# Comparative Personalization for Multi-document Summarization

**Anonymous ACL submission**


## Abstract

Personalized multi-document summarization (MDS) is essential for meeting individual user preferences of writing style and content focus for summaries. In this paper, we propose that for effective personalization, it is important to identify fine-grained differences between users' preferences by comparing the given user's preferences with other users' preferences. Motivated by this, we propose ComPSum, a personalized MDS framework. It first generates a structured analysis of a user by comparing their preferences with other users' preferences. The generated structured analysis is then used to guide the generation of personalized summaries. To evaluate the performance of ComPSum without reference, we propose AuthorMap, a fine-grained reference-free evaluation framework for personalized MDS. It evaluates the personalization of a system based on the authorship attribution between two personalized summaries generated for different users. For robust evaluation of personalized MDS, we construct PerMSum, a personalized MDS dataset in the review and news domain. We evaluate the performance of ComPSum on PerMSum using AuthorMap, showing that it outperforms strong baselines.


## 1 Introduction

Multi-document summarization (MDS) aims to generate a summary with the salient information from multiple documents on a certain topic, such as multiple news articles about an event (Fabbri et al., 2019) or reviews of a product (Bražinskas et al., 2020). However, different users often have different or even conflicting *preferences* of *writing styles* or *content focuses* for summaries (Jang et al., 2023). While writing style refers to the manner or tone in which the summaries are written, content focus refers to which aspects are emphasized when presenting a certain topic. Users can have different preferences for writing style. For example, for product reviews, some users may prefer a formal and analytical tone, while others may prefer a conversational tone. User preferences can also differ on *content focus*. Some users may prefer focus on price and utility of the product while others, might prefer quality and durability. Therefore, to meet these individual user preferences, personalized MDS is essential.

Personalized MDS is related to personalized text generation. Recent works on personalized text generation use Large Language models (LLMs) and assume access to the *profile* of individual users–set of documents previously authored by the user. They then either retrieve related documents from a user's profile (Salemi et al., 2024; Li et al., 2023a), include a summary of the user's profile (Richardson et al., 2023), or tune different models for different users based on their profiles (Tan et al., 2024). However, most of these works only include general features of the user and ignore finer differences between users. To identify the finer differences, it is important to compare a user's profile documents with comparable profile documents written by other users. Ideally, the profile documents of two users can be comparable if they are on the same topic but differ on personal preferences. In general personalized text generation, identifying such comparable profile documents of different users can be difficult since the differences between profile documents of different users can stem from either personal preferences or topic differences. Contrarily, for MDS, since all input documents are about the same topic (e.g. reviews from different users about the same product), their differences are more likely to stem from differences in personal preferences of their authors (users).

Motivated by this, we propose ComPSum (**Com**parative Personalization for Multi-Document **Sum**marization), a personalized MDS framework. Specifically, ComPSum considers two key preference dimensions: writing style and content focus (Zhang et al., 2024). ComPSum first

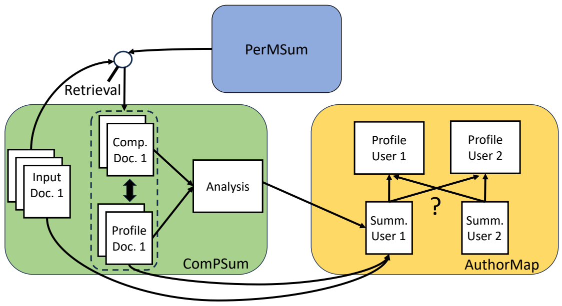


Figure 1: Overview of personalized MDS framework, ComPSum, and reference-free evaluation framework, AuthorMap.

generates a structured analysis of these two dimensions for a user by comparing profile documents with other documents authored by different users on the same topic. ComPSum then uses the generated structured analysis to guide the generation of personalized summaries that capture the user's writing style and content focus.

Apart from generating personalized summaries, their evaluation is also a major challenge. To address this issue, we propose AuthorMap, a fine-grained reference-free evaluation framework for personalized MDS that independently assesses writing style and content focus. To control the inherent differences in writing styles or content focuses between different systems, AuthorMap evaluates the personalization of a system based on the authorship attribution between two personalized summaries generated for different users by the same system. We evaluate the accuracy of AuthorMap on human-written documents in the news and review domain and show that it achieves reasonable accuracy.

For robust evaluation of personalized MDS, we construct PerMSum, a MDS dataset spanning reviews and news domains. For evaluation, we need documents labeled with their authors (users). While there are MDS datasets with user labels in the review domain (Ni et al., 2019), the news domain still lacks such datasets. To construct such a dataset, we use news articles from the All The News dataset [1]. We collect and process 14K document sets and 1.4K users each of whom authored at least 10 documents. These document sets and corresponding author information are then combined with the document sets sampled from the Amazon dataset (Ni et al., 2019) to form PerMSum, which results in 45K document sets and 5.3K users in total.

Using AuthorMap, we find that ComPSum achieves consistent improvement on PerMSum with different LLMs while maintaining other critical qualities of summaries, such as relevance and factuality.

Our contributions are four-fold:

- We propose ComPSum, a personalized MDS framework based on comparative personalization;
- We propose AuthorMap, a fine-grained reference-free evaluation framework for personalized MDS;
- We propose PerMSum, a personalized MDS dataset in the news and review domain;
- We evaluate the performance of ComPSum on PerMSum using AuthorMap, showing that it outperforms strong baselines.

## 2 Related Work

Personalized text generation aims to generate a personalized text for a given user based on their profile documents. Recent works address personalized text generation using user's profile documents. For example, Salemi et al. (2024) retrieve related documents from a user's profile and Li et al. (2023a) train models to summarize and synthesize the retrieved documents. However, one problem with retrieval is information loss. To address this issue, Richardson et al. (2023) include a summary of user profile in addition to the retrieved documents. However, these works generally model user individually. Recently, Sun et al. (2025) use other similar users' profile to infer a user's profile when existing data about the user is sparse. In a recent but concurrent work, Qiu et al. (2025) improve personalized review generation by comparing a user's review with other user's review. However, their design is specific to the review domain and may not generalize well to other domains. We also perform experiments to show that ComPSum outperforms the proposed method in Sec. 7.3.

Most previous works on personalized text generation (Salemi et al., 2024; Ao et al., 2021) use reference-based metrics that evaluate the similarity between generated texts and human-written references, such as ROUGE (Lin, 2004) and BERTScore (Zhang et al., 2019). Recently, Salemi et al. (2025), proposes to evaluate personalized text generation from writing style and content, which are similar to the dimensions used by AuthorMap, but it still needs access to reference

[1] https://components.one/datasets/all-the-news-2-news-articles-dataset/

| |
|---|
| **Style analysis**: User X's writing style is characterized by its concise and straightforward narrative, focusing on delivering information clearly and concisely without excessive embellishment. The texts maintain a neutral yet respectful tone ... |
| **Content analysis**: User X's profile texts tend to focus on personal reflections and positive developments, often highlighting celebrities' growth and empowerment. Unlike other users, User X avoids sensationalism ... |

Table 1: Structured analysis of a user on dimensions of writing style and content focus.

texts. For reference-free evaluation, Wang et al. (2023) propose AuPEL, which evaluates personalization based on pairwise authorship attribution (Bozkurt et al., 2007) between two personalized texts from different systems for the same user. However, AuPEL overlooks various dimensions of personalization and does not control the inherent differences in writing styles or content focuses between different systems. Zhang et al. (2025) uses aspect and sentiment similarity between personalized summaries and user profiles to evaluate personalization. However, their design is specific to the review domain and may not generalize well to other domains.

## 3 Problem Statement

The input of personalized MDS is a document set $D$ containing multiple documents on the same topic to be summarized. For personalization for user $u$, the input also contains a profile $P_u$ containing multiple profile documents $p_u^i \in P_u$ authored by the user $u$. Given these inputs, the output of personalized MDS is a personalized summary $s_u$ of the document set $D$ that capture the individual preference of user $u$ as expressed in their profile $P_u$.

## 4 `ComPSum`

In this section, we describe our proposed framework for personalized MDS, `ComPSum`. We first describe how `ComPSum` generates a structured analysis $a_u$ of a user $u$ that captures their distinctive features of writing styles and contents focuses by comparing with documents written by other users. We then describe how it uses the structured analysis $a_u$ to generate a personalized summary $s_u$.

**Generating structured analysis:** `ComPSum` uses an LLM to generate structured analysis, $a_u$, of a user $u$ from two dimensions: writing style and content focus. Tab. 1 shows an example. `ComPSum` explicitly focuses on these two dimensions so that it only captures preferences but not unrelated information, like a general summary of each profile document. To generate the structured analysis, following Salemi et al. (2024), `ComPSum` first retrieves the top $k$ documents from user $u$'s profiles $P_u$ using a retrieval model $\mathcal{R}$. For the retrieval query, `ComPSum` uses the concatenation of all documents belonging to document set $D$ and retrieves $k$ profile documents most similar to the query: $\mathcal{R}(D, P_u, k)$.

However, generating the structured analysis $a_u$ only based on the retrieved profile documents can make the analysis focus on general features of the user $u$ but ignore finer differences compared to other users. To address this issue, comparing documents on the same topic written by other users can be useful. Therefore, for each retrieved profile document $p_u^i \in \mathcal{R}(D, P_u, k)$, `ComPSum` identifies a set of documents, $C_{\neg u}^{p_i}$, that belong to the same document set as $p_u^i$ (and hence are on the same topic) but are written by different users. `ComPSum` then retrieves one comparative document $p_{\neg u}^i \in C_{\neg u}^{p_i}$ that is most dissimilar to $p_i$ using the retrieval model $\mathcal{R}$. By comparing every pair of profile document $p_i$ and its comparative document $p_{\neg u}^i$, `ComPSum` then instructs an $LLM$ to generate the structured analysis $a_u$ that focuses on distinctive features of writing style and content focus that set the user $u$ apart:

$$a_u = LLM(p_u^1, p_{\neg u}^1, ..., p_u^k, p_{\neg u}^k) \quad (1)$$

**Generating personalized summary:** Using this structured analysis $a_u$ and the retrieved profile documents $p_u^1, ...p_u^k$, `ComPSum` generates a personalized summary $s_u$ for the document set $D$:

$$s_u = LLM(p_u^1, ..., p_u^k, a_u, D) \quad (2)$$

Specifically, `ComPSum` instructs the summarizing $LLM$ to generate a summary $s_u$ that mimics the writing style and content focus based on retrieved profile documents $p_u^1, ..., p_u^k$ and structured analysis $a_u$, while ensuring that the summary $s_u$ includes only contents presented in the document set $D$. We show the prompts used for `ComPSum` in App. A.1.

## 5 `AuthorMap`

In this section, we describe our proposed fine-grained reference-free evaluation framework, `AuthorMap`. `AuthorMap` evaluates personalization along two key dimensions: writing style and content focus. The underlying idea behind `AuthorMap` is that if the generated summary is well-personalized, it will be possible to infer the user's preferences from the summary and use them for the task of authorship attribution. `AuthorMap` considers two profiles, $P_{u_1}$ and $P_{u_2}$, and two personalized summaries, $s_{u_1}$ and $s_{u_2}$, of the same input document set, $D$, generated for user $u_1$ and $u_2$ respectively. `AuthorMap` then evaluates whether each profile $P_{u_*}$ can be correctly attributed to its user based on personalized summaries.

`AuthorMap` performs such evaluation separately based on writing style and content focus. However, users can have different preferences for the two dimensions on different topics. Therefore, when evaluating based on a certain dimension, `AuthorMap` first retrieves the top $n$ profile documents from each user's profile $P_{u_*}$ most similar to the concatenation $s_{u_1}$ and $s_{u_2}$ using the retrieval model $\mathcal{R}$: $\mathcal{R}(s_{u_1} \circ s_{u_2}, P_{u_*}, n)$, where $\circ$ denotes the concatenation. `AuthorMap` uses concatenated summaries instead of just one summary to ensure that no summary has inherent advantages. For simplicity, we use $P_{u_1}$ and $P_{u_2}$ to denote the retrieved profiles. For each retrieved profile $P_{u_*}$, `AuthorMap` instructs a judge LLM to predict which user, $u_1$ or $u_2$, is more likely to be the author of the retrieved profile $P_{u_*}$ given their personalized summaries, $s_{u_1}$ and $s_{u_2}$ for the given dimension:

$$\hat{u}_1 = LLM_{judge}(P_{u_1}, s_{u_1}, s_{u_2}) \quad (3)$$

$$\hat{u}_2 = LLM_{judge}(P_{u_2}, s_{u_1}, s_{u_2}) \quad (4)$$

where $\hat{u}_*$, the predicted author of the profile $P_{u_*}$, can be $u_1$, $u_2$ or tie. If the summary $s_{u_1}$ is well personalized for user $u_1$, the LLM judge will be able to attribute the profile $P_{u_1}$ to user $u_1$. The same should also apply to user $u_2$.

To mitigate positional bias (Huang et al., 2023), `AuthorMap` performs such prediction twice with different orders of $s_{u_1}$ and $s_{u_2}$, which results in four predictions in total. `AuthorMap` evaluates the personalization capability of a personalized MDS system as the percentage of samples where the judge LLM correctly predicts the author of the retrieved profile in the majority of four predictions. A larger percentage value indicates better personalization capability on the corresponding dimension of the personalized MDS system. The prompts for `AuthorMap` are shown in App. A.2.

## 6 `PerMSum`

In this section, we describe how we construct the `PerMSum` dataset. We first describe how `PerMSum` obtains document sets where each document in a set is labeled with a user (its author).We then describe how to select samples from `PerMSum` for the evaluation using `AuthorMap`.

**Obtaining Document Set with User Label:** To obtain document sets with user labels in the news domain, `PerMSum` uses the All the News dataset, which includes details such as author names, publishing media, and publishing dates. However, the news articles from this dataset have two issues for direct application in personalized MDS and its evaluation. First, some news articles contain explicit mentions of the author or media outlet (e.g., "(CNN) – Washington…" or "XXX reports in New York"). These direct mentions can make the system only focus on these shallow features for personalization, and also be undesirable shortcuts for personalization evaluation. To address this issue, `PerMSum` removes all sentences containing author names or publishing media. Second, some news articles have more than three authors or list media organizations as authors. These news articles might not truly reflect the preference of their individual authors. Therefore, `PerMSum` identifies and labels them accordingly so that they are not used as profile documents.

After labeling documents with users, we want to construct document sets–groups of articles about the same event. For this, `PerMSum` clusters the articles into document sets based on token overlap, named entities, and publishing dates, following Liu et al. (2022).

To obtain document sets with user labels in the review domain, `PerMSum` uses reviews from the book category of the Amazon dataset (Ni et al., 2019) following Wang et al. (2023). `PerMSum` then preprocesses the reviews and obtains document sets following Bražinskas et al. (2019). Specifically, `PerMSum` only keeps reviews that are between 50 to 150 words and are written in English. To prevent certain users from dominating the dataset, `PerMSum` additionally filter out reviews written by users who write more than 200 reviews.

For both domains, `PerMSum` only considers users that write at least 10 documents and splits the users into training, validation, and test sets using the user split motivated by Salemi et al. (2024). To prevent information leakage, document sets are also split into training, validation, and test sets. Hence, there is no overlap between users or document sets in the three splits of the dataset. More details of data curation process are in App. A.3.

**Sample selection for AuthorMap:** Each sample for evaluation with AuthorMap requires a document set $D$ and two personalized summaries for users $u_1$ and $u_2$. However, randomly sampling two users from the dataset for evaluation can face the issue of sparsity in personalization (Dong et al., 2024). For example, for a user whose profile documents are all about entertainment news, it can be difficult to get enough from their profile for generating a personalized summary of international news. To alleviate the issue, for each document set $D$, PerMSum only selects pairs of users $u_1$ and $u_2$ who write documents belonging to the document set $D$. However, in such cases, when generating a personalized summary $s_{u_*}$ for a user $u_*$, the personalized MDS systems might identify and copy information from the input documents written by the user $u_*$. To prevent this, we remove all documents written by the users from the input document set. The generated pairs of personalized summaries are then used for evaluation using AuthorMap. To prevent users from dominating the evaluation, PerMSum limits each user to appear in at most 100 samples. Statistics of PerMSum are reported in Tab. 2.

# 7 Experiments

In this section, we describe experiments on AuthorMap and ComPSum.

## 7.1 Implementation Details

For AuthorMap, we use Llama3.3-70b-Instruct (AI@Meta, 2024) as the LLM judge. For authorship attribution, AuthorMap retrieves $n = 5$ profile documents using BM25 (Robertson et al., 1995). All retrieved profile documents are truncated to 100 words so that the evaluation is not based on the length of documents. Motivated by Huang et al. (2024), when evaluating writing style, the prompt additionally instruct the LLM judge to focus on lingustic features like modal verbs and typos.

For ComPSum, we experiment with Llama3.1-8b-Instruct (AI@Meta, 2024), Qwen2.5-14B-Instruct (Yang et al., 2024), and Llama3.3-70b-Instruct. For personalization, ComPSum retrieves $m = 5$ profile documents and corresponding comparative documents also using BM25. The token limit for personalized summaries is 100 words. To match the token limit, all retrieved profile documents are also truncated to 100 words. All LLMs used in experiments use the default sampling parameter. Hyperparameters and prompts are tuned on the validation set.

## 7.2 Evaluation of AuthorMap

In this section, we evaluate the accuracy of AuthorMap. The straightforward way is to evaluate its accuracy on reference personalized summaries, but they are not available. However, for evaluating AuthorMap, reference summaries are not the only choice. Any pairs of documents that are about the same topic but reflect the preferences of the two users can also be used. Therefore, for this evaluation, we use documents from the same document set but written by the two users of interest. To further mimic the setting of AuthorMap, the documents are truncated to 100 words, matching the length of a typical generated personalized summary. We report the accuracy of AuthorMap on human-written documents in the test sets of PerMSum. For comparison, we also report the accuracy of AuthorMap when profile documents $P_{u_*}$ are not retrieved but randomly sampled from user profiles. This setup closely resembles the setting of Wang et al. (2023). The results are shown in Tab. 3.

From the table, we can observe that AuthorMap shows reasonable accuracy on the documents, suggesting that it can reliably evaluate personalization in different dimensions. Besides, AuthorMap outperforms its variant without retrieval, which is used by Wang et al. (2023), showing that retrieval is useful to capture the varying preferences of users on different topics.

In the above setup, the documents to which users were attributed differed on both writing style and content focus. However, they are independent dimensions (Jafaritazehjani et al., 2020) and AuthorMap should be able to evaluate them independently of each other. So, for a more controlled evaluation, we test the accuracy of AuthorMap on paraphrased (to alter the writing style). Specifically, we evaluate the accuracy of AuthorMap on two types of document pairs : $d_{u_1}$ vs $para(d_{u_2})$, and $d_{u_1}$ vs $para(d_{u_1})$, where $d_{u_*}$ denotes the original document written by user $u_*$, $para(d_{u_*})$ denotes a paraphrased document following the writing style of the other user. The first document pair, help us in evaluating from the perspective of the content focus keeping similar styles. The second document pair, help us in evaluating from the perspective of the writing style keeping similar content focus. We use LLama3.3-70b-Instruct to paraphrase the human-written documents to mimic the writing style of the other user based on their profiles. The prompt for paraphrasing is shown in App. A.4. Please note

| | #User | #Doc. Set | #Sample | Prof. Size | Doc. Set. Size | Doc. Len. |
|---|---|---|---|---|---|---|
| News | 828/293/296 | 10730/1393/1463 | -/2085/2360 | 39.72 | 3-10 | 216.72 |
| Review | 2400/763/766 | 27725/1878/1795 | -/2774/2757 | 19.77 | 8 | 86.40 |

Table 2: Statistics of `PerMSum`. We report Numbers of users, document sets, and samples in training, validation, and test sets. We also report average profile size per user, size of input document sets, and length of documents.

| | News | | Review | |
|---|---|---|---|---|
| | style | content | style | content |
| `AuthorMap` | 76.65 | 71.64 | 89.00 | 82.69 |
| w/o retrieval | 75.10 | 68.71 | 87.88 | 81.27 |

Table 3: Accuracy of `AuthorMap` on documents. `AuthorMap` shows reasonable accuracy in this task and outperforms its variant without retrieval.

| | News | | Review | |
|---|---|---|---|---|
| | style | content | style | content |
| $d_{u_1}$ vs $para(d_{u_2})$ | 61.34 | 58.76 | 70.34 | 70.58 |
| $d_{u_1}$ vs $para(d_{u_1})$ | 68.77 | 31.68 | 77.93 | 54.10 |

Table 4: Accuracy of `AuthorMap` on paraphrased human written documents. The changes in accuracy shows that

that the paraphrasing may not be perfect as it can hallucinate and may not completely mimic the writing style of the given user. However, it is sufficient for us to test the independence based on changes in `AuthorMap`'s accuracies. If `AuthorMap` evaluates writing style and content focus independently, `AuthorMap` should show higher accuracy on $d_{u_1}$ vs $para(d_{u_2})$ when evaluating content focus since the document pair has differ in content focus but not much in style. Conversely, when evaluating writing style, `AuthorMap` should show higher accuracy on $d_{u_1}$ vs $para(d_{u_1})$ since the document pairs differ in style but not much in content focus. The results are shown in Tab. 4.

From the table, we observe the desirable pattern: `AuthorMap` shows higher accuracy on $d_{u_1}$ vs $para(d_{u_2})$ when evaluating content focus and higher accuracy on $d_{u_1}$ vs $para(d_{u_1})$ when evaluating writing style. The result shows that `AuthorMap` can evaluate personalization based on either writing style or content focus independently.

### 7.3 Evaluation of `ComPSum`

In this section, we evaluate the qualities of personalized summaries generated by `ComPSum`. To evaluate this, we consider both personalization levels as well as general qualities of summaries. For personalization, we consider two dimensions: writing style and content focus using `AuthorMap`. For general qualities, we consider factuality, which measures whether summaries only contain information supported by the input document set, and relevance, which measures whether summaries only include important information from document sets (Fabbri et al., 2021). To evaluate factuality, we use FactScore (Min et al., 2023). To evaluate relevance, we use G-Eval (Liu et al., 2023). To match the scales of other measures, we map its score to 1-100. We additionally report an overall score, which is the arithmetic average of the four measures. A higher value indicates better overall quality.

Using these measures, we compare `ComPSum` with the following baselines.

**RAG** (Salemi et al., 2024) retrieves profile documents from a user profile and generates a personalized summary following the preference of retrieved profile documents.

**CICL** (Gao and Das, 2024) extends RAG by additionally retrieving comparative documents authored by other users and incorporating them when generating personalized summaries.

**RAG+Summ.** (Li et al., 2023a) extends RAG by first generating a summary of the retrieved profile documents, which is then used with the profile documents to guide generation of personalized summaries.

**DPL** (Qiu et al., 2025) first generates a analysis for each retrieved profile document by comparing its comparative documents. These analyses are aggregated into a profile summary, which is subsequently used to generate the personalized summary.

**Rehearsal** (Zhang et al., 2025) begins with a general summary, which is iteratively refined through a user agent that proposes modifications and a supervisor agent that evaluates them.

More details for implementation of these baselines are shown in App. A.6. We report the results of `ComPSum` and these baselines on the test set of `PerMSum` in Tab. 5.

From the table, we observe that `ComPSum` generally outperforms all baselines on personalization and general summary qualities and also achieves

| | News | | | | | Review | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | style | content | fact. | rele. | overall | style | content | fact. | rele. | overall |
| *Llama3.1-8b-Instruct* | | | | | | | | | | |
| RAG | 54.88 | 49.61 | 98.00 | 96.05 | 71.15 | 55.57 | 54.12 | 98.16 | 92.71 | 72.33 |
| CICL | 56.86 | 48.89 | 97.34 | 95.47 | 71.29 | 59.31 | 55.83 | 96.87 | 88.91 | 73.08 |
| RAG+Summ. | 58.35 | 50.89 | 98.03 | 97.17 | 72.93 | 58.98 | 57.10 | 97.67 | 92.02 | 74.17 |
| DPL | 53.56 | 47.90 | 97.91 | 96.30 | 70.13 | 60.33 | 59.13 | 97.05 | 87.68 | 74.23 |
| Rehearsal | 99.45 | 99.49 | 23.16 | 28.75 | 50.66 | 98.69 | 98.40 | 57.28 | 37.62 | 67.64 |
| CompSum | 60.04 | 53.94 | 98.01 | 95.32 | **74.17** | 63.09 | 57.89 | 98.03 | 91.99 | **75.76** |
| *Qwen2.5-14B-Instruct* | | | | | | | | | | |
| RAG | 55.38 | 48.26 | 98.07 | 96.77 | 70.97 | 57.17 | 51.18 | 97.76 | 91.76 | 71.58 |
| CICL | 55.85 | 48.64 | 97.11 | 96.68 | 71.07 | 59.06 | 55.90 | 96.95 | 88.91 | 73.04 |
| RAG+Summ. | 53.39 | 49.32 | 98.17 | 97.93 | 70.93 | 59.56 | 59.75 | 97.40 | 90.97 | 74.94 |
| DPL | 52.63 | 46.31 | 98.04 | 97.37 | 69.45 | 57.86 | 57.53 | 96.83 | 89.42 | 73.27 |
| Rehearsal | 98.86 | 99.41 | 22.86 | 26.94 | 49.60 | 97.93 | 98.69 | 53.20 | 33.63 | 64.49 |
| ComPSum | 57.63 | 57.08 | 97.96 | 96.58 | **74.69** | 65.37 | 63.92 | 96.51 | 89.98 | **77.61** |
| *Llama3.3-70b-Instruct* | | | | | | | | | | |
| RAG | 43.77 | 36.67 | 98.59 | 97.98 | 62.75 | 45.41 | 41.83 | 98.76 | 93.16 | 64.66 |
| CICL | 45.17 | 40.24 | 98.55 | 98.03 | 64.73 | 49.14 | 46.81 | 98.70 | 92.79 | 67.75 |
| RAG+Summary | 46.68 | 41.65 | 98.70 | 98.08 | 65.87 | 47.61 | 43.64 | 98.68 | 93.43 | 66.15 |
| DPL | 44.03 | 37.94 | 98.81 | 98.17 | 63.44 | 47.48 | 42.56 | 98.50 | 93.10 | 65.61 |
| Rehersal | 93.08 | 97.29 | 21.74 | 24.90 | 47.05 | 93.47 | 93.90 | 62.03 | 33.81 | 65.50 |
| ComPSum | 47.99 | 43.03 | 98.64 | 98.03 | **66.85** | 53.02 | 47.21 | 98.70 | 93.35 | **69.30** |

Table 5: Evaluation of ComPSum. A higher value indicates better performance. The best-performing method based on overall score is **bolded**. ComPSum shows the best overall performance.

the best overall scores. All differences except for Llama3.1-8b on the review domain are statistically significant compared to the second-best performing method using paired bootstrap resampling ($p < 0.05$) (Koehn, 2004).

Comparing with Rehearsal, we observe that although Rehearsal achieves high performance on personalization, its performance on general qualities is pretty low. To investigate the performance gap, we examine its summaries and find that many summaries resemble user profiles rather than faithful summaries of input document sets. Further analysis of the 'modification suggestions' generated by Rehearsal shows that they often suggest adding information that is only present in the corresponding user profile but not input document sets. This can be caused by the fact that neither the user agent nor the supervisor agent has access to input document sets when generating the suggestions. The findings also shows the importance of both personalization and general qualities during evaluation.

Comparing with DPL, we observe that while both methods use comparative documents when generating analysis of users, ComPSum outperforms DPL especially in the news domain. This can be caused by two reasons. First, DPL is designed specifically for reviews. It instructs the LLM to focus on aspects like emotional style that do not generalize to domains beyond reviews (and in this sense this comparison is not fair to DPL). Second,

| | Llama3.1-8b | | Qwen2.5-14b | | |
|---|---|---|---|---|---|
| | News | Review | News | Review | Avg. |
| ComPSum | **74.17** | 75.76 | **74.69** | 77.61 | **75.56** |
| w/o comp. doc. | 72.26 | 74.81 | 71.16 | 76.89 | 73.78 |
| w/o structure | 70.84 | **78.78** | 68.32 | 77.09 | 73.76 |
| w/ sim. comp. | 70.29 | 75.02 | 71.57 | **77.81** | 73.67 |
| w/ multi. stage | 68.80 | 76.64 | 67.23 | 75.48 | 72.04 |

Table 6: Overall performance of ComPSum and its ablated variants. The best-performing method is **bolded**. ComPSum outperforms its ablated version, showing the effectiveness of ComPSum design.

DPL's analysis is initially generated from a single profile document, which is generally not enough to infer the preference of a user. Even though DPL later summarizes multiple analyses, information loss is still inevitable. Contrarily, ComPSum generates the structured analysis of a user directly conditioned on multiple profile documents of the user. A fairer comparison with DPL using the same aspect as ComPSum is provided in Sec. 7.4.

### 7.4 Ablation Study of ComPSum

In this section, we validate the design of ComPSum by comparing it with the following ablated variants:

**w/o comp. doc.** generates structured analysis of a user only using retrieved profile documents but not comparative documents.

**w/o structure** does not instruct LLMs to generate

| | Llama3.1-8b | | Qwen2.5-14b | | |
|---|---|---|---|---|---|
| | News | Review | News | Review | Avg. |
| ComPSum | 80.93 | 82.63 | 78.81 | 81.18 | 80.89 |
| w/o comp. doc. | 83.18 | 82.74 | 81.73 | 82.42 | 82.52 |

Table 7: Average similarity between structured analysis of different users. Comparative documents can make structured analysis more diverse for different users.

a separate analysis for writing style and content focus. Instead, it directly generates a profile summary of a user without enforcing the structure.
**w/ sim. comp.** generates the structured analysis based on comparative documents that are most similar to profile documents instead of most dissimilar; **w/ multi. stage** generates the structured analysis in multiple stages, similar to DPL, but focusing on writing style and content focus instead of dimensions used by DFL.

For these ablated variants, we report their overall scores in Tab. 6 which evaluates personalization and general qualities as described in Sec. 7.3 on the test set of PerMSum. The detailed scores for each dimension and implementation details are shown in App. A.6.

From the table, we observe that ComPSum outperforms w/o comp. doc. and w/o structure, which shows the effectiveness of comparative documents and structure constraints. Besides, ComPSum also outperforms w/ multi. stage, which shows that directly generating analysis based on multiple profile documents is more effective than generating multiple analyses based on one profile document and summarizing them afterward. Overall, ComPSum outperforms all of its ablated version based on average performance across LLMs and datasets. We show examples of summaries generated by ComPSum in App. A.8.

### 7.5 Analysis Generated by ComPSum

In this section, we examine whether using comparative documents leads to more diverse structured analysis for different users. To evaluate this, for each sample in the test set of PerMSum, we measure the average similarity between the structured analysis generated for two different users for the same input document set. We then compare the similarity scores produced by ComPSum with those from its ablated variant, **w/o comp. doc.**, which generates structured analysis without using comparative documents. To measure the similarity, we use cosine similarity of structured analysis's embedding

| |
|---|
| **ComPSum**: User X's writing style is characterized by a clear and concise narrative voice, often incorporating direct quotes and specific details to support their points. Their texts tend to be well-structured and easy to follow, with a focus on conveying complex information in an accessible way. **Unlike other users, who may rely on sensational language or emotional appeals**, User X's tone is measured and informative, making their content feel more authoritative and trustworthy. |
| **w/o comp. doc.**: User X's writing style is characterized by a conversational tone and a focus on storytelling. They often use anecdotes and quotes from celebrities to illustrate their points, making their content feel more relatable and engaging. The text is also well-structured and easy to follow, with a clear and concise writing style. User X tends to use a more informal tone, often incorporating colloquial expressions and contractions, which creates a sense of familiarity with the reader. " |

Table 8: Structured analysis for writing style generated by ComPSum and w/o comp. doc. The structured analysis generated by ComPSum additionally includes comparison with other users (in **bold**), which helps in better personalization.

generated by gte-Qwen2-1.5B-instruct (Li et al., 2023b). We report the average cosine similarity in percentage in Tab. 7.

From the table, we observe that ComPSum has lower similarity score than w/o comp. doc., suggesting that using comparative documents leads to more diverse structured analysis for different users. We also show examples of structured analysis for writing style generated by ComPSum and w/o comp. doc. in Tab. 8. From the examples, we can observe that the structured analysis generated by ComPSum additionally includes comparison with other users, which helps the MDS system to better differentiate different users. We show additional examples of structured analysis in App. A.7.

## 8 Conclusion

We propose ComPSum, a personalized MDS framework. It captures the finer differences between users by comparing profile documents with other documents authored by different users on the same topic. We also propose AuthorMap, a reference-free fine-grained evaluation framework. We evaluate the accuracy of AuthorMap on human-written documents in the news and review domain and show that it achieves reasonable accuracy. For robust evaluations of ComPSum, we construct PerMSum, a personalized MDS dataset in the news and review domain. We evaluate the performance of ComPSum on PerMSum using AuthorMap, showing that it outperforms strong baselines.

## 9 Limitation

One limitation of ComPSum is its reliance on comparable documents that share the same topic as the profile documents. Otherwise, the differences between profile documents and comparable can stem from topic difference but not individual preference differences. Therefore, ComPSum cannot be directly applied to general personalized text generation as identifying such comparable documents can be difficult for other tasks. Future work could explore methods for automatically identifying or generating comparable documents to broaden the applicability of ComPSum to more general personalized text generation

When constructing the PerMSum dataset, we define the profile documents for a user as documents written by the user. However, for the news domain, defining the profile documents as documents clicked or liked by the user seems to be more similar to the real-world application. Unfortunately, existing publicly available news datasets with user interaction data are not suitable for personalized MDS. For example, the PENS dataset (Ao et al., 2021) lacks publishing dates of news articles, which makes it difficult to efficiently create input document sets where all documents are about the same event. MIND dataset (Wu et al., 2020) lacks both publishing dates and full texts of news articles. Therefore, we construct PerMSum using articles from All the News dataset, which is the only large-scale dataset that includes publishing dates, author information, and full article texts.

## 10 Ethical Consideration

The datasets we use are all publicly available. All the models used in this paper are publicly accessible. The inference and finetuning of models are performed on four Nvidia A6000 or Nvidia L40 GPUs. We do not annotate any data on our own. We do not hire any human annotators for annotation.

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# A Appendix

## A.1 Prompt for `ComPSum`

`ComPSum` first generates a structured analysis for a user by comparing profile documents with other documents authored by different users on the same topic. `ComPSum` then uses the generated structured analysis to guide the generation of personalized summaries that capture the user's writing style and content focus. The prompt for generation of structured analysis is shown in Fig. 2.The prompt for generation of personalized summaries is shown in Fig. 3.

## A.2 Prompt for `AuthorMap`

`AuthorMap` separately evaluates writing style and content focus. The design of prompt for evaluating writing style is motivated by Huang et al. (2024). The prompt for evaluation of writing style is shown in Fig. 4. The prompt for evaluation of content focus is shown in Fig. 5.

## A.3 Preprocessing detail of `PerMSum`

For the news domain, `PerMSum` clusters the news articles into document sets based on token overlap, named entities, and publishing dates, following Liu et al. (2022). Specifically, each news articles is treated as a node in a graph. If two news articles are published within two days, share at least one named entity in their titles or first three sentences, have cosine similarities based on TF-IDF embedding over 0.30, there will be a line between these articles. The news articles are then clustered based on the maximum cliques of the graph. We filter out clusters where more than three articles are written by the same author to prevent the author have too much impact on that cluster. To control the context length, we further divide clusters that contain more than 10 news articles into smaller clusters and truncate all news articles to 300 words.

## A.4 Prompt for Paraphrasing

To test whether `AuthorMap` can independently measure writing style and content focus, we instruct Llama3.3-70b-Instruct to generate paraphrased documents that are originally written by certain users to follow the writing style of other users. We show the prompt for paraphrasing in Fig. 6

## A.5 Experiment Details for Evalation of `ComPSum`

To evaluate factuality, we use FactScore (Min et al., 2023), which measures the proportion of atomic content units that are supported by input document sets. To evaluate relevance, we use G-Eval (Liu et al., 2023), which rates summaries based on their relevance from 1 to 5. For FactScore, we use Llama3.1-8b-Instruct to extract ACUs and judge whether ACUs are supported by input document sets. For G-Eval, we use Llama3.3-70b-Instruct to rate the relevance of summaries. To reduce the computation cost, we report the results for FactScore and G-EVaL on subset of test set of `PerMSum`, which contains 25 percent of samples.

For all baselines, we retrieve 5 profile documents using BM25 for a fair comparison. For DPL, in its original implementation, it retrieves comparable documents based on the embeddings of user profiles. However, in `PerMSum`, not all documents have valid user. Therefore, we retrieve comparable documents based on the embeddings of document themselves.

## A.6 Experiment Details for Ablation Study

The full results of ablation study are reported in Tab. 9. To reduce the computation cost, we report the results for FactScore and G-EVaL on subset of test set of `PerMSum`, which contains 25 percent of samples.

## A.7 Example Analysis Generated by `ComPSum`

In this section, we show additional examples of structured analysis generated by `ComPSum`and its ablation variant with out comparative documents for writing style and content. We show the example analysis for writing style in Fig. 7. We show the example analysis for content in Fig. 8.

```
You are a helpful assistant. Respond only with a JSON object including two key elements:
        {
          "content_analysis": a single-paragraph analysis of unique aspect and content preferences,
          "style_analysis": a single-paragraph analysis of unique writing styles,
        }
You are asked to analyze the distinctive features of User X's profile texts in comparison to those written by other users on similar topics. Specifically, you should first generate an analysis of unique aspect and content preferences that set User X apart. It should be written in a consecutive paragraph with less than 150 words (denoted as "content_analysis"). You should then generate an analysis of unique writing styles that set User X apart. It should be written in a consecutive paragraph with less than 150 words (denoted as "style_analysis").
***********
Below are pairs of profile texts. Each pair describes the same product—one version is written by the User X, and the other by a different user.
Pair 1(written by User X): {profile document 1}
Pair 1(written by a different user): {comparative document 1}
*************
Pair 2(written by User X): {profile document 2}
Pair 2(written by a different user): {comparative document 2}
*************
...
```

Figure 2: Prompt used by ComPSumto generate structured analysis.

```
You are requested to generate a personalized summary with less than 100 words for multiple query texts about the same product for the User X based on the User X's profile texts and the anlysis of User X's aspect and content preference as well as writing style.   The personalized summary should cover the main information of the query texts while mimic the aspect and content preference and writing style of the User X.
***********
A list of profile texts for the User X are shown below:
<profile_document>
***********<end_of_list>***********
The analysis of the User X are shown below, where "content_analysis" denotes the analysis of aspect and content preference, "style_analysis" denotes the analysis of writing style:
<structured_analysis>
***********<end_of_analysis>***********
A list of query texts to be summarized are shown below:
<input_document_set
***********<end_of_list>***********
Please write a single personalized summary with less than 100 words for the query texts. The summary should only include contents from the query texts but not from the profile texts. Do not list sources of contents in the summary. Please directly output the personalized summary without any explanation. The summary should not be first person.
```

Figure 3: Prompt used by ComPSumto generate personalized summaries.

You are a helpful assistant. Respond only with a JSON object including two key elements:

{

"analysis": Reasoning behind your answer,

"answer": query texts more likely to be written by the author of the profile texts (Query Text 1 or Query Text 2 or Tie)

}

You are given a set of profile texts with a certain author and two query texts (Query Text 1 and Query Text 2) on the same topic.

Your task is to determine which query text is more likely to be written by the author of the profile texts solely based on writing style.

Specifically, first identify the differences in writing style between Query Text 1 and Query Text 2. Focus on linguistic features such as phrasal verbs, modal verbs, punctuation, rare words, affixes, quantities, humor, sarcasm, typographical errors, and misspellings. Then, detemine which query text's writing style is more closely aligned with the writing style presented in the profile texts. Please disregard the differences in contents and aspects during the comparison. If you cannot determine which query text is more likely to be written by the author of the profile texts solely based on content and aspect preference, output Tie.

The profile texts written by a certain author are shown below. The profile texts are delimited with two vertical bars: ||.

<profile_documents>

The query texts are shown below.

Query Text 1: <personalized_summary_for_user1>

***********

Query Text 2: <personalized_summary_for_user2>

Figure 4: Prompt used by AuthorMapto evaluate writing style.

You are a helpful assistant. Respond only with a JSON object including two key elements:

{

"analysis": Reasoning behind your answer,

"answer": query texts more likely to be written by the author of the profile texts (Query Text 1 or Query Text 2 or Tie)

}

You are given a set of profile texts with a certain author and two query texts (Query Text 1 and Query Text 2) on the same topic.

Your task is to determine which query text is more likely to be written by the author of the profile texts solely based on content and aspect preference.

Specifically, first identify the differences in content and aspect focus between Query Text 1 and Query Text 2. Then, detemine which query text's content and aspect focus is more closely aligned with the content and aspect presented in the profile texts. Please disregard the differences in writing style during the comparison. If you cannot determine which query text is more likely to be written by the author of the profile texts solely based on content and aspect preference, output Tie.

The profile texts written by a certain author are shown below. The profile texts are delimited with two vertical bars: ||.

<profile_documents>

The query texts are shown below.

Query Text 1: <personalized_summary_for_user1>

***********

Query Text 2: <personalized_summary_for_user2>

Figure 5: Prompt used by AuthorMapto evaluate content focus.

Given a set of profile texts with a certain writing style and a query document, please paraphrase the query document following the writing style of the profile texts. The paraphrased query document should have exatcly the same information as the original query document. The paraphrased query document should not include any additional information from the profile texts that are not mentioned by the original query document. The paraphrased query document should have the same length as the original query document.

Profile texts are shown below. The profile texts are delimited with two vertical bars: ||.

<profile_document>

Query Document: <query_document>

Please directly output the paraphrased query document

Figure 6: Prompt for paraphrasing.

| **ComPSum** | |
|---|---|
| **User 1:** User X's writing style is characterized by a conversational tone, often incorporating direct quotes from celebrities and using a more informal language. This approach makes the content feel more approachable and relatable. In contrast, other users tend to write in a more formal and objective tone, focusing on delivering factual information without adding a personal touch. User X also tends to use a more narrative-driven approach, weaving together multiple sources and ideas to create a cohesive story, **which sets them apart from other writers who may rely on a more straightforward reporting style.** | **User 2:** User X's writing style is characterized by a clear and concise narrative voice, often incorporating direct quotes and specific details to support their points. Their texts tend to be well-structured and easy to follow, with a focus on conveying complex information in an accessible way. **Unlike other users, who may rely on sensational language or emotional appeals**, User X's tone is measured and informative, making their content feel more authoritative and trustworthy. This style suggests that User X prioritizes clarity and accuracy in their writing, setting **them apart from users who may prioritize other factors like entertainment value or clickbait headlines**. |
| **w\o comp. doc.** | |
| **User 1:** The writing style of User X appears to be conversational and engaging, with a focus on storytelling and anecdotal evidence. The use of quotes from celebrities and behind-the-scenes details adds a sense of intimacy and immediacy to the articles. The tone is generally lighthearted and celebratory, particularly in the pieces about celebrity collaborations and magazine covers. However, when discussing more serious topics like gun violence and aging, the tone shifts to one of gravity and concern. Overall, the writing style is approachable and accessible, suggesting that User X aims to inform and entertain their audience | **User 2:** User X's writing style is characterized by a conversational tone and a focus on storytelling. They often use anecdotes and quotes from celebrities to illustrate their points, making their content feel more relatable and engaging. The text is also well-structured and easy to follow, with a clear and concise writing style. User X tends to use a more informal tone, often incorporating colloquial expressions and contractions, which creates a sense of familiarity with the reader. Overall, the writing style is approachable and accessible, making it easy for readers to stay engaged and interested in the content. |

Figure 7: Example analysis of writing style generated by ComPSumand its ablation variant with out comparative documents. The structured analysis generated by ComPSum additionally includes comparison with other users (in **bold**), which helps in better personalization.

| | News | | | | | Review | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | style | content | fact. | rele. | overall | style | content | fact. | rele. | overall |
| *Llama3.1-8b-Instruct* | | | | | | | | | | |
| CPS | 60.04 | 53.94 | 98.01 | 95.32 | **74.17** | 63.09 | 57.89 | 98.03 | 91.99 | 75.76 |
| w/o comp. doc. | 56.34 | 50.69 | 98.16 | 97.29 | 72.26 | 61.13 | 57.21 | 97.07 | 92.28 | 74.81 |
| w/o structure | 56.74 | 47.33 | 98.08 | 95.62 | 70.84 | 69.58 | 67.26 | 95.58 | 86.11 | **78.78** |
| w/ sim. comp. | 54.49 | 47.29 | 97.95 | 96.71 | 70.29 | 61.74 | 57.17 | 97.74 | 91.80 | 75.02 |
| w/ multi. stage | 52.16 | 45.42 | 98.16 | 96.31 | 68.80 | 64.61 | 59.93 | 97.57 | 91.34 | 76.64 |
| *Qwen2.5-14B-Instruct* | | | | | | | | | | |
| CPS | 57.63 | 57.08 | 97.96 | 96.58 | 74.69 | 65.37 | 63.92 | 96.51 | 89.98 | 77.61 |
| w/o comp. doc. | 55.76 | 48.73 | 98.03 | 96.25 | 71.16 | 63.38 | 61.74 | 97.98 | 91.17 | 76.89 |
| w/o structure | 50.47 | 45.42 | 97.84 | 97.12 | 68.32 | 64.72 | 63.19 | 96.59 | 89.39 | 77.09 |
| w/ sim. comp. | 53.18 | 51.44 | 97.83 | 98.05 | 71.57 | 65.81 | 64.50 | 96.15 | 89.83 | **77.81** |
| w/ multi. stage | 48.05 | 44.62 | 98.23 | 96.98 | 67.23 | 62.07 | 59.75 | 96.73 | 90.50 | 75.48 |

Table 9: Full ablation results of ComPSum. A higher value indicates better performance. The best-performing method based on overall score is **bolded**.

| ComPSum | |
|---|---|
| **User 1:** User X tends to focus on the positive and empowering aspects of celebrity news, often highlighting the personal growth and self-acceptance of public figures, such as Miley Cyrus embracing her past, Kim Kardashian West's loving family moments, and Cameron Diaz's openness about aging. **In contrast, other users often focus on controversy, drama, or sensationalized aspects of celebrity news.** User X also tends to emphasize the intersection of celebrity culture and social issues, such as gun violence and body positivity, in a way that is uplifting and inclusive. | **User 2:** User X's profile texts stand out for their in-depth analysis of current events, particularly in the realms of feminism and social justice. They delve into the nuances of the topics, often referencing specific quotes and details from the individuals involved. This level of depth and specificity suggests that User X values accuracy and context when discussing complex issues. Additionally, their texts often highlight the personal stories and experiences of individuals, such as Miley Cyrus and Bella Thorne, to illustrate the human impact of these issues. This approach creates a more empathetic and relatable tone**, setting User X apart from other users who may focus on more sensational or surface-level aspects of the news**. |
| **w\o comp. doc.** | |
| **User 1:** The content preferences of User X seem to revolve around entertainment, celebrity culture, and social issues. The topics of the provided texts include Miley Cyrus's past controversy, the Kardashian-Jenner family, and celebrities speaking out on social issues. The content also touches on fashion, with articles about celebrity appearances in Calvin Klein campaigns and magazine covers. Additionally, there is a focus on female empowerment and self-expression, as seen in the discussion of Miley Cyrus's unapologetic attitude and Cameron Diaz's openness about aging. This suggests that User X is interested in celebrity news, social justice, and feminist themes. | **User 2:** The content preferences of User X appear to be centered around social justice, feminism, and celebrity culture. The user frequently discusses topics such as body positivity, sexual harassment, and assault, often using high-profile figures like Miley Cyrus and Bella Thorne as examples. User X also seems to be interested in news and updates on social movements like #TimesUp and the prosecution of Harvey Weinstein. Additionally, they have a strong interest in celebrity relationships and personal stories, as evident from their coverage of Miley Cyrus's marriage and new music releases. Overall, User X's content preferences suggest a focus on current events, social issues, and celebrity culture. |

Figure 8: Example analysis of content focus generated by ComPSumand its ablation variant with out comparative documents. The structured analysis generated by ComPSum additionally includes comparison with other users (in **bold**), which helps in better personalization.

### A.8 Example Summary Generated by ComPSum

In this section, we show example summaries generated by ComPSumand its ablation variant with out comparative documents. We compare two summaries personalized for different users for the same input document set and show them in Fig. 9. We observe that summaries generated by ComPSumshow more diverse style and content focus.

| ComPSum | |
|---|---|
| **User 1:** It's a double-edged sword for Julian Assange - a UN ruling says he's been unlawfully detained, but the UK and Sweden aren't budging. The UN panel's decision is a "vindication" for Assange, but a British government spokesman called it "ridiculous." Assange has been living in the Ecuadorian embassy since 2012, avoiding arrest and extradition to Sweden over rape allegations. He's hailed the ruling as a "victory of historical importance," but the UK has made it clear they'll arrest him if he leaves the embassy. It's a stalemate that's left Assange stuck in limbo. | **User 2:** A United Nations panel has ruled that Julian Assange has been arbitrarily detained at the Ecuadorian embassy in London since his arrest in 2010 over allegations of sex crimes. The UN Working Group on Arbitrary Detention called on Sweden and the UK to let Assange move freely and ensure his safety, and to provide compensation. However, British authorities have stated they will arrest and extradite Assange to Sweden if he leaves the embassy. Assange has hailed the decision as a "vindication" and a "victory of historical importance." |
| **w\o comp. doc.** | |
| **User 1:** A United Nations panel has ruled that Julian Assange has been arbitrarily detained in the Ecuadorian embassy in London since 2010. The UN Working Group on Arbitrary Detention called on Sweden and the UK to respect Assange's rights, including his freedom of movement and physical integrity. The ruling is not legally binding, but Assange sees it as a "vindication" and a "victory of historical importance." The UK and Sweden have rejected the decision, with the UK's Foreign Secretary calling it "ridiculous." Assange remains in the embassy, where he has been living for over three years. | **User 2:** A United Nations panel has ruled that WikiLeaks founder Julian Assange has been arbitrarily detained by Sweden and the UK, with the decision calling for his release and compensation. Assange, who has been living in the Ecuadorian embassy in London since 2012, hailed the ruling as a "vindication" and a "victory of historical importance." However, the UK and Swedish governments have rejected the ruling, with the British Foreign Secretary describing it as "ridiculous" and stating that Assange will be arrested if he leaves the embassy. |

Figure 9: Example summaries generated by ComPSumand its ablation variant with out comparative documents.