FLAME: A New Dataset on FLemish Accounts of Momentary Experiences

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Abstract

We introduce FLAME (FLemish Accounts of Momentary Experiences), a new corpus of nearly 25,000 daily personal narratives in Belgian-Dutch (Flemish), designed to support research on underrepresented language varieties in Natural Language Processing (NLP). Personal narratives of this kind hold rich potential for uncovering culturally grounded, everyday themes, yet extracting meaningful topics from such data is non-trivial, given the informal register, cultural specificity, and low-resource nature of the Flemish variety. We therefore ask: which topic modeling approach is best suited to reveal the latent themes in this corpus? To answer this, we benchmark three widely used methods: K-Means Clustering, Latent Dirichlet Allocation (LDA), and BERTopic, evaluating their ability to identify coherent and culturally relevant topics. While LDA achieves strong performance on automated coherence metrics, human evaluation reveals that BERTopic consistently produces the most coherent and culturally resonant topics, exposing the limitations of purely statistical methods on narrative-rich data. The diminished performance of K-Means compared to prior work on similar Dutch corpora further highlights the unique linguistic challenges posed by this dataset. Our findings demonstrate that contextual embeddings are critical for robust topic modeling in low-resource, culturally specific domains, and underscore the importance of human-centered evaluation alongside automated metrics.

1 Introduction

Topic modeling is a cornerstone of text mining, facilitating the unsupervised discovery of latent thematic structures in large corpora. While traditional probabilistic models such as Latent Dirichlet Allocation (LDA) (Blei et al., 2003) have been foundational, their underlying bag-of-words assumption limits their ability to capture complex semantics. A recent paradigm shift towards models like BERTopic (Grootendorst, 2022), a state-of-the-art (SOTA) model which leverages contextualized embeddings from pre-trained transformers, has shown significant promise in generating more semantically coherent topics. These models can capture nuanced relationships, including domain-specific named entities and morphologically rich constructs, critical for structurally diverse data.

Yet even as topic modeling methods advance, the data they are applied to has remained remarkably narrow. Research has overwhelmingly focused on high-resource, standardized languages and on structured or short-form text such as news articles and social media posts (Egger and Yu, 2022; Schäfer et al., 2024). This leaves two important territories underexplored. First, underrepresented language varieties (regional dialects, sociolects, and low-resource languages), remain largely absent from the topic modeling literature. Models trained on standard corpora often fail to capture the unique lexical and semantic patterns of such varieties, risking a technological bias in which the nuances of smaller linguistic communities are systematically overlooked (Kamiloğlu et al., 2025). This is particularly evident in Belgian-Dutch, where even modern LLMs have been shown to underperform compared to standard NLP tools when applied to informal Flemish narratives (Kandala and Hoemann, 2025). Second, open-ended personal narratives present a fundamentally different challenge compared to decontextualized social media posts. Daily narratives provide granular, contextually grounded accounts of lived experience, capturing a wide spectrum of activities, affective states, and cognitive processes, constituting a rich but demanding corpus for studying naturalistic language use. Comparable efforts to document everyday informal language have been undertaken for other linguistic communities, most notably the ORD corpus of Russian daily communication (Asinovsky et al., 2009; Bogdanova-Beglarian et al., 2016), yet no

equivalent resource exists for Belgian-Dutch, leaving Flemish speakers largely absent from the NLP landscape.

To address both gaps, we introduce FLAME (FLemish Accounts of Momentary Experiences), a new corpus of nearly 25,000 daily personal narratives in Belgian-Dutch (Flemish). FLAME presents a unique challenge for topic modeling: its texts are informal, fluid in thematic structure, and written in a culturally specific low-resource language with high lexical variability. Having assembled this corpus, a natural question arises - which topic modeling approach is best suited to uncover the latent themes embedded in data of this kind? To answer this, we validate the corpora by exploring three widely used methods: Term Frequency-Inverse Document Frequency (TF-IDF) (Salton and Buckley, 1988; Ramos, 2003) based KMeans clustering approach (MacQueen, 1967; Lloyd, 1982; Berkhin, 2006; Sinaga and Yang, 2020), the probabilistic LDA model (Blei et al., 2003; Shin et al., 2025), and BERTopic (Grootendorst, 2022), assessing which best captures the coherent and culturally grounded themes that FLAME contains.

Critically, this validation moves beyond automated coherence metrics alone, which we argue can be insufficient or even misleading for embedding-based models on narrative data. We therefore complement automated metrics with a human evaluation of topic interpretability and cultural relevance. Our results show that while LDA scores strongly on automated metrics, BERTopic consistently surfaces the most coherent and culturally resonant topics, demonstrating that contextual embeddings are critical for this type of data, and that human-centered evaluation is indispensable when working with low-resource, narrative-rich corpora.

The remainder of this paper is structured as follows: Section 2 provides an overview of K-Means, LDA, and BERTopic. Section 3 discusses the methodology (including data collection and data analysis) employed for this study. Section 4 presents the results. Section 5 discusses the findings, Section 6 presents the limitations, and Section 7 concludes the study.

2 Methodology

We conduct a comparative analysis of KMeans, LDA, and BERTopic on a novel corpus of Flemish daily narratives. Our evaluation framework is twofold, comprising a suite of automated topic coherence and diversity metrics, supplemented by human evaluation to assess topic interpretability.

2.1 Data and Data Collection

The dataset consists of open-ended responses of daily narratives in Flemish with a total of 24,854 texts. Participants ($N = 102, age : 18 - 65, M = 26.47, SD = 8.87$) were recruited via flyers, online posts, and word-of-mouth. Eligible individuals were native Dutch speakers living in Belgium, had to be at least 18 years old, and had to be in possession of a working smartphone. Over 70 days, participants received four prompts per day via a smartphone app called m-Path (Mestdagh et al., 2023), responding to the question: *"Wat speelt er nu of sinds de vorige beep, en hoe voel je je daarover?"* ("What is going on now or since the last prompt, and how do you feel about it?"). They provided either a one-minute voice message or a 3-4 sentence text response.

Recorded descriptions were automatically transcribed using a Dutch automatic speech recognition (ASR) system developed in-house (Tamm et al., 2024). This model was trained on approximately 270 hours of Flemish Dutch speech from the Spoken Dutch Corpus (Oostdijk, 2000), following protocols similar to the baseline described by (Poncelet and Van Hamme, 2023). The resulting transcripts contain system-generated punctuation and adhere to the orthographic transcription conventions of the Spoken Dutch Corpus, which include detailed annotation tags for foreign words, dialect, disfluencies, and other phenomena. Subsequent preprocessing removed these annotation tags and non-content markers, retaining only the core textual content for further analysis. For additional details on participant recruitment, study procedures, data collection, and preparation, see Appendix.

To illustrate the nature of the transcripts, Table 1 presents a few representative examples from the dataset. Each entry includes the raw Dutch text, its English translation, the valence score, and the word count. These examples reflect the naturalistic, diary-style language characteristic of the corpus, ranging from workplace experiences to social and leisure activities.

2.2 Data Analysis

2.2.1 Preprocessing

The raw texts underwent a multi-step preprocessing pipeline: (i) removal of dataset-specific annotation

Raw Text (Dutch)	Translation (English)	Words
net een vermoeiende maar wel echt goede groepsessies gehad op mijn studentenjob. ik voel me wat overprikkeld, maar op zich voel ik me wel echt goed. nu ben ik bij vrienden voor de verjaardag van een vriendin dus ben wel blij om ze terug te zien.	Just had exhausting but really good group sessions at my student job. I feel a bit overstimulated, but overall I feel really good. Now I'm with friends for a girlfriend's birthday, so I'm happy to see them again.	46
Ik heb net een hele tijd in de auto gezeten en dat heeft me wat suf gemaakt. Het doet me uitkijken naar de wandeling die we gaan maken. Autoritten maken me snel overprikkeld dus ik hoop dat dat snel wegtrekt door buiten te zijn.	I've just been in the car for long time and that made me a bit groggy. Makes me look forward to the walk we're going to take. Car rides tend to overstimulate me, so I hope being outside will help me snap out of it soon.	44
ik ben in een meeting momenteel op het werk. het is best saai. ik ben ook mijn simulaties aan het checken, en ze zien er een beetje raar uit. ik ben een klein beetje gedemotiveerd, maar ik ga proberen om mijn motivatie terug te vinden. hopelijk lukt dat	I'm in a meeting at work right now. It's pretty boring. I'm also checking my simulations, and they look a bit strange. I'm a little demotivated, but I'm going to try to get my motivation back. Hopefully it'll work out.	48
ik heb nog in de avond in het atelier geweest. gewoon wat tijd met mezelf en heb verschillende kommen gemaakt. dat deed goed, het kriebelde al de hele dag om te creëren. ik heb ook met, mijn lief gebeld en afgesproken voor morgen. het deed goed om met hem te bellen. nu ben ik met m'n ouders tv aan het zien	I spent some time in the studio this evening. Just some time to myself, and I made a few bowls. That felt good - I'd been itching to create all day. I also call my boyfriend and made plans for tomorrow. It was nice to talk to him. Now I'm watching TV with my parents.	62

Table 1: Representative examples from the FLAME dataset

tags, and author-identifying references (ii) lemmatization using the Stanza (Qi et al., 2020) model for Dutch, and (iii) filtering of documents shorter than 15 words. A custom, corpus-specific stopword list was also applied [1]. The final processed corpus contains 24,752 documents.

To quantitatively define 'medium-length,' we report word count statistics for both unfiltered and filtered corpora. Prior to filtering, transcripts had a mean of 109.34 words (SD = 70.29), with a median of 101 words (range: 1–965). After applying the 15-word minimum filter, the mean was 109.84 words (SD = 70.11), with a median of 102 words (range: 10–965). The minimal difference between unfiltered and filtered statistics indicates that very short responses were rare, and that medium-length responses are a consistent feature across the study population.

2.2.2 Embedding Model Selection for BERTopic

To identify the optimal sentence-level embeddings for Flemish, we evaluated three multilingual models: (a) *robert-2022-dutch-sentence-transformers* (Netherlands Forensic Institute, 2024): A Dutch-specific model fine-tuned for semantic similarity task (b) *gte-multilingual-base* (Zhang et al., 2024): A general-purpose multilingual encoder optimized for long-context retrieval (c) *jina-embeddings-v3* (Sturua et al., 2024) : A multilingual model leveraging Task LoRA for adaptable semantic representation. Qualitative assessment of the resulting topics indicated that *jina-embeddings-v3* produced the most coherent themes for our specific corpus. We attribute this to its XLM-ROBERTa architecture augmented with Rotary Position Embeddings and Task LoRA adapters. Consequently, all BERTopic experiments utilize this model, which generates 1,024-dimensional embeddings via the SentenceTransformers library (Reimers and Gurevych, 2019). We then utilized Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018) to reduce these embeddings to a 5-dimensional space.

2.2.3 Model Configuration and Hyperparameter Optimization

KMeans Clustering

For the KMeans baseline, documents were vectorized using TF-IDF, a classical, non-semantic feature space following the approach of (Kamiloğlu et al., 2025). To establish a robust baseline, we conducted a systematic exploration of vectorizer

[1] https://anonymous.4open.science/r/FLAME-5223/

parameters, testing various combinations of min_df and max_df, including both absolute counts and proportional thresholds. The final configuration reported in this study (min_df=0.01, max_df=0.9) was selected to generate a compact vocabulary focused on high-frequency terms, resulting in a document-term matrix (DTM) of size 24,725 $\times$ 326. Sublinear term frequency scaling (Manning et al., 2008) was also applied to reduce the influence of high-frequency terms. For the clustering step, the optimal number of clusters (k) was determined via Silhouette analysis (Rousseeuw, 1987) over a range of $k = 2$ to 200, which indicated a peak score at $k = 128$ (see Appendix). KMeans clustering was performed using Euclidean distance as the distance metric, which is the standard metric used in KMeans optimization (Lloyd, 1982). The entire pipeline was implemented using Python's scikit-learn (Pedregosa et al., 2011) library with fixed random seeds to ensure reproducibility.

LDA

For the LDA baseline, we used the scikit-learn implementation (Pedregosa et al., 2011). We tuned the number of topics(k)(ranging from 5 to 150), α (`doc_topic_prior`), and β (`topic_word_prior`) over [0.01, 0.1, 1.0, 0.5]. Model selection was guided by coherence scores computed with the Gensim coherence model (Rehurek and Sojka, 2011).

BERTopic

We systematically tuned BERTopic's hyperparameters using *jina-embeddings-v3* to optimize topic coherence and diversity. For dimensionality reduction, we tested `umap_n_neighbors` with values [10, 15, 20, 25, 30] and `umap_min_dist` with values [0.0, 0.1]. For clustering, we evaluated `hdbscan_min_cluster_size` with values [5, 10, 15]. For the model, we tested `min_topic_size` with values [5, 10, 15] and `nr_topics` with the value [`auto`]. Initial clustering with BERTopic labeled 59% of documents (n = 14,600) as outliers. To mitigate this, we employed the *Approximate Distribution Method*, which probabilistically assigns outliers to the nearest topic based on cosine similarity in embedding space (Grootendorst, 2022). This reduced outliers to 7.56% (n = 1,872) for the best BERTopic C_v score observed.

2.3 Evaluation Metrics

To provide a comprehensive comparison, we evaluate the models on both automated metrics and human judgments.

2.3.1 Automated Metrics

We employ a suite of four standard topic coherence metrics (Mimno et al., 2011) to evaluate the interpretability and semantic consistency of topics generated by BERTopic and LDA. C_v measures coherence based on a combination of Normalized Pointwise Mutual Information (NPMI) and cosine similarity over a sliding window (size 110), closely aligning with human judgments of word co-occurrence (Röder et al., 2015). C_{npmi} is a normalized PMI score robust to frequency biases, scaled between -1 (dissociation) and +1 (perfect association), making it suitable for comparing embedding-based models (where semantic similarity extends beyond raw co-occurrence), and count-based models. As a normalized and stable variant of PMI, it is less susceptible to biases from word frequency, making it a valuable metric for comparing embedding-driven models like BERTopic (which prioritize semantic similarity over raw co-occurrence) against count-based models like LDA. U_{mass} evaluates topic quality based on the log conditional probability of word co-occurrences, favoring probabilistic models like LDA. Finally, U_{uci} uses raw PMI as a baseline co-occurrence measure. We also compute topic diversity, defined as the percentage of unique words in the top-10 words of all topics.

2.3.2 Human Evaluation of the Topics

To complement the automated coherence metrics, we conducted a human evaluation study to assess the semantic coherence of the topics generated by each model. Two human annotators, both Dutch speakers, participated in a word intrusion task. This task is used to probe whether topic words form a semantically cohesive group by asking annotators to identify a word that does not semantically belong (Chang et al., 2009; Bhatia et al., 2018), and is a widely used method for evaluating topic coherence.

For each of the three models (KMeans, LDA, BERTopic), we randomly sampled 40 topics. For each topic, we constructed a six-word set comprising the top five words associated with the topic and a sixth "intruder" word. Intruder words were drawn from high-probability terms of unrelated topics within the same model. Specifically, an intruder was sampled with uniform probability from the top 10 words of a randomly selected, non-related topic.

This method ensures that the intruder is a plausible, high-frequency word in its own right, making the task a robust test of the target topic's semantic coherence. The order of the sixth (intruder) word was randomized for each trial to minimize position bias. Annotators were instructed to independently identify the single word in each set that did not semantically fit with the others. We report two evaluation metrics in this regard: (i) Topic Coherence Accuracy: This constitutes the proportion of topic sets in which the annotator correctly identified the intruder word. This serves as an estimate of the interpretability and semantic coherence of the topics (Chang et al., 2009) (ii) Inter Annotator Agreement (IAA): To assess annotation reliability, we computed Krippendorff's Alpha α (Krippendorff, 2004; Artstein and Poesio, 2008), a standard metric for agreement on categorical judgments. Here, agreement reflects whether annotators identified the same intruder word in each set. High agreement indicates consistent judgments about topic coherence across annotators. Figures illustrating annotator accuracy and inter-annotator agreement are provided in the appendix.

3 Results and Analysis

Our analysis compares the embedding-based BERTopic model against a probabilistic LDA baseline and a TF-IDF-based KMeans baseline on a corpus of over 24,000 Flemish daily narratives. The results reveal a significant divergence between automated coherence metrics and human-perceived topic quality, highlighting the limitations of traditional evaluation paradigms for semantically-aware models on structurally diverse data.

3.1 Quantitative Analysis

The quantitative evaluation, summarized in Tables 2 and 3, presents a nuanced picture. In line with prior work on topic models applied to short or medium-length texts, performance of both BERTopic and LDA peaked at an optimal number of topics before declining, particularly in datasets with limited word counts per document (Aggarwal and Zhai, 2012; Muthusami et al., 2024; Mutsaddi et al., 2025).

When comparing the best-performing configurations of each model, we found that LDA produced higher C_v topic diversity scores than BERTopic (Table 2). Specifically, LDA achieved a C_v score of 0.5430 for 120 topics, and BERTopic achieved 0.3412 for 76 topics. The higher score for LDA suggests stronger word-level topical coherence, likely due to its reliance on explicit term co-occurrence statistics, which aligns with traditional interpretability expectations (Röder et al., 2015). On the other hand, the lower C_v score of BERTopic could reflect its dependency on contextual embeddings, which prioritize semantic similarity over lexical overlap, a known limitation of PMI-based metrics in embedding-driven models (Grootendorst, 2022). Table 2 presents the C_v scores for selected topic counts with both models. Topic counts with very poor coherence scores have been omitted.

Model	No. of Topics	C_v Score
BERTopic	60	0.296
	76	**0.341**
	110	0.337
	117	0.337
LDA	76	0.519
	100	0.505
	120	**0.543**
	148	0.542

Table 2: C_v scores for selected topic counts with BERTopic and LDA.

However, BERTopic produced higher scores on the other coherence metrics (C_{npmi}, U_{mass}, U_{uci}) than LDA, suggesting that C_{npmi}'s stability accommodated BERTopic's embedding-based semantics better than raw PMI (Lau et al., 2014). Furthermore, U_{mass}, which penalizes rare word pairs, may align better with BERTopic's ability to cluster medium-length texts without overfitting to sparse co-occurrences. Table 3 compares the scores of the best BERTopic and best LDA models across four coherence metrics and topic diversity.

In terms of topic diversity, LDA achieved a higher score of 0.967 for 120 topics, compared to BERTopic's 0.845. We interpret these findings to indicate that LDA's Dirichlet prior encourages distinct topic distributions, while BERTopic's HDBSCAN clustering allows overlapping semantic themes, which could reduce diversity but potentially capture nuanced relationships (see Appendix for details on Topic Distribution).

The KMeans baseline, optimized using geometric metrics like the Silhouette score, favored a high number of clusters (k=128) (see Appendix). However, this granularity resulted in a marked decline in topic coherence and interpretability, underscoring

Model	No. of Topics	C_v	C_{npmi}	U_{mass}	U_{uci}	Topic Diversity
BERTopic	76	0.3412	**-0.1619**	**-12.2167**	**-5.6599**	0.8455
LDA	120	**0.543**	-0.21	-16.39	-5.93	**0.9675**

Table 3: Topic coherence and topic diversity for the best hyperparameter configurations.

the potential mismatch between geometric partitioning objectives and the goal of extracting semantically meaningful themes (Aggarwal and Zhai, 2012).

3.2 Qualitative Analysis: Best KMeans vs. Best LDA vs. Best BERTopic

While automated metrics like C_v favour LDA, human evaluation revealed significant discrepancies in semantic coherence and contextual relevance, particularly evident in the morphologically rich and regionally specific Flemish corpus. BERTopic consistently generated thematically cohesive and culturally resonant topics, while LDA and KMeans struggled with semantic fragmentation and noise. The themes identified by BERTopic were specific and interpretable, for example, differentiating everyday routine ('workday routine', 'planning and communication', and 'studying') from activities ('horse riding', 'travel and outdoor recreation', and 'film evenings'), "Chiro" (Belgium's largest youth organization), "rains" (as it frequently rains in Belgium) and overall emotional and mental state ('headaches and migraine-related pain', 'academic stress and assignments').

BERTopic's superior ability to capture relevant themes can be illustrated with the topics related to "studying and academic life" (Table 4). It successfully captures "*aula_vriend*" (*lecture hall friend*) and "*bibliotheek*" (*library*), while the LDA model conflated academic terms with noisy co-occurrences like "*bus*" and "*toekomst*" (*future*), likely due to its reliance on document-level word distributions, which struggle with sparse co-occurrence patterns in medium-length texts. KMeans clustered high-frequency but semantically unrelated verbs "*eten*" (*to eat*) and "*slapen*" (*to sleep*), failing to isolate domain-specific themes.

This pattern persisted in domains like "fitness" (Table 5). BERTopic cohesively grouped terms such as "*fitnessen*" (*to work out*), "*gym*," and "*kracht_training*" (*power training*), while LDA's topic included semantically discordant words such as "*broer*" (*brother*) and "*baby*." KMeans conflated fitness with unrelated daily activities such as "*eten*" (*to eat*) and "*moe*" (*tired*). Another trend observed in our KMeans analysis is that many common words (underlined in the tables) reappeared across clusters.

Model	Top Words
BERTopic	**studeren** (to study), bibliotheek (library), tevreden (satisfied), aula_vriend (lecture hall friend), studie_tijd (study time), leeszaal (reading room), bib (library), dezeochtend (this morning), basically
LDA	**studeren** (to study), bus, snappen (to understand), interessant (interesting), deadline, toekomst (future), af_sluiten (to wrap up), practicum (lab session), focus
KMeans	**studeren** (to study), goed (good), vandaag (today), eten (to eat), beginnen (to begin), rest, dag (day), ver, moe (tired), tijd (time), oké (okay), weten (to know), slapen (to sleep), morgen (tomorrow), zin (motivation)

Table 4: Topics identified by BERTopic, LDA, and KMeans related to "studying and academic life."

Model	Top Words
BERTopic	**fitnessen** (to work out), fitness, workout, gym, oefening (exercise), trainen (to train), joggen (to jog), kracht_training (power training), sport_les (sports class), sport_school (sports school)
LDA	**fitnessen** (to work out), time, baby, start, haasten (to hurry), toe_voegen (to add), quality, model, aanpassing (adjustment)
KMeans	**fitnessen** (to work out), goed (good), eten (to eat), dag (day), vandaag (today), weten (to know), leuk (nice/fun), zin (mood), vanavond (tonight), moe (tired), beginnen (to begin), studeren (to study), rest, werken (to work), proberen (to try)

Table 5: Topics identified by BERTopic, LDA, and KMeans related to "fitness."

3.3 Human Evaluation Results

Our evaluation showed that BERTopic achieved notably higher precision (Annotator 1: 95.0 %, Annotator 2: 87.5 %) compared to KMeans (Annotator 1: 60.0 %, Annotator 2: 52.5.0 %) and LDA (Annotator 1: 20.0%, Annotator 2: 25.0%). This substantial gap indicated that topics produced by BERTopic have better interpretability.

To assess the consistency and ensure the reliability of annotators' judgments, we also computed the Inter-Annotator Agreement (IAA) using Krippendorff's Alpha (Krippendorff, 2004). Agreement

was high for BERTOPIC ($\alpha = 0.874$), further reinforcing confidence in the model's topic coherence. In contrast, moderate agreement levels were observed for KMeans ($\alpha = 0.545$) and LDA ($\alpha = 0.547$), suggesting relatively lower coherence and greater ambiguity in topics generated by these models. These results highlight BERTopic's strength in producing semantically coherent and intrepretable topics.

4 Discussion

This study's findings reveal a critical tension in topic model evaluation: the divergence between automated coherence metrics and human judgments of topic quality, particularly when applied to structurally diverse corpus of Flemish daily narratives.

The superior C_v score achieved by LDA, juxtaposed with its poorer performance in human evaluation, points to a systemic limitation of metrics that rely on surface-level co-occurrence. As evidenced by the qualitative analysis, LDA's inclusion of frequent but semantically irrelevant co-occurrences (e.g., "*bus*" near "*studeren*" [*to study*]) could reflect its bias toward "syntagmatic associations" (statistical proximity) rather than true "paradigmatic relevance" (thematic consistency). In contrast, BERTopic's embeddings prioritize contextual relationships (e.g., "*bibliotheek*" [*library*] ↔ "*studie_tijd*" [*study time*]), aligning with human intuition (Lau et al., 2014). This becomes especially problematic when one uses these methods to extract topics that are specific to a particular culture. Within this dataset, for example, BERTopic was able to identify Flemish-related topics related to the youth organization Chiro, national holidays like Christmas, and the weekly commute of university students from Leuven to home and back. Our results thus underscore the necessity of adopting hybrid evaluation frameworks that integrate human-in-the-loop validation, especially for under-resourced languages and non-standard text genres (Muthusami et al., 2024).

This discrepancy strongly suggests that an over-reliance on automated metrics like C_v can be misleading for evaluating embedding-based models, whose strengths lie in capturing semantic nuances that bag-of-words approaches miss. Furthermore, the high inter-annotator agreement for BERTopic (Krippendorff's α = 0.874), compared to the moderate agreement for the baselines, indicates that BERTopic's topics are not only more coherent but also more clearly and consistently interpretable.

Beyond the choice of topic modeling approach, our results also point to the importance of model configuration. The best-performing BERTopic configuration combined a multilingual sentence transformer for contextual embeddings with HDBSCAN for density-based clustering and c-TF-IDF for topic representation, underscoring that no single component alone drives performance. Crucially, we attribute BERTopic's success not merely to its use of contextual embeddings, but to the synergy between those embeddings and HDBSCAN's density-based clustering strategy. Unlike partition-based methods such as KMeans, which force every document into a cluster, HDBSCAN is specifically designed to handle noise and outliers, a property that proves essential for FLAME, where 59% of documents were classified as outliers. This high outlier rate reflects the inherently open-ended and thematically diffuse nature of daily personal narratives, and suggests that density-based clustering is better suited to this kind of data than partition-based alternatives.

Finally, our results with the K-Means baseline warrant discussion. While prior work demonstrated the efficacy of KMeans on Dutch texts (Kamiloğlu et al., 2025), our experiments did not replicate this success, instead yielding generic and incoherent clusters. We posit that this is not a failure of the algorithm itself, but rather a limitation of the TF-IDF feature space when applied to the unstructured, highly variable style of personal narratives. The vocabulary pruning inherent in TF-IDF, even with systematic tuning, appears insufficient to create a vector space where thematically distinct narratives form separable geometric clusters, resulting in the observed low-quality output.

To our knowledge, FLAME is the first large-scale corpus of daily personal narratives in Belgian-Dutch (Flemish), and the validation study presented here provides an initial foundation for its use in topic modeling and beyond. We hope it serves as a stepping stone for future research on underrepresented language varieties, culturally grounded NLP, and the computational analysis of everyday human experience.

5 Limitations

Our study, while providing a focused analysis of topic modeling on a unique dataset, is subject to several limitations that frame the scope of our conclusions. First, the generalizability of our findings is constrained by our use of a single, highly

specific corpus: daily personal narratives from a predominantly young adult, Dutch-speaking population. The linguistic characteristics of this genre: informal, unstructured, and reflective differ significantly from other text types like news articles or formal documents. Consequently, the relative performance of BERTopic and the baseline models may not directly translate to other domains, languages, or demographic groups. The topics themselves, such as "studying" and "internships," reflect the life stage of our participants and are not representative of the entire population. Second, our methodology is dependent on the quality of upstream NLP components, which have known limitations for non-standard language variants. We selected the *jina-embeddings-v3* model after a qualitative comparison, but even state-of-the-art multilingual models may not optimally capture the dialect-specific nuances of Flemish compared to a hypothetical native model. Furthermore, our preprocessing pipeline relied on Stanza for lemmatization. Errors or inconsistencies in lemmatizing dialectal or informal terms (e.g. *dezeochtend*) can introduce noise that disproportionately affects the performance of count-based models like LDA and the TF-IDF-based KMeans, potentially impacting the fairness of our comparison. Finally, while this study advocates for the superiority of BERTopic's qualitative output, we acknowledge the inherent subjectivity of topic model evaluation. Our conclusions are based on a combination of automated metrics and human judgment, yet both have constraints. Automated coherence scores are imperfect proxies for human interpretation, and human evaluation, while essential, is difficult to scale and can be influenced by the specific task design and the evaluators' own biases.

6 Conclusion and Future Work

We introduce FLAME, a new corpus of nearly 25k daily personal narratives in Flemish, and explored which topic modeling approach is best suited to uncover the latent themes embedded in data of this kind. Our findings demonstrate that while traditional models like LDA can achieve higher scores on co-occurrence-based metrics such as C_v, BERTopic generates qualitatively superior topics that are more semantically coherent and culturally resonant. This work highlights a critical challenge in the field: the potential for automated metrics to be misleading when evaluating modern, embedding-based models on morphologically rich and context-dependent text, underscoring the need for hybrid evaluation frameworks and human-in-the-loop validation.

Beyond its methodological contributions, FLAME opens up new possibilities for computational social science research on underrepresented language varieties. Traditional text analysis in this domain often relies on lexicon-based tools like LIWC (Pennebaker et al., 2001), which are limited by their static, non-contextual nature. FLAME, combined with contextual topic modeling approaches validated here, offers a more nuanced, data-driven lens into the thematic content of everyday personal experience in a culturally specific community, one that has been largely invisible in NLP research to date.

Ethical Considerations

All participants provided informed consent and were fully briefed on the study's procedures, including the secure collection of self-reported responses and sensor data. Personal and sensitive information was anonymized and handled with the highest standards of confidentiality. Compensation was provided uniformly according to the study protocol, ensuring fair treatment throughout the 70-day experience sampling process.

Data Availability Statement

The dataset of Flemish daily narratives used in this study contains sensitive personal information and was collected from participants in Europe under the General Data Protection Regulation (GDPR). To protect participant privacy while supporting scientific reproducibility, the anonymized dataset will be made available to qualified researchers for non-commercial research purposes. The code used to conduct the experiments reported in this paper, including preprocessing scripts and model implementations, will be made publicly available on a GitHub repository upon publication.

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Appendix

A Participants

Participants were a community sample recruited through flyers, online posts, and word-of-mouth. To be eligible, participants needed to be native Dutch speakers at least 18 years old, living in Belgium, with a smartphone in good condition. Interested individuals were directed to an eligibility survey, and these criteria were later verified during the online introduction session.

Participants were compensated up to €250 for completing a 70-day (10-week) experience sampling protocol, including biweekly online surveys. They earned €0.50 for each completed experience sampling prompt (4 prompts $\times$ 70 days = 280 prompts or €140 max), €10 for each short online survey (2, 4, 6, and 8 weeks; €40 max), and €15 for each long online survey (0 and 10 weeks, €30 max). Participants who remained in the study for at least 60 days received a bonus of €40. Compensation was provided as a lump sum at the study's end. To remain in the study, participants needed to complete at least 75% of prompts and submit verbal descriptions of at least 25 words. Compliance was monitored via periodic checks and summary reports.

A total of 115 participants enrolled (age: 18–65, M = 27.26, SD = 9.86; gender: 58 women, 56 men, 1 other). Of these, 10 chose to leave the study after partial completion and 3 were dismissed for poor compliance (i.e., response rate under 50%). The remaining 102 participants ranged in age from 18 to 65 (M = 26.47, SD = 8.87): roughly 14% of participants were under 20 years old, 63% between 20 and 30, 15% 30-40, 5% 40-50, 3% 50-60, and 1% over 60. The sample comprised 52 women (51%), 49 men (48%), and 1 other (1%). Ninety-four (92%) participants described themselves as having a Flemish, Belgian, European, or White background, 3 (3%) described a mixed Belgian and other origin background, 1 (1%) reported another ethnic background (Chinese), and 4 (4%) chose not to say.

Study procedures and materials were reviewed and approved by the KU Leuven Social and Societal Ethics Committee (SMEC), protocol G-2023-6379-R3(AMD). Data collection occurred from August 2023 through July 2024, with all study instructions provided in Dutch.

Procedure and Materials

Participants completed 70 days of experience sampling, receiving four prompts daily via a dedicated smartphone app (*m-Path*) (Mestdagh et al., 2023). Prompts were sent pseudo-randomly between 9 AM and 9 PM, with at least an hour between them. At each prompt, participants responded to: "What is going on now or since the last prompt, and how do you feel about it?" Responses were recorded as one-minute voice messages or 3–4 sentence typed responses.

While completing prompts, the *m-Path* app used phone sensors to record GPS coordinates, ambient noise levels, step count, and recent phone app usage (Android devices only, app names recorded). Participants also completed biweekly online surveys assessing well-being and emotional functioning, but these data were not used in the current analysis.

Data Preparation

Recorded descriptions were automatically transcribed using a Dutch automatic speech recognition (ASR) system developed in-house at the KU Leuven Department of Electrical Engineering (ESAT) (Tamm et al., 2024). This model was trained on approximately 270 hours of Flemish Dutch speech from the Spoken Dutch Corpus (Oostdijk, 2000), following protocols similar to the baseline described by Poncelet and Van hamme (Poncelet and Van Hamme, 2023). The resulting transcripts contain system-generated punctuation and adhere to the orthographic transcription conventions of the Spoken Dutch Corpus, which include detailed annotation tags for foreign words, dialect, disfluencies, and other phenomena. Subsequent preprocessing removed these annotation tags and non-content markers, retaining only the core textual content for further analysis.

Model evaluations were performed using an NVIDIA RTX-5000 GPU and implemented in PyTorch.

B An Overview of The Three Topic Modeling Approaches: KMeans, LDA, and BERTopic

In this section, we compare and detail the key components of the specific topic modeling approaches chosen for this study: a TF-IDF based KMeans clustering baseline, the probabilistic Latent Dirichlet Allocation (LDA), and the embedding-based BERTopic.

B.1 KMeans

To represent a non-probabilistic, geometric clustering baseline, we employ KMeans (MacQueen, 1967; Lloyd, 1982; Berkhin, 2006; Sinaga and Yang, 2020). For vectorization, we use TF-IDF, as it is a standard feature extraction method for classical document clustering and provides a stronger baseline than raw term counts due to its ability to down-weight frequent, uninformative words (Salton and Buckley, 1988; Ramos, 2003). Following prior work demonstrating its efficacy on Dutch texts (Kamiloğlu et al., 2025), we apply KMeans to partition the resulting TF-IDF document vectors, where each cluster centroid represents a latent topic.

We deliberately avoided using embedding-based vectorizers for this baseline to ensure a clear comparison between distinct modeling paradigms. The objective of this study is to contrast an end-to-end, embedding-native model (BERTopic) against established, non-embedding methods. Using embeddings to generate features for KMeans would position it as a hybrid model, which, while a valid approach, falls outside the scope of this direct comparison.

B.2 Latent Dirichlet Allocation (LDA)

As a canonical probabilistic baseline, we include LDA, a traditional probabilistic topic modeling technique that assumes a hierarchical Bayesian structure, where documents are generated by sampling topics from a Dirichlet-distributed prior, with words subsequently sampled from topic-specific multinomial distributions (Blei et al., 2003; Shin et al., 2025). It employs CountVectorizer (Pedregosa et al., 2011) to transform preprocessed text into a document-term matrix (DTM), where each row represents a document, and each column corresponds to a unique term.

B.3 BERTopic

BERTopic is a relatively recent topic modeling approach that leverages transformer-based embeddings to capture nuanced semantic relationships in textual data and generate topics (Grootendorst, 2022). The modular, multi-stage pipeline primarily involves three steps: dimensionality reduction, document clustering, and topic extraction.

B.3.1 Dimensionality Reduction

To address the challenges posed by the high dimensionality of the embeddings, we employ Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018) to reduce the high dimensional embeddings to a low dimensional space. UMAP is a non-linear technique adept at preserving both the local and global structure of the data from the high-dimensional space, which is crucial for effective subsequent clustering (Grootendorst, 2022).

B.3.2 Clustering

The reduced embeddings are then clustered using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) (Campello et al., 2013). We selected HDBSCAN as the default clustering component of BERTopic for several reasons that make it particularly well-suited for our corpus of open-ended personal narratives.

First, unlike centroid-based algorithms such as KMeans, HDBSCAN does not require the number of topics to be specified *a priori*. This is a significant advantage when exploring a novel dataset where the thematic structure is unknown. Second, HDBSCAN is a density-based algorithm that identifies clusters of varying shapes and densities, which is a better fit for the fluid and unstructured nature of narrative text than the globular cluster assumption of KMeans.

More crucially, HDBSCAN can classify data points as noise (outliers) rather than forcing every document into a topic. This is invaluable for our dataset, as personal narratives can often be non-topical or too ambiguous to be assigned to a coherent theme. By treating these as noise, we ensure that the resulting topic representations are cleaner and more semantically cohesive. While BERTopic's modularity allows for other clustering algorithms, our use of HDBSCAN is a deliberate choice to align the modeling approach with the inherent characteristics of our data (Grootendorst, 2022).

B.3.3 Topic Extraction

To provide interpretable representations of each topic, the key terms are extracted using BM25-weighted class-based TF-IDF (c-TF-IDF) (Grootendorst, 2022). This method treats all documents within a given cluster as a single composite document. It then calculates term frequencies within this composite document and weighs them by the inverse frequency of the term across all other clusters. This process extracts words that are most representative of a specific topic cluster.

C Silhouette Analysis

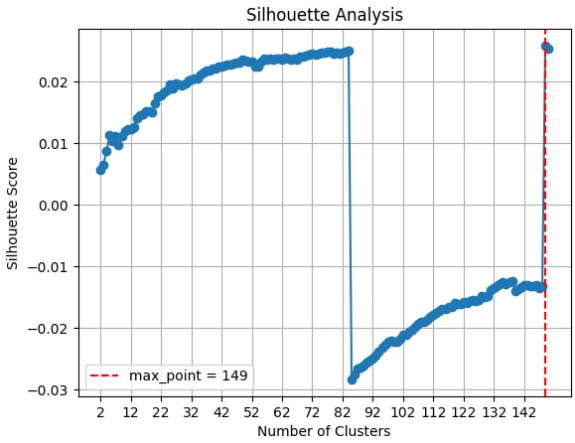

Figure 3: Silhouette Score vs Number of Clusters

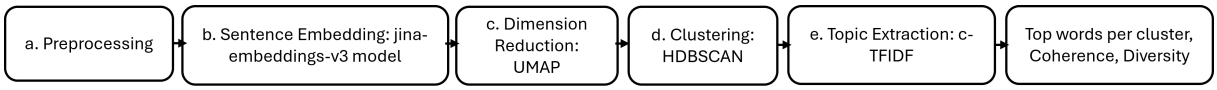

Figure 1: BERTopic implementation pipeline

Figure 2: Word clouds of representative BERTopic topics (English translations). Each cloud displays the top words for a selected topic, with font size proportional to word relevance within the topic.

D Human Annotation

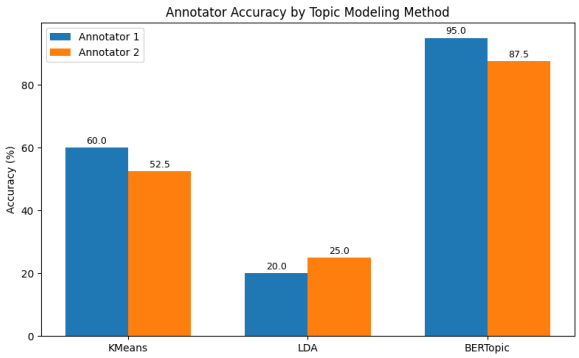

Figure 4: Annotator's Accuracy

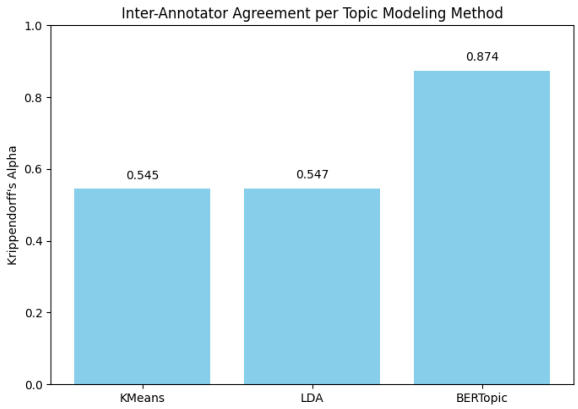

Figure 5: Inter-Annotator Agreement

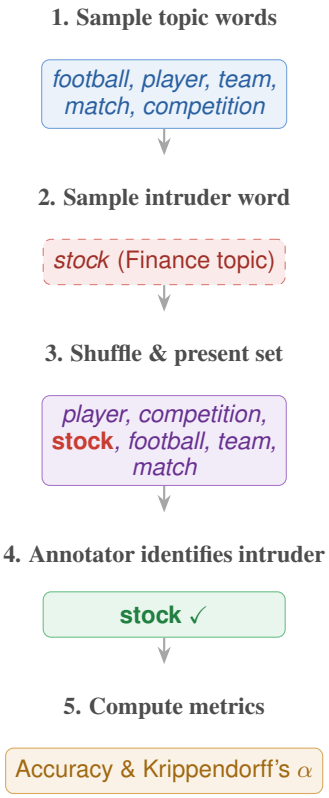

Figure 6: Schematic of the word intrusion task. The intruder word (**stock**, shown in red) is sampled from a high-probability term of an unrelated topic (Finance) and inserted at a random position in the six-word set.

E Topic Distribution (BERTopic)

We extracted the continuous probability [0,1] that each text loaded onto each topic. To account for the fact that texts often included content corresponding to multiple themes or events, we considered a topic to be mentioned if its loading probability surpassed a threshold of 0.01 (i.e., binarizing the data), with this threshold established based on an examination of the distribution of loading probabilities. We observed that the 75 topics (excluding -1) were used across a range of texts (min = 24 [0.1%], max = 20,186 [82%], M = 1,085 [4%], SD = 2,311 [9%]). Likewise, texts typically touched on multiple topics (min = 0, max = 21 [28%], M = 4 [6%], SD = 3 [4%]).