IMPACTFUL: Interactive Multi-Persona Analysis for CollaboraTive Framework Using Large Language Models

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Abstract

This study explores the potential of large language models (LLMs) to facilitate collective decision-making processes, with a focus on the legislative decision-making of the National Assembly of South Korea. LLMs are employed to interpret and analyze perspectives from diverse stakeholders, thereby enhancing transparency and public understanding of legislative activities. We propose a novel multi-persona collaborative framework that not only underscores the utility of LLMs as powerful tools for broadening public comprehension of legislative decision-making processes but also lays the groundwork for expanded application across various public governance contexts.

Ⅰ. Introduction

In the realm of organizational operations and public administration, collective decision-making stands as a pivotal yet complex process due to the challenges in integrating diverse stakeholder perspectives and preferences [1]. As these complexities mount, negotiating and converging on cohesive decisions become more difficult. Despite the pivotal role that legislative decision-making processes play in the public sector, access to and understanding of such processes remain elusive for the general public, largely due to the limited availability of detailed, comprehensible information. However, advancements in large language models (LLMs) present a promising solution, as LLMs adeptly handle the subtleties of human language, enabling precise extraction and analysis of massive textual data. Can LLMs play a crucial role in enhancing the public's understanding of legislative decision-making processes, thereby promoting public value? We propose a novel method that broadens the comprehension of collective decision-making in the case of the National Assembly of South Korea. The research questions for this study can be articulated as follows:

RQ1: Can LLMs effectively extract and analyze key thematic elements from extensive documents for in-depth discussion?

RQ2: Can the multi-persona approach of LLMs enhance the transparency and public understanding of legislative decision-making processes?

RQ3: Can LLMs effectively function as zero-shot rankers to prioritize legislative documents based on their relevance to policy outcomes?

Ⅱ. Background

Multi-Persona. Previous research has demonstrated that assigning a specific role, defined as 'persona', to an LLM can enhance its performance [2]. Moreover, a single model can be divided into multiple personas that collaborate to address reasoning-intensive problems [3].

Zero-shot Ranking. Recent studies explore zero-shot learning within the context of LLM ranking. This process involves evaluating the relevance of documents based on the model's implicit understanding of language structures, semantics, and contextual cues. As zero-shot rankers, LLMs provide nuanced insights that improve decision-making through sequential interactive instructions as model inputs, without the prerequisites of additional training [4].

Ⅲ. Multi-Persona Collaborative Framework

Vanilla Prompting. The initial approach utilizes default prompt settings at each stage of an experiment. This method generates outputs via a single inference cycle, where the LLM sequentially extracts key issues from raw data, compares these findings with actual legislative applications, and identifies the most influential statements recorded in the legislative minutes.

IMPACTFUL Prompting. To dissect the collective decision-making processes in legislative texts through zero-shot prompting, we introduce the **Interactive Multi-Persona Analysis for Collaborative Framework Using LLMs**. This framework employs two agents—AnalyzerLLM(①, ②, ④, ⑤) and CollaboratorLLM(③)—assigned to execute the following procedures as depicted in Figure 1: ①*Agenda Mining:* Extract and analyze key issues under discussion from raw data and format it appropriately; ②*Persona Identification:* Identify distinct opinions as multiple personas; ③*Multi-Persona Collaboration:* Derive a consensus based on collaborative dialogue among virtual members; ④*Comparative Validation:* Compare and analyze the discrepancies between the proposed consensus and the actual application of legislation to identify variances; and ⑤*Relevance Ranking:* Evaluate and rank agenda-related legislative statements based on their relevance to the outcomes derived from Comparative Validation step (④).

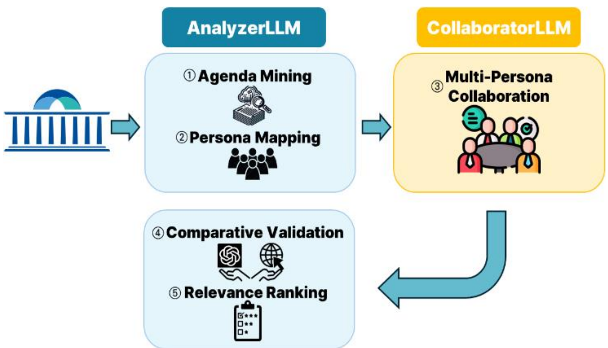

Figure 1. IMPACTFUL framework.

Given an input sequence x and a large language model $\mathcal{M}$, we let a prompt to the input to be p, the final output to be y, and the multiple stages of the process to be z. Under this formulation, Vanilla Prompting and IMPACTFUL Prompting can be described as:

Vanilla prompting: $y = \mathcal{M}_{\mathcal{V}}(x)$

IMPACTFUL prompting:

$$y = \mathcal{M}_{\mathcal{A}}(p_{impact} \parallel x \parallel z_1, z_2, z_4, z_5)$$
$$z_3 = \mathcal{M}_{\mathcal{C}}(p_{impact} \parallel z_2)$$

Ⅳ. Experimental Results

We evaluate the performance on relevance ranking in terms of NDCG using National Assembly Minutes datasets (https://losi-open.nanet.go.kr/main.do). Table 1 summarizes the performance comparison of our method using the case of “Minutes of the 20th National Assembly Standing Committee on Trade, Industry, Energy, SMEs and Startups" in 2018.

Table 1. Performance comparison on ranking.

	Vanilla Prompting	IMPACT Prompting	
		Zero-shot	Few-shot
NDCG	0.703	0.858	0.95

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