethics Statement

According to institutional guidelines, this study did not require formal ethics approval as it involved annotation of publicly available documents and did not involve sensitive personal data.

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A Relation Labels

Relation	Definition
Acknowledgement	B shows understanding or acceptance of A, or signals to move on.
Alternation	Logical OR operation; marks a disjunction between A and B.
Background	B provides context or stage-setting for the event in A (or vice versa).
Clarification_question	B seeks clarification regarding the content of A.
Contrast	A and B share structure but express opposing ideas or negate expectations.
Correction	B identifies and fixes an error in A.
Comment	B provides an opinion or evaluation of the content associated with A.
Conditional	Connects a hypothesis to a consequence (If A, then B).
Continuation	B extends or adds to the content of the previous utterance A.
Elaboration	B provides additional details to A via examples or sub-event listing.
Explanation	B provides the cause or reasoning behind what happened in A.
Narration	Events in A and B occur in a sequential temporal order.
Parallel	A and B share a common theme, property, or semantic structure.
Q-Elab	B is a follow-up question to a prior question A to elicit more info.
Question-Answer Pair	A poses a question, and B provides the corresponding answer.
Result	Shows a cause-effect relationship (A, therefore B).
Interruption	B interrupts A to shift the topic or seize conversational control.

Table 10: Definitions of the 17 discourse relations annotated in the DIAM corpus.

B Non-Tree Structural Properties

Structural Property	Count	Percentage
Multi-parent nodes	746	7.62%
Multi-child nodes	1,779	18.17%
Node pairs with multiple relations	41	0.42%

Table 11: Distribution of non-tree structural properties in the DIAM dataset.

Table 11 shows several structural properties of DIAM. A total of 746 nodes (7.62%) have more than one parent, meaning that a single unit can be linked to multiple earlier units. Additionally, 1,779 nodes (18.17%) have multiple children, indicating that one unit can connect to several subsequent units. There are also 41 node pairs (0.42%) connected by more than one relation, although this is relatively rare. Overall, these statistics show that DIAM is not organized as a simple tree structure. Instead, the discourse graph forms a directed acyclic graph (DAG), where units may have multiple incoming or outgoing connections.

C Relation Specific Distance Analysis

Table 12 presents the distribution of relation distances broken down by relation type. Consistent with the overall statistics, most relations exhibit strong locality, with a median distance of 1 and the majority of instances occurring at distance 1. However, several relation types show comparatively higher proportions of non-local links ($d \geq 4$). In particular, Question-answer_pair stands out with a median distance of 4 and 51.4% of instances occurring at $d \geq 4$, reflecting the fact that answers in parliamentary discourse may be delayed or embedded within extended turns. Other relation types with noticeable long-distance proportions include Clarification_question (20.5%), Comment (19.5%), Correction (9.6%), Elaboration (8.4%), and Acknowledgement (8.3%). These patterns suggest that while the discourse structure is predominantly local, interactive and dialogically responsive relations are more likely to span larger distances.

D Speaker-Role Discourse Patterns

Parliamentary debate is moderated, inducing a structural asymmetry between the Chair (the Speaker of the House) and ordinary MPs. Partitioning source EUs by speaker role (2,270 Chair vs. 8,224 MP), the Chair produces proportionally far more *Acknowledgement* (16.3% vs. 8.1%) and *Interruption* (10.1% vs. 6.3%) relations, consistent with a floor-management role of granting turns and curbing digressions. Conversely, MPs dominate the argumentative relations *Elaboration* (19.8% vs. 9.2%) and *Contrast* (5.4% vs. 2.4%), reflecting extended position-building turns. This role-conditioned distribution is a distinctive property of formal moderated debate, absent in the unmoderated peer-to-peer settings of STAC and Molweni.

E Reproducibility and Implementation Details

We release the dataset, train/development/test splits, all model configurations, and evaluation scripts at the repository linked in Section 1. SDDP (Chi and Rudnicky, 2022) is trained over 20-EU windows (stride 10); Seq2Seq-DDP (Li et al., 2024) is a

Relation	Median	% $d = 1$	% $d = 2$	% $d = 3$	% $d \geq 4$
Interruption	1	96.7	3.1	0.3	0.0
Conditional	1	93.9	5.7	0.4	0.0
Alternation	1	93.8	4.2	2.1	0.0
Continuation	1	89.0	8.0	2.2	0.8
Background	1	88.8	6.5	2.3	2.3
Explanation	1	85.3	10.4	2.9	1.4
Contrast	1	80.6	14.2	3.0	2.2
Acknowledgement	1	80.1	8.3	3.4	8.3
Q-Elab	1	80.0	13.3	3.3	3.3
Parallel	1	76.0	14.0	4.3	5.8
Elaboration	1	75.1	11.6	4.8	8.4
Narration	1	73.8	16.0	4.8	5.3
Correction	1	61.6	13.7	15.1	9.6
Result	1	61.4	25.9	5.7	7.0
Comment	1	57.8	16.7	6.0	19.5
Clarification_question	1	51.5	15.5	12.5	20.5
Question-answer_pair	**4**	**32.5**	**10.4**	**5.7**	**51.4**

Table 12: Discourse relation distances by type in DIAM. Distance (d) represents the numerical gap between linked EDUs. Relations are sorted by locality (% $d = 1$). While most relations are predominantly local, Question-Answer_pairs are a significant outlier, with a median distance of 4 and over half of all instances spanning 4 or more units.

fully fine-tuned T0-3B over 8-EU windows; GPT-forDDA (Fan et al., 2024) uses ChatGPT-3.5-Turbo over the full dialogue. The vanilla LLM probe uses Llama-3.1-8B-Instruct without fine-tuning, evaluated both on the full dialogue and over 20-EU windows (stride 10), with greedy decoding and a generation budget of 32,768 tokens (required so that a relation can be emitted for every EU in the full-dialogue regime). Addressee recognition uses ChatGPT (gpt-5.2) with the prompt in Appendix H. All discourse-parsing results use the set-based link and link+label F1 described in Section 4.

F Distance-wise F1-score for SDDP and Seq2Seq-DDP

Model	d=1	d=2-3	d=4-8	d≥9
SDDP	0.588	0.285	0.084	0.000
Seq2Seq-DDP	0.532	0.207	0.136	0.236

Table 13: Distance-wise F1-Score (Link + Type) for SDDP and Seq2Seq-DDP. Seq2Seq-DDP shows stronger performance for longer-distance relations despite a smaller context window.

G Example of Long-Distance Relation Prediction

The following excerpt illustrates a long-distance prediction case. Several consecutive EDUs elaborate on edu44, which lies outside the visible 8-EDU input window for Seq2Seq-DDP:

```
[edu61] ...
...
[edu64] ... is Elaboration of [edu44];
[edu65] ... is Elaboration of [edu44];
[edu66] ... is Elaboration of [edu44];
[edu67] ... is Elaboration of [edu44];
[edu68] ... is Elaboration of [edu44];
Predicted answer:
[edu69] is Elaboration of [edu44]
```

H Addressee Prediction Prompt Template

The prompt template used for multi-addressee prediction is shown in Figure 2. Replace the placeholder with the actual prompt text.

```
You are an assistant specializing in dialogue analysis. Given a conversation,
    identify the addressee(s) for EVERY utterance (EDU).

Candidates Pool (possible addressees):
{candidates_str}

Conversation:
{edus_str}

Instructions:
1. For each EDU in the conversation (identified by [edu0], [edu1], etc.),
    identify who the speaker is addressing.
2. The addressee(s) MUST be EXACTLY one or more items from the Candidates Pool
    above.
3. If an utterance is directed to everyone, use "everyone".
4. Multiple addressees are allowed (e.g., ["Speaker A", "Speaker B"]).
5. Return a JSON object with a key "addressees" containing a list of lists of
    strings.

Output format:
{
  "addressees": [
    ["everyone"],
    ["Name 1"],
    ["Name 2", "Name 3"]
  ]
}
```

Figure 2: Prompt template for addressee identification.