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Topic modelling as a method for framing analysis of news coverage of the Russia-Ukraine war in 2022–2023

Anna Verbytska [1]

Martin-Luther-Universität Halle-Wittenberg, Institut für Musik, Medien- und Sprechwissenschaften (IMMS), Halle (Saale), Saxony-Anhalt, Germany

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ABSTRACT

This study critically analyses the representation of the Russia-Ukraine war in Western (the Euronews) and Eastern (the Kyiv Post) media discourses. It examines how media organisations shape narratives through strategic framing. Employing the Natural Language Processing technique – Topic Modelling – with a generative probabilistic model LDA and a transformer-based language model BERT, the study reveals generic frames elaborated by more specific extensions, shedding light on media portrayal of economy, public opinion, security & defence, external regulations, policy evaluation, and health & safety sectors. Through Named Entity Recognition with roBERTa, Sentiment Analysis with distilBERT, and Corpus Linguistics methods with LancsBox X, interpretation of these overarching frames provides a comprehensive analysis of the nuances in narratives, societal perceptions and policy decisions amidst the ongoing war.

1. Introduction

The February 24, 2024 has been described as 'a beginning of the third year of a three-day special operation in a 10-year war that has been lasting for hundreds of years' (translated from a Facebook post by RockRadio UA).[2] The full-scale Russia-Ukraine war resulted in a reshape of all global systems: geopolitical, financial, military, energy, social systems for the last two years. A number of decisions has been made to recover from the shock of the war and balance the structures. Decision-making mechanisms and the role of media in them became of primary importance during the times of conflicts and wars. In behavioural psychology, people make irrational choices depending on the presentation of a decision to them (Korteling et al., 2018). Making this heuristic-driven information processing principle central, media organisations prime and frame the events to better control the reactions of their audience.

Thus, the overarching *aim* of this research is to compare frames in Western and Eastern media, in this particular case, the Euronews newspaper as a representative of a European Union perspective, and the Kyiv Post newspaper as a Ukrainian media outlet. These frames present judgments and evaluations on a global arena, targeting the international audience and highlighting or excluding aspects of the full-scale war in Ukraine. Framing analysis underpins this research theoretically. Topic Modelling is a central method for framing analysis here as it detects more subtle frames that may not be immediately obvious through traditional content analysis. While employing Topic Modelling is not new for framing analysis (Ylä-Anttila et al.,

E-mail address: verbytska.anna@outlook.com.
[1] Present affiliation address - Mansfelder Straβe 56 (MMZ), 06108 Halle (Saale), Germany.
[2] RockRadioUA: https://www.facebook.com/RockRadioUA.

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2022; Haddadan et al., 2023), we show how it can be instrumental for war narratives in news coverage. Technical novelty of the paper lies in a complementary usage of models to perform this task.

Framing analysis has a long-established tradition as an important research method in multiple disciplines such as sociology, communication studies, media studies, psychology, anthropology, linguistics, and political science. Framing involves how communication sources like news outlets shape and define political issues or public controversies, giving them specific meanings and perspectives (Entman, 1993; Nelsen et al., 1997; Nabi and Oliver, 2009). Consequently, media frames can guide how people interpret events, influencing public opinion and, by extension, decision-making, especially for those who do not hold pre-existing strong opinions (Matthes, 2008). In Gitlin's view, news frames represent 'persistent patterns of selection, emphasis, and exclusion that furnish a coherent interpretation and evaluation of events' (Norris et al., 2003, p. 4). Decisions about what to emphasize or exclude in media coverage lead to the formation of 'thematic sets of interrelated ideas, imagery, and arguments, which tend to cohere and persist over time' (Card et al., 2015, p. 438). Persistency in framing conflicts, terrorism, or wars may present dangers of one-sided coverage or reinforcement of propaganda that leads to irrational and harmful decisions. The exclusion of certain events from media coverage has an equal effect as has been studied by Zollmann (2023) who contends that the frame emphasizing NATO's eastward expansion as the context for Russia's invasion was downplayed by the Western mainstream news media, compared to the frame focusing on Russia's imperial ambitions, and this has influenced the portrayal of the Russia-Ukraine war as a result. Tracking down such narratives and frames with Topic Modelling algorithms – a statistical model LDA on the one hand, and BERTopic model that captures contextual meanings, on the other, reveals dominant themes, regional differences, and subtle biases in conflict reporting.

2. Materials and methods

2.1. Data collection

As this research is a follow-up of a previous project that inspected distress narratives in media discourse during the first four months of the Russia-Ukraine full-scale war (Verbytska, forthcoming in 2025), the current study explores further the thematic content and conceptual representation of the war defining the one-year time frame between the June 23, 2022 (the day when Ukraine was granted the candidacy for the EU-member state) and the June 24, 2023. The data scraping was performed by using a software tool Diffbot[3] with the search queries 'Russian invasion' and 'Ukraine', then cleaned from missing information and duplicate articles that, as a result, yielded a total of 562 articles in the Euronews newspaper (further referred to as the EU corpus) and 478 articles in the Kyiv Post newspaper (further referred to as the UA corpus) published online. The average length of the articles in *the Euronews* is 631 words and in *the Kyiv Post* – 809 words. The number of unique authors in *the Euronews* reaches to 160 with the most frequent contributions from Reuters (215 articles), Euronews (29 articles), and Euronews with AP (25 articles), and 69 unique authors in *the Kyiv Post* with AFP (135 articles), Kyiv Post (111 articles), Stefan Korshak (17 articles), and Aleksandra Klitina (17 articles), leading the number of entries. For our analysis, we collected texts from both media outlets in English, as they aim to reach a global audience with their coverage of the war in Ukraine.

2.2. Methodology

The article offers a computational analysis of framing news about the Russia-Ukraine full-scale war in 2022–2023. Implementation of the Natural Language Processing (NLP) technique called Topic Modelling enabled identification of key concepts iterating in EU and Ukrainian news coverage to frame the major events or milestones in the course of the war. The performance of a traditional generative probabilistic Latent Dirichlet Model (LDA) (Blei et al., 2003) with spaCy and Gemsim libraries is complemented by a state-of-the-art transformer-based language model Bidirectional Encoder Representations from Transformers (BERT) developed by Google (Devlin et al., 2018), in particular, BERTopic library (Grootendorst, 2022),[4] which enables the uncovering of hidden themes or topics within a collected group of articles and their balance within each of these documents. Hereby, Topic Modelling collects valuable insights into the significant topics. These can be interpreted as generic frames that often capture recurrent themes or concepts that are prevalent across different texts or contexts (de Vreese et al., 2001).

We employed the two most used models for this NLP task to test the output and receive as precise a picture of the topics discussed in two media outlets as possible. However, two models extract topics differently. LDA is a generative probabilistic model, which since 2003 is an established classical model for the Topic Modelling task. It thrives on the idea that documents are represented as random mixtures over latent topics, where each topic is characterised by a distribution over words (Blei et al., 2003, p. 996). Its powerful point is three levels of clustering and the topic node is sampled repeatedly within the document that as a result can be associated with multiple topics, whereas BERTopic allocates only one topic for one document. Considering the text-heavy data of our corpora with the lengthiest article amounting to 3050 words in the Euronews and 4146 words in the Kyiv Post, there is a high probability of multiframing in a majority of articles. BERTopic, in its turn, is a relatively new model that has already proved efficient in providing a clear cut between any identified topics and generating novel insights using its embedding approach (Egger and Yu, 2022). BERTopic leverages transformers and c-TF-IDF to create

[3] Diffbot software tool: https://www.diffbot.com/.
[4] Grootendorst, Maarten. BERTopic. *GitHub*: https://maartengr.github.io/BERTopic/index.html.

dense clusters, allowing for easily interpretable topics whilst keeping important words in the topic descriptions. Embeddings are powerful tools that help to improve the performance of NLP models. Being numerical representations of a piece of information, they capture the semantic meaning of what is being embedded, that is, the words or phrases and their relationships in the text. By representing words as vectors, embeddings enable the models to capture the context and meaning of the text. BERTopic differs from LDA because it provides continuous rather than discrete Topic Modelling. Continuous modelling enables entrenchment of the texts in a wider historical and social context that produced them, while preserving the access to the three-dimensional causal structure (Viola, 2023).

Topic models use algorithms to identify clusters of words that frequently occur together, which can be seen as reflecting concepts/schemas/frames in a corpus, that is, mental structures that organise knowledge about objects, events, or situations (Fillmore, 1982). Topics are seen as frame approximations (Ylä-Anttila et al., 2022) that with human interpretation and domain knowledge help explore the important concepts connected with the Russian invasion in Ukraine. Such frames fall under the hood of general-purpose meta-frames or framing dimensions (Card et al., 2015) and are further elaborated into more specific context-dependent ones. Frame naming was prompted by anchor words that unlike those that appear in many other topics, e.g. *ukrainians*, *war*, or *eu*, only occur with significant probability in a single topic (Arora et al., 2012) and therefore can be treated as proxies for the entire frame, 'allowing large changes in a topic model with only a few interactions' (Dasgupta et al., 2019). Anchor words by the LDA model are lemmas – base forms of the words, and by BERTopic – 1- or 2-g words in their form as they appear in the context. For example, the word cloud in Fig. 1 visualises the keywords of the topic that conceptualises a frame on financial and energy resources (see the analysis of Frame 2 in Subsec. 3.2.2).

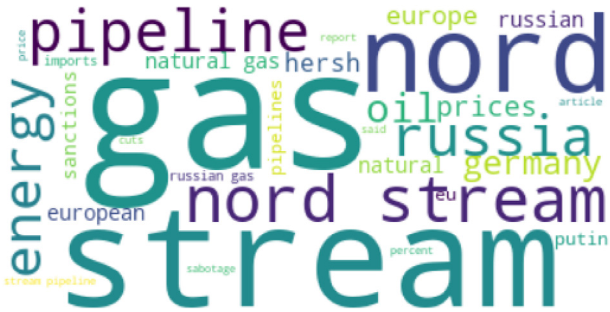

Fig. 1. Word Cloud of the topic 13 in the Kyiv Post (by BERTopic).

Interpretation of frames is complemented with Corpus Linguistics methodology to get a glimpse into the context of the clusters of related words that represent these topics and another NLP technique – Named Entity Recognition. Corpus linguistic entry points include the analysis of concordances (Key-Word-In-Context (KWIC) function) for words and word classes (e.g. democracy_NOUN) and collocates (GraphColl function) with the Lancaster University software tool LancsBox X[5] for the most salient words for each topic previously identified by the models (see Fig. 2 and Table 1 below). The KWIC tool enables search for patterns of language use or complex linguistic structures and their frequencies after it has generated a list of all instances of a query, that is, a search term in a corpus. Table 1 shows such analysis with a search term as a node of the structure and its left and right distributions.

Table 1
Example of KWIC analysis with a query *export*.

Left	Node	Right
EU corpus/76 (203.40)[6]		
en route to Malawi under a previously brokered united Nations	Export	Deal, a spokesperson for the UN secretary general said
Japan also hopes to further ease restrictions on arms	Export	To strengthen the country's defence industry.
"If … due to Russian blockades we are unable to	Export	Our foodstuffs, the world will face an acute and severe food crisis and famine
And ensuing economic havoc has disrupted agriculture, supply lines and	Export	Routes alike. In fact, the war in Ukraine is singled
UA corpus/69 (171.24)		
Negotiations are ongoing between the US and Korean companies to	Export	Ammunition, in order to make up for the shortage of
A statement to parliament. As noted by kyiv post, the '	Export'	Version of the missile has a 300 km range and
Grain deal could be at risk while Ukraine's european	Export	Routes are under pressure. During May 7 and 8, necessary
2023. As a result, in April we were able to	Export	Through the grain corridor less than 3 million tons, which

[5] Brezina, V. & Platt, W. (2023) *#LancsBox X* [software], Lancaster University, http://lancsbox.lancs.ac.uk.

Shared collocates extracted with the GraphColl function of LancsBox X enable further investigation of relationships between several search terms. Fig. 2 displays the collocate analysis for the keywords extracted for topics in a frame on external regulations (See analysis of Frame 4 in Subsec. 3.2.4).

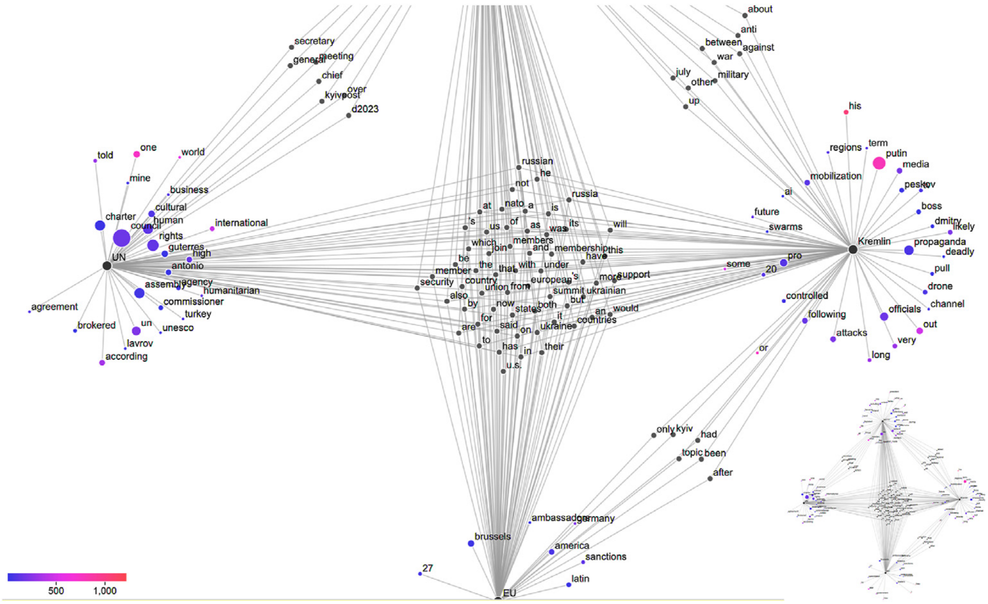

Fig. 2. Sample of a collocate analysis with a GraphColl function for the ORG entities 'UN', 'EU', 'Kremlin', and 'NATO' in the UA corpus.

Named Entity Recognition (NER) with spaCy and roBERTa is another text classification task that extracts named entities, chunks them and identifies as names, locations, companies, events, products, times, monetary values and percentages, that is, it is engaged in two phases of entity detection and classification/typing (Grishman and Sundheim, 1996; Derczynski et al., 2015). It is one of the key information extraction tasks that is used in this research to dig deeper into the role of these entities in the topic understanding and interpretation, trace relations between these entities and draw more meanings from them, which underpins further Critical Discourse Analysis. It is becoming more and more popular to use this NLP technique for news articles and media data analysis, as it recognises specific information from large volumes of unstructured texts with high accuracy. For the current project, English transformer pipeline en_core_web_trf[7] with roBERTa (Liu et al., 2019) base with high accuracy evaluation for tokenization, tagging, sentence segmentation, and named entity recognition was used. From the list of entities we chose the ones with the following label scheme: ORG for companies, agencies, institutions etc., PEOPLE including fictional characters, NORP for nationalities or religious or political groups, GPE for countries, cities, states; LOCATION for non-GPE locations, mountain ranges, bodies of water; EVENT for historical, social, and naturally occurring events. These entities name real-world objects as in the word cloud above (Fig. 1): 'EU' – ORG, 'Hersh', 'Putin' – PEOPLE, 'Russian', 'European' – NORP, 'Germany' – GPE, 'Europe' – LOCATION. Some of the most frequent categorised named entities occur as the most salient words to form topics and, consequently, their further investigation is crucial for frame interpretation. We see NERs as a valuable source of information on representation of participants in the narratives about the war in media or social actors that, in Statham's parlour, 'are important indicators of the ideologies being communicated in a text' (2022, p. 120). Van Leeuwen (1996, 2008) elaborated the scheme for Social Actor Analysis to decode meanings behind certain ways to represent people through the categories of im/personalisation, individualisation or collectivisation, and categorisation/nomination/functionalisation. They shape how responsibility, power, and agency are understood in different contexts e.g. functionalisation through the use of honorifics gives more importance to the actors by emphasing their professional or social status, impersonalisation may conceal exercise of power and shift responsibility, collectivisation will ignore heterogeneity of individuals, etc. In our view, organisations, NORP and GPE entities can be considered social actors in a metonymic sense, pointing at specific behaviours and attitudes.

[6] 76 is the total number of occurrences of the query *export* within the EU corpus, 203.40 indicates the frequency of the query per unit, such as per 1000 words in the corpus.

[7] English transformer pipeline: https://spacy.io/models/en#en_core_web_trf.

2.3. LDA tuning

Pretraining the LDA model included text preprocessing, measuring the Coherence Score to find the optimal number of topics for human interpretation, and hyperparameter tuning of the specific LDA model.[8] An open-source spaCy library prepares the data for analysis by breaking down the text in all the documents into tokens and lemmas, e.g. *clear*, *landmine*, *ukraine*, *require*, *operation*. The tagger assigns Part-Of-Speech (POS) tags based on spaCy's English language pre-trained model en_core_web_md so that later we can remove unwanted tags or stopwords (in our case these were pronouns, coordinating conjunctions, punctuation, particles, determiners, adpositions, spaces, numbers, and symbols) to leave only those keywords in the topics which bear meaning for further interpretation. The next step was to build a dictionary from the tokens that allocates each token a unique ID number. The latter is then used to create a corpus or Bag-of-Words representing the frequency of the tokens with the doc2bow() function. To optimise the running of the model, low-frequency (in less than 5 texts) and high-frequency (in more than 50% of texts) tokens have been filtered out. The unsupervised machine learning model is trained on the corpus data with LdaMulticore.[9] The list of the top-30 keywords in two corpora for every topic is presented in Sec. 3.2., where the first word term has the highest frequency in the cluster, e.g. 0.014*"gas".

2.4. BERTopic tuning

To extract topics using the transformer model, we performed semi-supervised Topic Modelling with BERTopic. It involves extraction of embeddings with a small yet powerful model all-MiniLM-L6-v2[10] which runs fast and offers a good quality for such tasks as: clustering and semantic search; reducing the dimensionality of embeddings with Uniform Manifold Approximation and Projection model (UMAP); clustering the documents with Hierarchical Density-Based Spatial Clustering of Applications with Noise model (HDBSCAN); and creating topic representations with the CountVectorizer and the class-based term frequency-inverse document frequency (c-TF-IDF) components that ensure extraction of features from the sentences and create a Bag-of-Words[11]. Training BERTopic model didn't include text preprocessing as an embedding approach thrives on the original structure that provides the context. However, the CountVectorizer model was hypertuned for removal of English stopwords such as articles. e.g. 'the', conjunctions, e.g. 'and', auxiliary verbs, e.g. 'is', modal verbs, e.g. 'can't', pronouns, e.g. 'yourself', and prepositions, e.g. 'between' (a list of stopwords from the Natural Language Toolkit (NLTK) suite)[12] that carry little semantic meaning in themselves and prevent interpretation of the topics based on more meaningful terms. Additionally, it enabled us to extract 1- and 2-g as keywords. With 3-g, a number of topics shrank to three that were completely disproportional. Other important parameters that directly influenced the number and quality of topics were n_components of the UAMP model, min_cluster_size of HDBSCAN model, and diversity in the representation model. To create good clusters and obtain a meaningful, representative, and balanced number of topics, we fine-tuned: 1) the UMAP models for reducing the dimensionality of the embeddings; 2) diversity parameter, the MaximalMarginalRelevance (MMR) method, to enhance the performance of density-based clustering by calculating the similarity of keywords with the document and other already selected keywords or phrases; and 3) c-TF-IDF model to reduce the impact of words that appear too frequently. Also, we chose appropriate metric for our corpora to compute the similarity between data points and generate better distributed topics; set random state parameter to ensure reproducibility; lessened noise of outliers (the articles in which topics were not identified) by tuning HDBSCAN model and reduce_outliers() method with the further topic representation update. The end result of the top-30 keywords in the two corpora is summarised in Sec. 3.2., where the first term has the highest frequency in the topic, e.g. *eu*, 0.021.

3. Results

In this section, we will present and interpret the LDA and BERTopic results, discuss topic clustering, distribution of the topics across the articles in two corpora, summarise, and analyse frames in two media outlets. Latent topics extracted by the two models were interpreted into the following set of frames.

- Frame 1 'Security & Defence: Military actions in the East, South of Ukraine & North of Ukraine';
- Frame 2 'Resources: Financial resources, energy resources';
- Frame 3 'Resources & external regulations: Export/import';
- Frame 4.1 'External regulations: Alliances, negotiations for international support with weapons';
- Frame 4.2 'External regulations: Alliances, negotiations for international support and global security';
- Frame 5 'Public opinion: Art & media coverage';
- Frame 6 'Health & Safety: Refugees';
- Frame 7 'Policy prescription & evaluation'.

[8] Codes with parameter settings are available on the GitHub repository https://github.com/AnnaVerbytska, data are private and can be accessed for reproducibility by contacting the author.
[9] Gensim documentation: https://tedboy.github.io/nlps/generated/generated/gensim.models.LdaMulticore.html.
[10] Sentence-transformers/all-MiniLM-L6-v2. *Hugging Face*. https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2.
[11] Semi-supervised Topic Modeling. *GitHub*. https://maartengr.github.io/BERTopic/getting_started/semisupervised/semisupervised.html.
[12] NLTK's list of english stopwords. *GitHub*. https://gist.github.com/sebleier/554280

Thus, clustering and distribution helped understand similarities between the topics and their importance in the bulk of articles in the corpora.

3.1. Clustering and distribution

LDA and BERTopic automatically group or cluster data into discrete topics using different clustering methods. LDA models the value of individual documents, and the class-based TF-IDF approach of BERTopic models the significance of words in clusters. As a result, we get a predefined number of word clusters or topic models. The maps below represent the similarity between topics. Topics that are close to each other are more similar in terms of the words they contain. Topics are plotted as 'circles in the two-dimensional plane whose centers are determined by computing the distance between topics, and then by using multidimensional scaling to project the intertopic distances onto two dimensions' (Sievert and Shirley, 2014). To visualise the topics extracted by BERTopic, we need to embed our c-TF-IDF representation of the topics in 2D using UMAP and then visualise the two dimensions with the same pyLDAvis[13] plot.

Interactive visualisation with pyLDAvis library enables users to hover over the circles that represent topics, the top-30 most salient keywords, and intertopic distance (see Fig. 3). The keyword frequency is in blue and estimated term frequency within the selected topic is in red. The map displays groups of topics that have higher levels of semantic similarity. In the Kyiv Post articles, topics are formed into three groups.

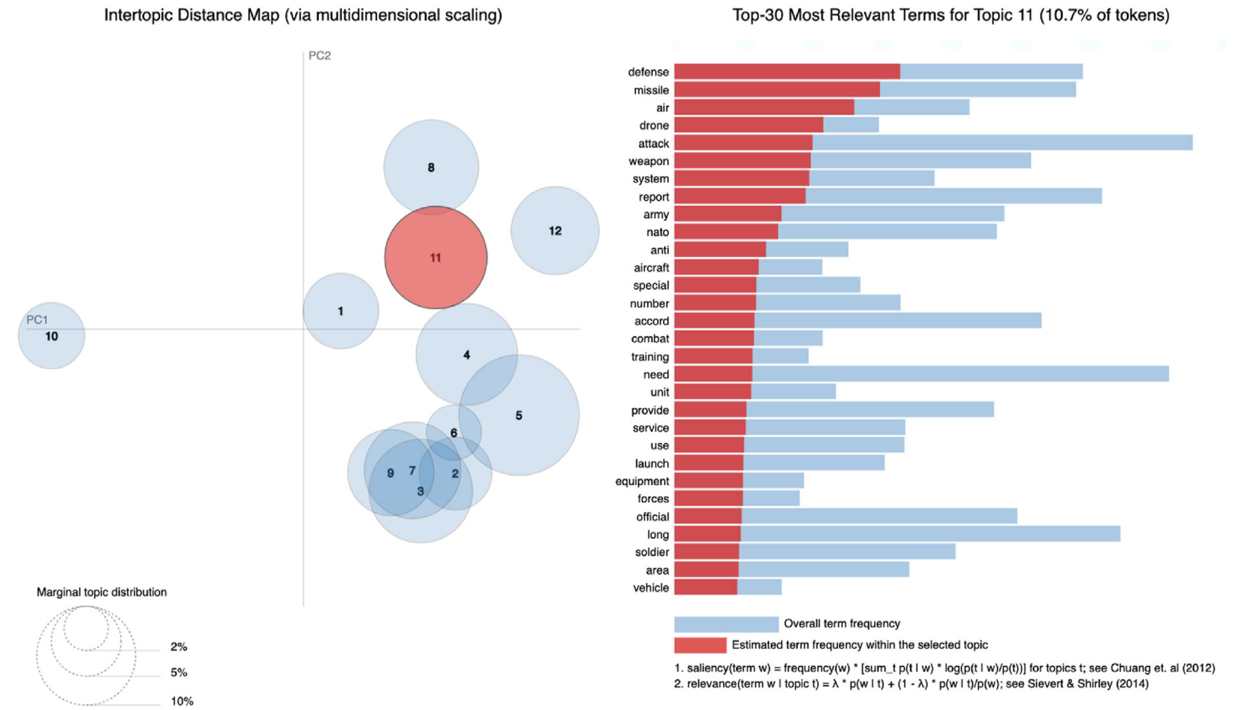

Fig. 3. Intertopic distance map for the Kyiv Post corpus by the LDA model.

- ***Group 1*** consists of a massive cluster of topics 2, 3, 4, 5, 6, 7, and 9, conceptualising such framed events as military actions in Ukraine to a great extent, alliances, negotiations for international support and negotiations for global security. Naturally, these events are interconnected with financial & energy resources, external regulations of import and export of natural resources like gas, oil, or wheat, and media coverage.
- ***Group 2*** with its topics 8 and 11 frames export/import relations and migration situation. Interestingly, this group intersects with Group 1 on topic 4, framing security & defense in Ukraine.
- ***Groups 3*** – topics 1, 5, and 8, framing policy prescription for the committed crimes based on collected evidence. In this line, refugee frame and art & media coverage frame come into play, reinforcing the plea.

Lastly, topics 1 and 2 stand separately, approaching Group 1 and framing policies. Topic 1 has the weakest similarity with all other topics and frames international support with weapons. The reasons for topic overlaps are claimed to be the insufficient statistical information for feature extraction (Cai et al., 2018) or documents not being identified separately (Campbell et al., 2015). However, it is meaningful in this research.

[13] pyLDAvis documentation https://pyldavis.readthedocs.io/en/latest/.

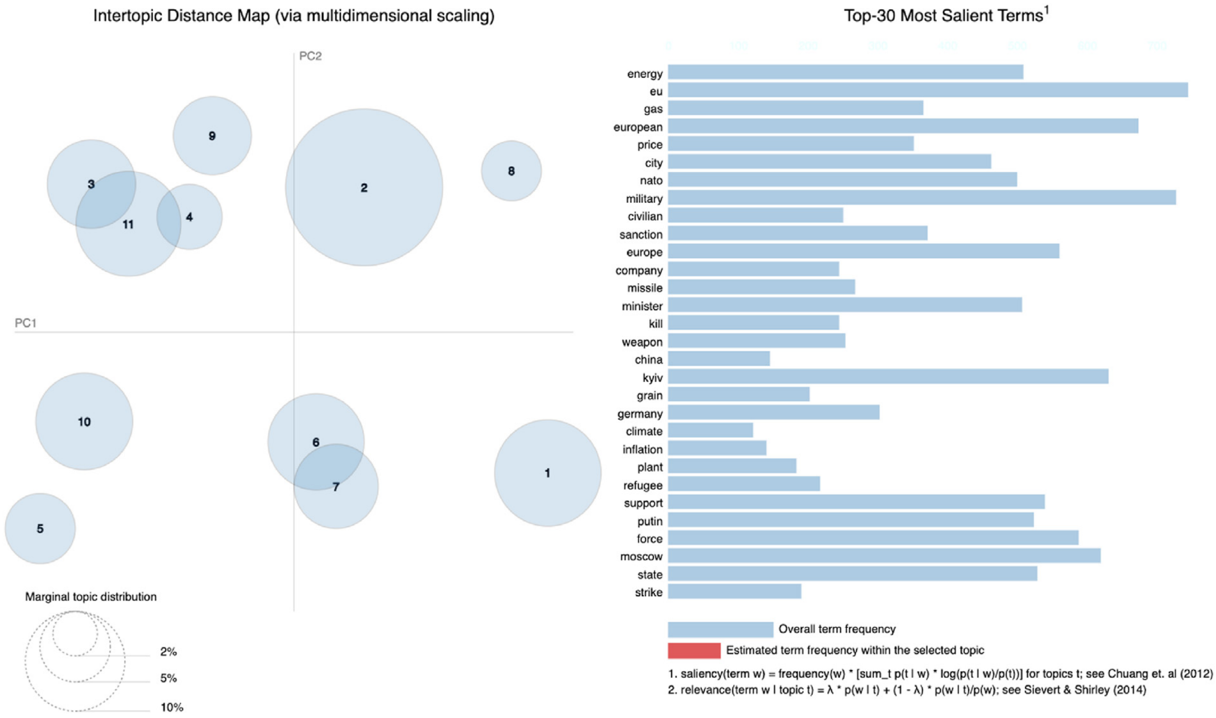

Fig. 4. Intertopic distance map for the Euronews corpus by the LDA model.

In the Euronews articles, we observe two distinct dense groups (see Fig. 4).

- ***Group 1*** is formed by topics 3, 4, 9, and 11, framing security and defense in different parts of Ukraine, external regulations on export and import, energy resources, and policies.
- ***Group 2*** and topics 6 and 7, framing negotiations on global security and public opinion.

More dispersed are topics 2, 8, 5 and 10, approaching Group 1 and framing financial resources, policy prescription & evaluation, negotiations & alliances, and refugees, and topic 1 which is in closer proximity to Group 2, framing policy prescription & evaluation.

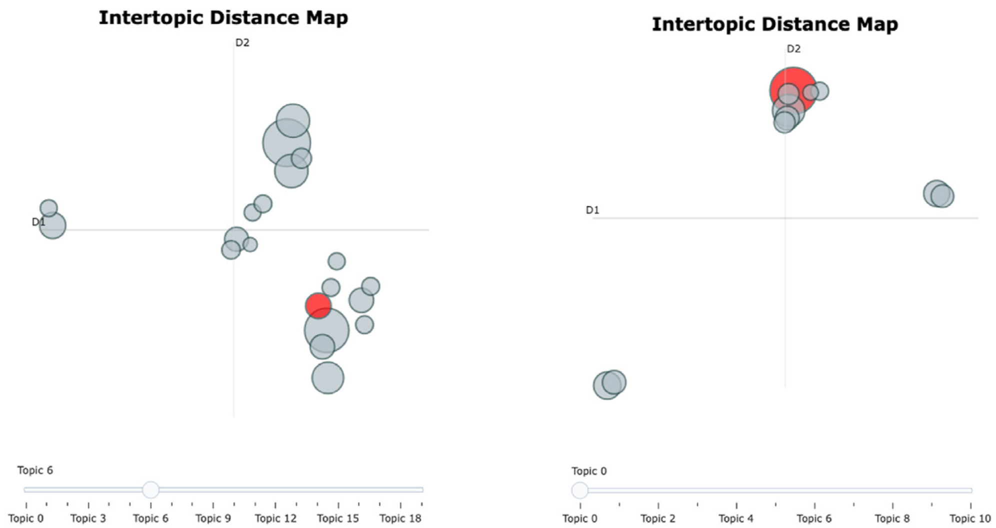

Fig. 5. Intertopic Distance Maps for the Kyiv Post (on the left) and Euronews (on the right) corpora with the BERTopic models.

Here we can see dense clustering of topics in the Kyiv Post articles with six groups (see Fig. 5).

- ***Group 1***, including topics 1, 3, 6, and 11, as well as ***Group 2***, including topics 18 and 20, frame alliances & negotiations, and policies at local and international levels.
- ***Group 3*** includes topics 5 and 15, public opinion about the war through media and artistic events.
- ***Group 4*** is formed by topics 10, 12, and 19, framing policies and financial & energy resources.
- ***Group 5*** clusters topics 2, 7, 8, and 17, framing negotiations for international support and weapon supplies, military actions, and policies that regulate them.
- ***Group 6*** includes topics 9 and 14, framing import/export of resources, and media coverage.

Topi 13, revealing finance and energy resources, is approaching in similarity ***Group 6***, and topics 16 and 6, framing well-being of refugees and military actions, has higher similarity score with ***Group 5.***

Topics in the Euronews corpus have slight overlap and are clearly distributed into three groups.

- ***Group 1*** includes topic 2 and 8, framing refugees and policy prescription and evaluation.
- ***Group 2*** is composed of: 1) topic 1 with subtopics 9 and 11, topics 4, 6, 7, and 10, framing security and defense, external regulations on international support and export/import, and art & media coverage of these events.
- ***Group 3*** with topics 3 and 5 conceptualises financial and energy resources.

This interplay of topics and frames they conceptualise, is further explained in the next section.

3.2. Frames

From general-purpose framing dimensions developed by Boydstun et al. (2014), identified in news articles and put into the Media Frames Corpus that according to Card et al. ‘subsume all specific frames that might be encountered on any issue of public concern’ (2015, p. 438), we distinguished Security & Defence, Resources, External regulations, Public opinion, Health & Safety, and Policy prescription & Evaluation frames that were further specified by the topic keywords. Two models, LDA and BERTopic, unanimously and accurately defined seven frames except for the frame 4.1 ‘External regulations: Alliances, negotiations for international support with weapons’ not identified by LDA model in the EU corpus.

Table 2
The distribution of topics and top-30 most salient keywords for Frame 1 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 3: *city, kyiv, **force**, **region**, **attack**, **kill**, **civilian**, moscow, **missile**, **military**, **strike**, zelenskyy, day, claim, **donetsk**, report, month, **kherson**, official, authority, **eastern**, accord, town, building, **soldier**, week, **damage**, area, include, **target***	**Topic 2:** *city, **bakhmut**, **kill**, **soldier**, afp, come, tell, month, **troop**, **wound**, building, old, theater, town, leave, life, film, civilian, take, **mariupol**, fire, station, work, russians, start, festival, **die**, video, **fighter*** **Topic 4:** *report, claim, likely, operation, kremlin, putin, official, continue, **mobilization**, information, **oblast**, accord, post, **prigozhin**, general, **service**, **security**, head, source, **defense**, **group**, medium, effort, **attack**, zelensky, conduct, investigation, **donetsk**, **wagner**, **mod***[14] **Topic 9:** ***region**, **attack**, **kherson**, **kharkiv**, **city**, **territory**, **damage**, **occupy**, **plant**, **area**, **nuclear**, **power**, **crimea**, **strike**, continue, water, sea, **donetsk**, **destroy**, report, **zaporizhzhia**, **control**, line, **troop**, southern, russians, river, **oblast**, infrastructure, supply*
BERTopic	
Topic 1: *ukraine, russian, said, russia, ukrainian, war, kyiv, **forces**, people, city, **military**, moscow, invasion, putin, president, **region**, country, **killed**, **civilians**, **russian invasion**, **russian forces**, zelenskyy, **kherson**, attacks, including, according, **donetsk**, **eastern**, new, says*	**Topic 2:** *russian, ukraine, said, ukrainian, **region**, russia, war, city, people, kyiv, **invasion**, children, **military**, **forces**, **missile**, **missiles**, **civilians**, russian **invasion**, **attacks**, **killed**, **air**, international, **power**, **nuclear**, **kharkiv**, 000,*[15] ***destroyed**, president, **plant**, russians* **Topic 4:** *russian, **forces**, ukrainian, **russian forces**, **oblast**, ukraine, **military**, **kherson**, likely, russia, **donetsk**, **ukrainian forces**, **prigozhin**, war, **operations**, city, kremlin, **bakhmut**, **attacks**, **kharkiv**, **troops**, reported, **occupied**, claimed, **defense**, **officials**, **wagner**, **mod**, **crimea**, **azov*** **Topic 17:** ***bakhmut**, said, year, **afp**,*[16] *says, ukrainian, tree, year old, old, war, russian, **wounded**, city, people, christmas, **killed**, ukraine, kyiv, near, like, christmas tree, road, husband, **invasion**, line, **forces**, **soldiers**, **fighting**, **donetsk**, dobrutskyi*

[14] The Ministry of Defence of Ukraine.

[15] Keyword *000* refers to the numbers, e.g., *500,000 immigrants* or *557,000 people emigrating*, which was stripped off from the whole figures during tokenization and lemmatization.

[16] AFP news agency.

3.2.1. Frame 1 'Security & Defence: Military actions in the East, South & North of Ukraine'

Frame 1 is manifested in anchor words in Table 2, denoting military actions or their results such as *attack*, *kill*, *strike*, *damage*, *destroy*, *fighting*, *occupy*, *conduct*, *control*, *send*, *defence*, *offensive*, *mobilisation*, *operation*, *troop*, *target*, *forces*, etc. GPE entities 'Ukraine', 'Kyiv', 'Kharkiv', 'Bakhmut', 'Kherson', 'Donetsk', 'Crimea', 'Mariupol', 'Zaporizhzhia', 'Russia', 'Moscow', and 'Kremlin', NORP entity 'Eastern' and keywords *nuclear*, *plant*, *power*, *infrastructure*, *water*, *river*, *station, city, town, theatre* reveal targets and offenders of military actions to signify milestones in the war such as Ukrainian resistance in Azovstal steel mill in Mariupol, occupation of Zaporizhzhia nuclear power plant, fierce battles for the salt-mining town Bakhmut, explosions on the Crimea peninsula, and others. In the Ukrainian media, ties to the frame that signifies international support with weapons and global security concerns are defined by the anchor words *supply*, *nuclear*, *defense*, *missile*, *drone, air.* This frame is equally important in two corpora judging by the average distribution among articles (26.06 % in the EU corpus and 30.74 % in the UA corpus) and by the query *attack** that yielded 446 hits in the EU corpus and 494 hits in the UA corpus: *aerial/explosive/massive/suicidal* – ADJ + attack* structure and *drone/terrorist/missile/(cross-)border/tank/(nuclear) plant* – NOUN + attack* structure. In both corpora, impersonalisation, presented by the keywords *russian/ukrainian forces*, *troops*, *civilians*, *officials,* denotes agents of the military actions and victims, and nominations with honorifics denote political actors (*president, putin, zelenskyy*). In Ukrainian media, there is an emphasis on collectivised social actors that perform the roles of victims – *children*, *wounded*, military agents/defenders/offenders – *soldiers*, *army*, *fighter, forces, occupier,* ORG entities 'Azov' (the Azov Assault Brigade) and 'MOD' (the Ministry of Defence). This frame intersects with Art & Media coverage frame, bringing together attacks and social events, especially during the mentioned event – Christmas. Social actors that perform a role of organisers are represented through personalisation, e.g. *dobrutskyi*, or offenders *prigozhin*, *wagner.* Keywords *milbloggers*, *afp*, *reported*, *claimed* extracted by BERTopic in the UA corpus connect this frame with media coverage. The keyword *afp* was extracted by roBERTa as one of the most frequent ORG entities with 135 occurrences in the UA corpus. AFP is a European news agency that collects evidence about the world wars, including Russian-Ukrainian. The Kyiv Post highlights the reporters covering events on-site (*an AFP photographer showed the drones swooping low across the skies of Kyiv*), or interviewing refugees (*Galina Korsakova from Donetsk told AFP. 'I really want to go home.'* (UA corpus)).

Table 3
The distribution of topics and top-30 most salient keywords for Frame 2 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 2: ***energy***, *eu*, ***gas***, ***price***, *european, europe, high, company*, ***euro***, *increase, government, economy, rise*, ***inflation***, ***bank***, ***crisis***, ***cost***, ***economic***, *world, supply, new*, ***market***, *month, time, state, global*, ***oil***, *import, report*, ***power*** **Topic 9:** ***pipeline***, *germany*, ***gas***, *support*, ***stream***, ***nord***, *company, foundation, hospital*, ***gazprom***, *state, help, accord, sanction*, ***energy***, *uk, project, board, fight, tell*, ***solar***, *space, service*, ***power***, *europe, need, government, work, satellite, german*	**Topic 3:** ***market***, ***rate***, *week*, ***price***, ***bank***, ***bond***, ***debt***, *increase, remain, government, month*, ***nbu***,[17] *bill*, ***financial***, ***fx***,[18] ***currency***, ***hryvnia***, *high*, ***economic***, *oil, investor, new, demand*, ***exchange***, ***finance***, *large*, ***cash***, ***dollar***, *view*
BERTopic	
Topic 3: *said*, ***bank***, ***inflation***, *ukraine*, ***prices***, *000, year*, ***economy***, ***economic***, *2022, european, invasion, eu, government, euro*, ***energy***, *russia*, ***billion***, *war*, ***rates***, *russian, growth, invasion ukraine, central*, ***usd***, *russian invasion, expected, high*, ***rate***, *global* **Topic 5:** ***energy***, ***gas***, *europe*, ***wind***, *eu*, ***climate***, ***prices***, ***electricity***, ***power***, *russian, year, european, said*, ***euros***, *germany*, ***renewable***, ***pipeline***, ***solar***, ***billion***, *russia, ukraine, says*, ***stream***, ***nord stream***, ***nord***, ***fossil***, ***oil***, *invasion, government*, ***price***	**Topic 10:** *ukraine*, ***billion***, *war*, ***debt***, *ukrainian*, ***assets***, *countries*, ***imf***,[19] *support, said*, ***bank***, *reconstruction, ukrainians, million, people, russian, russia, year, country, invasion, sector, private, private sector, international*, ***funding***, *development, new, world*, ***gdp***,[20] ***economic*** **Topic 12:** ***market***, *week*, ***rate***, ***nbu***, ***fx***, ***bonds***, ***bills***, ***hryvnia***, ***eurobonds***, ***currency***, *icu view*,[21] *icu*, ***exchange rate***, ***exchange***, ***debt***, ***cash***, *demand, view*, ***cents***, ***ministry finance***, ***finance***, ***denominated***, ***prices***, *government*, ***dollar***, *secondary*, ***borrowings***, ***rates***, *june*, ***hr***[22] **Topic 13:** ***gas***, ***stream***, ***nord***, ***nord stream***, ***pipeline***, *russia*, ***energy***, ***oil***, *germany*, ***prices***, *europe, hersh*, ***natural gas***, *european, russian*, ***natural***, ***sanctions***, ***pipelines***, *putin, eu*, ***russian gas***, *imports*, ***stream pipeline***, ***price***, *said, article*, ***percent***, ***cuts***, *sabotage, report*

3.2.2. Frame 2 'Resources: Financial resources, energy resources'

As to frame 2, anchor words denoting energy resources such as *energy*, *(natural) gas*, *oil*, *electricity*, *power*, *solar*, *fossil*, *renewable*, *wind* in the EU corpus prompt us to claim bigger disturbance by energy supplies, climate, the general impact of the

[17] National bank of Ukraine.
[18] Foreign Exchange Market (forex, or FX, market).
[19] The International Monetary Fund (IMF).
[20] Gross domestic product (GDP).
[21] Investment Capital Ukraine (ICU).
[22] hryvnia.

war on energy supplies, and looking for solutions to replace oil and gas with renewable sources of energy. A number of keywords in Table 3 comprising the topics by LDA (*european*, *europe*, *sanction*, *government*, *company*, *global*) and BERTopic (*eu*, *government*, support, *world*) create ties with the Policy prescription frame when power structures take decisions on resolving upcoming energy and inflation issues. Alongside, LDA model reveals NORP entity 'German', and GPE entity 'Germany' in the context of financial and energy resources in the Euronews that means a strong involvement of the country in the financial events. The UA corpus has a high density of anchor words denoting financial resources in LDA model (*market*, *rate*, *bond*, *bank*, *price*, *bill*, *currency*, *hryvnia*, *percent*, *economic*, *financial*, fund, *finance*, *cash, trade, demand*) and BERTopic (*billion*, *assets*, *eurobonds*) reveal deeper problems in economy sector (*debt*, *borrowings*: *Ukraine will emerge from the conflict with unsustainable debt*) in Ukraine and other countries (*American people suffer from* $<\ldots>$ *crippling national debt*), but also connections to the frame on international support (*investor*/-s, support, *reconstruction*). *Debt* is also used metaphorically, expressing values of security and freedom (*the most unacknowledged debt of security*; *the greatest debt concerns freedom*). BERTopic extracted a topic summarising the energy sector that directly intersects with finance and speaks of weaponization of energy sources by Russia, sanctioning Nord Stream pipeline to stop the Russian invasion, gas cuts in Europe due to the pipeline shutdown and increased prices. Named entities such as GPE 'Russia', 'Germany', LOCATION 'Europe', PEOPLE 'Hersh', etc, give more details about geographical orientation of the energy concern. The collocates of *energy* keyword disclose the questions of *facilities*, *security*, and *infrastructure*, such hazards as *attacks*, *strikes* (especially connected with *Ukrainian* energy), and energy types (*gas*, *atomic*). Disproportionate is the number of hits of the query *energy** in two corpora, reaching up to 164 hits in the UA corpus and 536 hits in the EU corpus. The right distribution of the collocates energy* + NOUN in the EU corpus results in two the most frequent words: *prices* (51 hits) and *crisis* (41 hits), denoting the cause of the energy crisis (*Russia has deliberately provoked an energy crisis*), expressing attitudes (*shock of/fears of looming energy crisis*) and other problems arising from it (*side effect of/migration is overshadowed by energy crisis*). In the UA corpus, the most frequent collocates are *energy infrastructure* (20 hits) and *energy prices* (17 hits), shifting the focus on the damages and fixing them (*to fix the country's battered/systematic attacks in Ukraine's/against energy infrastructure*). People entity speaks of another controversial issue – the media coverage of the Nord Stream shutdown and eruptions of leaks into the water by an American investigative journalist Seymour Hersh as a sabotage. ORG entities that came up as anchor words for the frame are *nbu* and *fx* that when serving as queries in a corpus manager show in the UA corpus the constant changes from *'FX market stabilizes', 'FX market maintains balance', or 'The FX market remains flush with cash' to 'FX: Hryvnia continues to weaken', 'Turbulence intensifies in cash FX market', 'The NBU slightly decreased interventions'.*

Table 4
The distribution of topics and top-30 most salient keywords for Frame 3 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 4: ***grain***, ***export***, ***food***, *defence*, ***port***, ***sea***, *tank*, ***black***, ***turkey***, *system*, ***supply***, *western*, *air*, *military*, *kyiv*, ***tonne***, *minister*, ***ship***, *world*, ***wheat***, *need*, ***send***, ***weapon***, *nato*, *global*, ***deal***, *month*, *jet*, *friday*, *help*	**Topic 6:** ***gas***, *germany*, *putin*, *peace*, ***stream***, ***pipeline***, ***nord***, *want*, *athlete*, *decision*, ***odesa***, *think*, *international*, ***come***, *new*, *europe*, *journalist*, ***turkey***, ***export***, *work*, *post*, *help*, *journalism*, *talk*, *european*, ***port***, *change*, *kherson*, *call*, *olympic* **Topic 11:** *un*, *international*, *world*, *need*, ***grain***, ***food***, ***global***, *south*, *crime*, *council*, *action*, *ukrainians*, *united*, *aggression*, *security*, *moscow*, *humanitarian*, *general*, *child*, *africa*, *law*, *human*, *peace*, *cause*, *right*, *organization*, ***export***, *community*, *address*, ***provide***
BERTopic	
Topic 7: ***grain***, *ukraine*, *said*, ***food***, ***sea***, ***tonnes***, ***turkey***, ***ports***, ***black sea***, ***black***, ***wheat***, *russian*, *ukrainian*, ***million tonnes***, *russia*, ***million***, ***exports***, *war*, ***ships***, *global*, ***corn***, *world*, ***harvest***, *mines*, ***farmers***, *invasion*, ***export***, ***port***, ***deal***, *year*	**Topic 9:** ***grain***, *ukraine*, ***odesa***, *ukrainian*, ***ftx***,[23] *ports*, *russian*, *russia*, *companies*, *money*, *company*, *zhevago*, ***food***, *according*, *post*, ***export***, *million*, ***weapons***, *kyiv*, *kyiv post*, *business*, *war*, *said*, ***sea***, *invasion*, ***agreement***, ***customs***, ***exports***, *2022*, ***deal***

3.2.3. Frame 3 'Resources & external regulations: Export/import'

Two models extracted topics that conceptualise Frame 3 and prompt us to summarise the milestones in international trade during the war, track changes in political regulations, and influences. Anchor words in Table 4 *grain*, *food*, *wheat*, *corn*, *farmers*, *harvest*, *product*, *million tonnes*, *export*, *sea*, *port*, *black sea*, *mines* explain Ukrainian food export across the Black Sea to Africa and Asia and disruptions of it caused by Russian attacks and mining Odesa seaport that could lead to a global food

[23] Futures Exchange (FTX).

crisis. The problem of Ukrainian farmers who are unable to export harvest due to the port blockade or a shortage of fuel to run equipment, or a risk of being bombed, is especially accentuated in the Euronews. In the Kyiv Post topic, LDA model identified *nord*, *pipeline*, *stream*, *gas* anchor words that bring us to the event of the eruptions on the Nord Stream 2 which was supposed to supply Germany with half of its needs for natural gas, and connect this frame with resources frame. Another event brought up in the UA corpus and revealed by the transformer model was the case with Kostyantyn Zhevago, a Ukrainian billionaire entrepreneur, who was involved in and changed with financial transactions/trading activities and businesses with Russia and Belarus. Thus, this frame is strongly intertwined with export of food and other natural resources (*corn*, *wheat*, *grain*, *food*, *gas*, *oil*), negotiating agreements (*talk*, *call*, *agreement*, *deal, decision, peace*) in both corpora, with a strong financial flavour in Euronews (*company*, *business*, *pay*, *usd*, *market*, *payment*, *bond*, *salary*) and milder in the Kyiv Post (*business*, *company/-ies*, *money*), export/import regulations (*customs*), reference to human rights violated by the disruption of supplies (*right, crime, council, action*) that tie the frame to the policy prescription and evaluation frame. Export/import matter is closely connected with external regulations frame touching upon the transportation of weapons (*tank, military, jet* – in EU, *weapons*, *drone* – in UA), negotiations for security and aid (*security*, *help, supply, humanitarian*), and information spread via media channels (*kyiv post*, *think*, *journalism, journalist*) in the UA corpus.

If we have a closer look at KWIC results of queries *export** (156 hits in the UA corpus, 281 hits in the EU corpus) and *import** (293 hits in the UA corpus, 334 hits in the EU corpus) where predominance to the matter is obviously given in the Euronews coverage, we will see that in the EU corpus, there has been discussed the Moscow's bombing of Ukraine's export infrastructure, Japan's restrictions on arm export, disruption of export routes, slowing of export growth, sanctions imposed on export to Russia, Russian blockage of exporting foodstuff, etc. In the UA corpus, export of drones, tanks, and other ammunition has been discussed, together with Seoul and Korea restrictive policies, agricultural export capacities and mechanisms, complications of export due to occupied territories and their mining, looting of grain and steel and the vulnerability of export chains exposed by the war. As to the import, the EU media cover the countries which continued importing raw materials from Russia, Russian oil import bans, or the standstill of Russian domestic production. The UA media discussed import bans from Belarus to prevent production of chemical and biological weapons, countries which abandoned the agreements for foodstuff imports from Ukraine, and import taxation. PEOPLE, NORP, and GPE entities induce more conclusions on accents in two corpora. In Euronews articles, two models unanimously extracted *turkey* keywords in the export/import (incl. across the Black Sea) context bringing into spotlight the bouncing sides of Turkey in supporting Ukraine with weapons and at the same time refraining from imposing sanctions on Russia, leading the policy of a mediator (being a 'gas hub'), a channel for communication between two combatant countries. This individualisation of social actors together with functionalisation represented by the keyword *minister* connect the frame to the policy prescription and evaluation frame.

3.2.4. Frame 4 'External regulations'

External regulations frame is represented by a high density of topics revealed by two models. The umbrella frame dimension is specified by subframe 4.1 'Alliances, negotiations for international support with weapons' and subframe 4.2 'Alliances, negotiations for international support and global security'.

Table 5
The distribution of topics and top-30 most salient keywords for Frame 4.1 in the corpora.

LDA	
Euronews	Kyiv Post
-	**Topic 10:** ***missile***, *defense*, ***tank***, ***air***, ***attack***, ***weapon***, ***drone***, ***army***, ***system***, ***artillery***, ***vehicle***, ***soldier***, ***unit***, *fight*, ***combat***, ***target***, ***long***, ***strike***, *civilian*, ***aircraft***, ***equipment***, ***launch***, *anti*, *special*, *nato*, ***send***, ***training***, ***rocket***, ***range***, *post*
BERTopic	
Topic 6: *ukraine*, *said*, *nato*, ***defence***, ***tanks***, ***military***, *russian*, *germany*, *countries*, ***weapons***, *russia*, ***air***, *ukrainian*, *poland*, ***jets***, *britain*, ***training***, *german*, *invasion*, *minister*, ***systems***, ***troops***, ***forces***, *states*, ***fighter***, ***supply***, *war*, *western*, ***arms***, ***ammunition***	**Topic 7:** *ukraine*, *air*, ***tanks***, ***military***, *said*, *nato*, ***uasof***,[24] *russian*, ***forces***, *ukrainian*, *special*, ***tank***, *russia*, *defense*, *operations*, ***drones***, ***aircraft***, ***systems***, ***vehicles***, *war*, ***leopard***, ***artillery***, ***army***, ***training***, *kyiv*, ***support***, ***weapons***, ***afu***,[25] ***missiles***, ***missile***

[24] The Ukrainian Special Operations Forces.
[25] The Armed Forces of Ukraine.

Table 6
The distribution of topics and top-30 most salient keywords for Frame 4.2 in the corpora.

Euronews	Kyiv Post
LDA	
Topic 5: *eu, nato, european,* ***minister****, need, johnson, uk, truss, military, kosovo, brussels,* ***support****, think, new,* ***prime****, policy, europe, scholz, want, come, long, serbia, security, foreign,* ***alliance****, defence, union, government, member, britain* **Topic 6:** *moscow, putin, military, nato, minister, united,* ***leader****,* ***sanction****, security, official, states, foreign, kyiv, western, state,* ***meeting****, force, west,* ***talk****, biden,* ***ally****, china, troop,* ***tell****, border,* ***support****,* ***call****,* ***end****, vladimir, defence*	**Topic 7:** *zelensky,* ***minister****, european, china, eu, nato,* ***visit****,* ***leader****,* ***summit****,* ***security****,* ***ally****, biden,* ***prime****, western,* ***aid****, europe,* ***meet****, united, long, new, moscow, iran,* ***meeting****,* ***tell****, states,* ***member****, poland,* ***provide****,* ***add****,* ***need***
BERTopic	
Topic 4: *russia, ukraine,* ***said****, russian, nato, putin, military, president, moscow, war, invasion, security, china, states, united, foreign, biden, minister, macron,* ***meeting****, united states, europe,* ***talks****, european, crisis, west, russian invasion,* ***sanctions****, ukrainian, countries* **Topic 9:** *ukraine, zelenskyy, johnson, said, ukrainian, president, russian, country, russia,* ***support****, minister, zelenskiy, kyiv, war, invasion, reznikov, defence, leader, volodymyr, western, leaders, year, party, sunak, russian invasion, uk, military, president volodymyr, government, prime minister*	**Topic 1:** *russian, ukraine, putin, russia, war, ukrainian, people, military, ukrainians, kyiv,* ***said****, russians, invasion, president, army, country,* ***peace****,* ***support****, time, world, today,* ***end****, fight,* ***state****, kremlin, europe, just, years, post,* ***want*** **Topic 3:** *china, russia, ukraine, said, south, president, war, invasion, peace, xi, moscow, russian, iran, africa, chinese, nuclear,* ***security****, taiwan, putin, african, countries,* ***global****, world, south africa, food,* ***united****, beijing,* ***meeting****, international,* ***foreign*** **Topic 6:** *ukraine, eu, european, ukrainian, german, zelensky,* ***said****, president, europe, war, russian, russia, minister,* ***countries****,* ***support****, kyiv, poland, invasion, ukrainians, union,* ***security****, country,* ***summit****,* ***nato****, germany, prime, prime minister, macron,* ***defense****, people* **Topic 20:** *ukraine, military,* ***defense****,* ***support****, states, russia, russian, said, invasion, canada,* ***assistance****, ukrainian, compact, greece, war, minister, nato, kyiv,* ***aid****, united, united states, new, austin, zelensky, germany, russian invasion, billion,* ***military assistance****, western, revisionism*

The LDA model failed to extract topics that manifest frame 4.1 in the EU corpus in Table 5, unlike BERTopic. In a one-year time-lapse, the course of the Russia–Ukraine war has changed and the win of Ukraine as much as global security depends heavily on the international support and negotiation skills of the politicians. Citing Josep Borrell: 'We are living, to my understanding, the most dangerous moment for security in Europe after the end of the Cold War.' (Euronews, February 06, 2022)[26] Anchor words that prompted us to name the frame in Tables 5 and 6 are as follows: *ally*, *alliance* (alliances), *tell, said, talk, add, meet, meeting, call, visit, summit* (negotiations), support, *help*, *aid*, *provide, (military) assistance* (support), *peace*, *defence*, *security* (security), *european*, *foreign*, *western*, *international*, *west*, *world*, *global* (international, global), *forces*, *operations*, *war*, *training*, *aircraft*, *air*, *systems*, *tank*, *army*, *arms missile/-s*, *artillery*, *combat*, *vehicles*, *tanks*, *drones*, *leopard*, *military*, *jets*, *fighter*, *weapons* (support with weapons).

On closer inspection, a query *weapon** results in 363 hits in the UA corpus and 306 hits in the EU corpus that emphasises topic priorities in media. In the UA corpus, such types of weapons as *the Grim heavy missile/air-launched/the longest-range/advanced/game-changing/'smart'* weapon, HARMS anti-radar missiles are being discussed alongside the prevention of Iran from developing a nuclear weapon and Russia using energy as a weapon.

In the EU corpus, weapon is addressed metaphorically when hunger and food, gas, grain, energy (as political and economical), and rape are weapons of war used by Russia throughout the history. The important questions are brought up in the context with weapon such as the US fears of inflaming tensions with Russia over weapon supply to Ukraine, enhancement of weapon production and speed of its delivery, the possibility of Kremlin using a nuclear weapon and its severe consequences, the necessity of weapon use for defence now by men who never have held weapon in their arms before disclosed in personal narratives, or the mentions of particular weapon types such as thermobaric rockets (*Russia's most fearsome weapon*), Kalibr weapon, tanks and weapon systems/Patriot air defense systems. Distribution of the search query support* (support, supporting, *supporter/-s*, supported, *supportive*) with 608 hits in the EU media and 713 hits in the UA media and the query *alli** (*allies*, *alliance/-s*, *allied*) with 205 hits in the UA media and 305 hits in EU media reveals the urgency of the topics and the importance of the frame. The KWIC helps us answer these W-questions.

- which support – *broad/new/financial/Ground Based Air Defense/logistical, military and diplomatic* (by Belarus to Russia), *economic and diplomatic* (by China to Russia)/*collective/overseas/wide* etc.;
- whose support – by *Canada, leading international businesses/Western government/Western partners and the entire global community/US public*, etc.;
- support for whom/what – *Ukraine's recovery/territorial integrity and unity of Ukraine/volunteer projects/Leopard 2 tank maintenance centre/a peace initiative* (by India)/*Kyiv in its fight/Taiwan*, etc.

[26] Ukraine crisis: Germany and US 'absolutely united' on Russia sanctions, Scholz says. *Euronews*. 06 February 2022. https://www.euronews.com/2022/02/06/german-leader-s-stance-on-russia-looms-over-first-visit-to-us.

The Russian invasion in Ukraine evoked a chain of economic, geopolitical, financial, societal, and climate changes. It has also launched a chain of transformations of alliances formed previously and functioning since the Cold War. Analysis of the query *alli** in context manifests growing tensions when North Korea claimed that NATO was *attempting to pressure America's Asia allies into providing weapons to Ukraine* (EU corpus) or China's peace proposals that were *greeted with scepticism by Ukraine and its allies* and tensions over the pressure *to* grant *Ukraine a roadmap for joining the alliance [NATO]* (UA corpus).

For this frame, ORG, PEOPLE, LOCATION, NORP, and GPE entities are deemed of extreme importance as they are well presented and extracted by two models with insignificant differences. Key personas identified for a negotiations and support with weapons subframe in UA media are 'Zelensky' and 'Putin' whereas in the EU news this is 'Scholz', and for the negotiations and global security subframe in UA media these personalised social actors are 'Zelensky', 'Macron', 'Xi', 'Putin', 'Biden', in the EU media – 'Putin', 'Johnson', 'Truss', 'Biden', 'Zelenskyy', 'Scholz', 'Reznikov', and 'Sunak', which speaks of key players on the international political arena and their positioning as such in the narratives about the war in Ukraine. Functionalisation of social actors as *president* and *prime minister* bears weight of responsibilities and spokespersons in the negotiation processes. Geographically, this positioning is revealed in the NORP and GPE entities that manifest the subframes.

Apart from the most frequent ones that rotate in both corpora, that is, 'Russian', 'Ukrainian' (NORP) and 'Ukraine', 'Russia', 'Kyiv', 'Moscow' (GPE), those that distinguish certain foci in the EU media for a subframe 4.1 are 'Western', 'German' (NORP); 'Germany', 'Britain', and 'Poland' (GPE). Those that define the subframe 4.2 ■ in UA media are 'Western', 'European', 'German', 'Chinese', 'African', (NORP); 'Poland', 'Germany', 'China', 'Taiwan', 'the United States', 'Austin', 'Iran', 'Beijing', 'Canada', 'Greece' (GPE); 'Europe', 'Africa' (LOCATION) and ■ in the EU media are 'European', 'Western', 'German' (NORP); 'the United States', 'China', 'UK', 'Britain', 'Serbia', 'Kosovo', 'Poland', 'Brussels' (GPE), and 'Europe' (LOCATION).

The Kyiv Post puts special emphasis on ORG entities with their respective frequencies in the UA corpus such as ('NATO', 267), ('UASOF', 35), and ('AFU', 62) for the subframe 4.1 and ('Kremlin', 161), ('EU', 235), ('NATO', 267), ('UN', 144) for the subframe 4.2. In contrast, for frame 4 there was just an entity ('NATO', 490) extracted in the EU corpus. The important concepts revealed by shared collocates between the ORG entities in the UA and EU corpora, fall into the categories in Table 7.

Table 7
Shared collocates for the ORG entities 'UN', 'EU', 'Kremlin', and 'NATO' in two corpora.

Category	UA corpus	EU corpus
Political entities and organisations	Russia, Ukraine, NATO, EU, UN, Kremlin, U.S., ***Kyiv***, European Union, states, members, summit, ***union***	*Kremlin, EU, UN, NATO, Ukraine, Russia, Turkish, Ukrainian, NATO, U.S., Poland, Europe, European Union, members, summit, states*
Actions and processes	Said, support, join, meeting, ***between***, against, had, been, ***over***, attacked	*said, support, join, meeting, been, had, attacked,* ***told***, ***invade***, ***sanctions***, ***added***, ***against***, *meet*
Time and temporal references	July, now, after, year	*now, after,* ***last***, ***week***, ***since***, ***time***, ***years***, *July,* ***next***
Geopolitical & military terms	Military, war, country, borders, chief, security	*war, military,* ***invasion***, *borders, security,* ***mission***, ***membership***, *chief,* ***defence***, *countries, country,* ***enlargement***
Leadership & governance	President, government, secretary, chief, leadership	*president, secretary, government, leaders, leadership, Putin,* ***ministers***, *governance*
Common adjectives & modifiers	More, not, other, this, their, will, also, about	*more,* ***new***, *their, other, not, also,* ***all***, ***further***, ***some***, *more,* ***same***, *this, about,* ***western***, ***first***, ***last***

Collocate analysis strengthens the security & defence, global security, or policy topics that involves the participation of alliances, emphasises urgency (*now* – 491 occurrences with EU and NATO queries in the UA corpus and 523 occurrences with UN in the EU corpus), transformations of these alliances with new members (*enlargement*, *join, should, allies, more, added, membership*). The UA corpus focuses more on specific entities like *Kyiv* and uses fewer geopolitical and temporal terms, while the EU corpus includes broader geopolitical references (e.g., *Poland*, *invasion*, *enlargement*) and more varied time references. The EU corpus also expands on leadership, governance, and modifiers compared to the UA corpus.

Table 8
The distribution of topics and top-30 most salient keywords for Frame 5 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 7: *event,* ***film***, *support, world,* ***video***, *work, win, take,* ***music***, ***culture***, ***festival***, *life, city, start, come,* ***play***, *putin,* ***cultural***, *stand, tell,* ***artist***, *time, place, new, include,* ***theatre***, ***eurovision***, ***director***, *uk,* ***feature***	**Topic 5:** ***archive***, ***project***, *serbia italian, help, italy, work, azov, animal, world, create, material,* ***news***, ***cultural***, ***artist***, *company,* ***social***, ***art***, ***medium***, ***culture***, ***book***, ***tv***, *start, need, odessa,* ***online***, ***digital***, *freedom,* ***write***, *government*

Table 8 (*continued*)

LDA	
Euronews	Kyiv Post
BERTopic	
Topic 10: *ukraine*, ***music***, *russian*, ***eurovision***, *russia*, *ukrainian*, *world*, *invasion*, ***art***, ***video***, ***contest***, ***event***, *year*, ***film***, ***song***, *war*, *people*, *country*, ***culture***, ***cultural***, ***festival***, ***artist***, ***exhibition***, *said*, ***museum***, *russian invasion*, ***artists***, *kyiv*, *city*, *lviv* **Topic 11:** *russian*, *ukraine*, *russia*, *war*, ***media***, ***disinformation***, ***rt***,[27] ***news***, ***websites***, *invasion*, *people*, *ukrainian*, ***information***, *said*, ***content***, *eastman*, ***vpn***, *invasion ukraine*, *says*, *just*, ***play***, ***meta***, ***journalism***, *space*, *really*, *like*, ***wikipedia***, ***online***, ***propaganda***, ***audiences***	**Topic 5:** *ukrainian*, *ukraine*, ***theater***, *war*, *said*, *world*, ***cultural***, *russian*, ***sculpture***, ***culture***, *people*, *city*, *works*, *invasion*, ***catherine***, *year*, ***exhibition***, ***museum***, ***unesco***, ***heritage***, *odesa*, ***picasso***, ***artist***, *great*, *ukrainians*, ***artists***, ***art***, *calendar*, ***sculpture***, *sea*, *history* **Topic 14:** *archive*, ***journalism***, ***media***, ***tv***, *war*, *ukrainian*, ***content***, *russian*, ***journalists***, ***information***, ***channel***, ***starlink***, *ukraine*, *post*, *russia*, ***news***, ***journalist***, ***social***, ***internet***, *new*, ***platform***, *kyiv*, ***public***, ***kyiv post***, *just*, ***rt***, *work*, ***youtube***, ***platforms***, *country* **Topic 15:** *zelensky*, *rapoport*, *president*, *people*, *kyiv*, ***berlinale***, ***film***, ***festival***, ***actor***, *penn*, *wearing*, *star*, *ukraine*, *russian*, *year*, *war*, *world*, *khaki*, *said*, *told*, *money*, *time*, *united*, *death*, ***films***, ***director***, *ukrainian*, *country*, *work*, ***directors***

3.2.5. Frame 5 'Public opinion: Art & media coverage'

Public opinion frame elaborated into Art & media coverage is instigated by the anchor words in Table 8: *news*, *media*, *play*, *write*, *video*, *film/-s*, *music*, *theater*, *cultural*, *sculpture*, *works*, *exhibition*, *culture*, *museum*, *heritage*, *picasso*, *artist/-s*, *berlinale*, *festival*, *director/-s*, *actor*, *star*, *archive*, *project*, and *create*. Both media outlets focus on media as a source for dissemination of dis/information or propaganda and artistic or cultural events that provide visibility of the war events, and additionally serve as a means to call for donations. When we inspect concordance lines of individual raw documents for certain keywords to have more understanding for more adequate frame interpretation, we see that in the Euronews a keyword *space* is connected with the Eurovision event ('Space Man' by British singer-songwriter Sam Ryder) in 2022 when the win of Kalush Orchestra 'Stefania' brought a significant publicity to the war in Ukraine and support, the keyword *culture* leads us to informing the world about the unique features of Ukrainians that distinguish them from Russians, or to the artwork 'The Ultimate Dictator' rendered by AI to composite faces of 40 dictators in one portrait. On close inspection, art is a means of fight against totalitarianism as that of the Vilnius-based *music* collective and their song 'Sound of Freedom', highlighting dreadful casualties of the war on the *film* and theatre festivals in London, Berlin, Sarajevo, Cannes, or Washington DC, through the work of Ukrainian artists (stone installation 'Palianytsia' by Kadyrova, images of war-torn Kharkiv to create alternate realities of the world without a war by Anisimova), or international (Banksy's works in Kyiv and an auction of 50 screen prints to raise funds facilitated by him); events in which celebrities make generous donations to Ukraine (e.g. prize money won from tennis tournaments donated by Andy Murray to children). The keywords *support*, *find*, *world* extracted by LDA signal the connection of this frame with refugee and International support frames that through art intend to help refugees find new ways of living abroad and cover their stay abroad in media.

In the Kyiv Post, the LDA model extracts keywords that refer to the concept of freedom, destruction of the cultural heritage (Drama Theater in Mariupol), creating visibility of the harrowing events of the war (*Ukrainian wartime theater*), reinforcement of Ukrainian identity through art. ORG entity 'UNESCO' shows that the war presents a great threat to the World Heritage Sites on the territory of Ukraine such as Odesa, 'The Black Sea pearl'. EVENTs such as 'Berlinale', *festival*, reveal the media coverage of *Ukrainian life in wartime*. Additionally, BERTopic extracted the topics that conceptualise the frame Public opinion with the information spread. ORG entities 'Kyiv Post', 'RT' (Russian television channel Russia Today), 'YouTube', 'Starlink' and anchor words *journalism*, *tv*, *journalist/-s*, *information*, *channel*, *post*, *social*, *internet*, *platform/-s*, *public*, *digital*, *vpn*, *wikipedia*, *online*, *content*, *websites* speak of the importance of the information share via multiple media channels and language modes. KWIC analysis of the query *journalist**, for instance, with 127 hits in the UA media and only 55 hits in the EU media speaks of the tasks to cover the talks linking this frame to external regulations frame, journalists being witnesses and documenting human rights abuses, the changes and prospects of the Ukrainian journalism during the wartime, or the hazards covering events in Ukraine for local as well as foreign journalists: 'I believe that journalists in Ukraine are like warriors—not just Ukrainians, but also the foreign media working here. During this time, Ukrainian journalism has grown a lot in my eyes. It has become more professional and has set an example for media outlets worldwide. Foreign journalists have also gained valuable knowledge about Ukraine' (Kyiv Post, June 6, 2023).[28] **information** (mis-, dis-) is another anchor word with substantial frequency in both corpora (189 hits in the UA corpus and 202 hits in the EU corpus). The quality of information presents the highest value in times of conflicts and wars when *inaccurate/unverified or unreliable/vague and insufficient/distorted/fake/false/sensitive information* or *leaked/the leak of information* can turn into a real weapon (*The word is a weapon*). Information is strategically used (*information operation*), it can be militarised, reshaped (e.g. *by the pro-Kremlin media*), or transferred to the enemy.

[27] Russia Today.

[28] Orlova, Alisa. Journalists' Day in Ukraine: Reflections on How Russia's War Transformed the Profession. *The Kyiv Post*. June 6, 2023. https://www.kyivpost.com/post/17950.

Table 9
The distribution of topics and top-30 most salient keywords for Frame 6 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 10: ***refugee***, ***flee***, ***help***, *child, world*, ***go***, *family, human*, ***change***, *want*, ***home***, *ukrainians, poland, find, thing*, ***border***, *tell, europe, euronews, time, news, work, live, woman*, ***need***, ***leave***, *young, think*, ***life***, ***way***	**Topic 8:** ***work***, ***help***, *child, family, know, ukrainians, come*, ***refugee***, *tell*, ***home***, *want*, ***life***, *trump, find, world*, ***go***, *house, poland*, ***start***, *think, old, city*, ***need***, ***live***, *polish, month, post*, ***way***, *fight, take*
BERTopic	
Topic 2: ***refugees***, *said, people, italy*, ***frontex***, *ukrainian, ukraine, million, countries, country, russian*, ***border***, ***travel***, *year, invasion*, ***migration***, *government, europe, eu, ukrainians, war, restrictions, poland, 000, covid*, ***ukrainian refugees***, *european*, ***far***, *meloni, agency*	**Topic 16:** *chernihiv, children*, ***refugees***, *said, polish, house, ukrainian, poland, year, home, uncle, russian, people, family, ukrainians, relatives, misha, uncle misha, village, war, 000, russians, aunt, old, coffee, told, ukraine, project, school, year old*

3.2.6. Frame 6 'Health & Safety: Refugees'

The frame 6 is extracted by two models and the name is instigated by anchor words in Table 9 that refer to the group of people presented as collectivised social actors (*refugees*, *ukrainian refugees*, *people*, *ukrainians*, *russians*, *children*, *family, old, young*), organisations (*agency*, *government*, *frontex*, *border*), place (*shelter*, *home*, *house*), actions (*fight*, *flee*, *change*, *leave*, *start*, *go*, *live*, *help*, *work, travel*, *take*, *come*), or states (*need*, *want*). As of December 28, 2023, more than 6.3 million refugees from Ukraine were recorded in Europe[29]. The query **migra** (migrant/-s, migration/-s, immigrant, emigrated) in the EU corpus yields 164 hits and in the UA corpus – only 40, which means that migration topic is of great importance for the Western countries and is in the media spotlight. Migrants as social actors are being presented in terms of aggregation (*thousands of migrants, mass migration, an increase in migration, an upsurge in migration*) and water metaphors (*the high levels of migration*, *migratory tsunami, a great migration wave*). The governments attempt to regulate it (*bring migration down/stop/prevent migrants/deter migrants from making the trip/summit to discuss migration/ migration management*), but narrative turns somewhat radical (*anti-migrant rhetoric/stricter migration/anti-migration champion Viktor Orban/hardline immigration views*) and reveals migration policy gaps *(no functioning migrant and asylum pact*). However, the Euronews brings up the migration issue not only of Ukrainians fleeing the Russian war in Ukraine, but also refugees from other countries (*trans-Mediterranean migration flows to Italy*, *increase in illegal migration*), the numbers of refugees (*million*), migration policies (*before the next European elections we will have a functioning Migration Pact*), and migration as a war strategy (*Russia has used migration to sow chaos*; *Russia is likely to further 'weaponise' migration from North Africa and the Middle East towards the EU this year in an attempt to destabilise and undermine*; *masterminding mass migration*). Comparing the frequencies, *Ukrainian refug** comprises only 37 hits in the UA corpus and 80 hits in the EU corpus.

Border regulations is still another issue extracted by BERTopic in Euronews referring to Frontex (*border*, *frontex*, *agency*), 'controversial' border agency as mentioned in the EU corpus. RoBERTa identified it as one of the most frequent ORG entities – ('Frontex', 66) and distilBERT and spaCy allocated a sentiment which is by far the most negative among all the entities in two corpora with an average negative and general score – −0.99. Frontex is cited to be accused of *violating human rights, intimidating migrants and abusing power, European law, human rights, maritime law and its own guidelines in recent years*, which refers to the event of mass drownings of refugees in the Mediterranean since 2014. Among NORP and GPE entities in the EU corpus 'Russian', 'Ukrainian', 'European', 'Ukrainians', 'Italy', and 'Poland' objectify the frame and specify the EU borders (< … > *authorities across eastern Europe are struggling to accommodate the swelling wave of refugees* < … > *Przemysl, a town near Poland's busiest border crossing that has become a transit hub for Ukrainian refugees*).

Another interesting topic offered by the LDA algorithm in the EU corpus only deals with travel restrictions that, however not necessarily, might apply to refugees and fall into the broader category of Health & Safety. The anchor words like *covid, restrictions* refer to cancellation of all restrictions: *restriction-free/no longer need to wear masks in Malta* after inspection of contexts on the one hand, and the link to the 'Resources: Financial resources, energy resources' frame as there were two disasters that directly influenced rises in costs: the pandemic and the war in Ukraine (*The loss of Ukrainian workers has deepened the problems companies are facing*). Although rare, in the Ukrainian corpus there are mentions that the increase of refugees provoked the spread of Corona again (*The disease moved over the borders with the fleeing refugees* (UA corpus)), or the bad situation during the wartime (*When war ripped through Ukraine, its COVID infection rate was at its highest spike*).

In the Kyiv Post corpus, keywords *fight*, *soldier* as well as GPE entity 'Chernihiv' connect the frame 'Health & Safety: Refugees' with the 'Security & Defence' frame and explain the focus of Ukrainian media on the current unsafe state of the country that forces Ukrainians to flee. BERTopic extracted keywords that function as individualised and categorised (relational identification) social actors: *uncle*, *misha*, *uncle misha*, *aunt* that point to personal stories of those living under Russian occupation and refugees who were employed abroad as e.g. translators into Ukrainian.

[29] Number of border crossings between Ukraine and Central and Eastern European (CEE) countries after Russia's invasion of Ukraine from February 24, 2022 to December 24, 2023, by selected country. *Statista*. https://www.statista.com/statistics/1293403/cee-ukrainian-refugees-by-country/.

Table 10
The distribution of topics and top-30 most salient keywords for Frame 7 in the corpora.

LDA	
Euronews	Kyiv Post
Topic 1: ***party***, ***election***, ***government***, ***right***, ***vote***, *italy*, *travel*, ***restriction***, *far*, *public*, *state*, ***political***, ***coalition***, ***voter***, *information*, *sweden*, ***minister***, *enter*, ***opposition***, *prime*, ***candidate***, *issue*, *support*, ***poll***, ***parliament***, ***democrats***, *long*, *italian*, ***campaign***, ***wing*** **Topic 8:** *international*, *nuclear*, *plant*, *state*, *agency*, *report*, ***government***, *information*, *military*, *operation*, *group*, *flight*, *crime*, *statement*, *civilian*, ***accuse***, *company*, *website*, *ban*, *attack*, ***court***, *take*, ***law***, *try*, *claim*, *add*, *call*, ***amnesty***, *medium*, *friday* **Topic 11:** *eu*, *european*, *moldova*, ***right***, ***political***, *citizen*, *putin*, ***government***, *support*, *new*, ***member***, *join*, *union*, *public*, *western*, ***law***, *georgia*, *international*, *way*, *believe*, *remain*, *fight*, ***parliament***, ***democracy***, ***membership***, *issue*, *take*, *long*, ***reform***, ***council***	**Topic 1:** *ukrainians*, *history*, *putin*, *german*, *soviet*, *world*, ***policy***, ***democracy***, *great*, ***leader***, *know*, *germany*, *biden*, *church*, *percent*, *fight*, ***democratic***, *language*, ***political***, *union*, *russians*, *point*, *century*, *national*, *think*, *claim*, *responsibility*, ***lead***, *speak*, *freedom* **Topic 12:** *putin*, *europe*, ***political***, *nuclear*, ***right***, *end*, *international*, *territory*, *crimea*, *european*, *kremlin*, *new*, *moscow*, *security*, *western*, ***vote***, *west*, *russians*, *come*, ***opposition***, *believe*, *belarus*, *weapon*, *fight*, ***government***, *army*, *peace*, ***election***, *nato*, *power*
BERTopic	
Topic 8: *eu*, *european*, *ukraine*, *kosovo*, *moldova*, *war*, *russia*, *roma*, *union*, *people*, *support*, *europe*, *russian*, ***party***, *nato*, ***political***, *invasion*, *country*, *said*, *think*, *european union*, *serbia*, ***membership***, *citizens*, *new*, *sweden*, ***leaders***, ***right***, *countries*, *years*	**Topic 8:** *ukraine*, ***tribunal***, *russian*, *ukrainian*, *kireyev*, *russia*, *president*, ***uoc***,[30] ***uoc mp***,[31] ***lavra***, ***mp***, ***sbu***,[32] *trump*, *said*, ***court***, *kyiv*, ***church***, ***security***, ***crimes***, *parnas*, *state*, *war*, ***head***, ***crime***, ***aggression***, *budanov*, *international*, *invasion*, *moscow*, ***council*** **Topic 11:** *biden*, ***president***, *ukraine*, ***democracy***, *said*, *house*, *pence*, ***republicans***, ***republican***, *russia*, *argentina*, *america*, *fernández*, *putin*, *people*, ***summit***, *world*, *russian*, ***support***, *invasion*, *war*, *netanyahu*, ***white house***, *white*, ***election***, *freedom*, *united*, *prime*, ***congress***, *trump* **Topic 18:** *ukraine*, *war*, *ukrainian*, ***football***, *russian*, *ukrainians*, ***rebrov***, *percent*, ***dynamo***, ***club***, *international*, *country*, *aid*, *russia*, *european*, ***clubs***, ***league***, *covid*, ***political***, *new*, *language*, *city*, *team*, *year*, *community*, *invasion*, *countries*, *world*, *international community* **Topic 19:** ***athletes***, ***ioc***,[33] ***olympic***, ***games***, ***sports***, *belarusian*, *russian belarusian*, ***fencing***, *international*, ***sport***, ***belarusian athletes***, ***compete***, *paris*, ***competition***, *russian*, *countries*, *kostyuk*, *said*, ***boycott***, ***olympics***, ***committee***, *russians belarusians*, ***fie***,[34] ***olympic committee***, ***olympic games***, ***decision***, ***statement***, *ukraine*, *year*, *belarusians*

3.2.7. Frame 7 'Policy prescription & evaluation'

Frame 7 has been summarised by topics detected in two corpora. This frame dimension explains the 'discussion of specific policies aimed at addressing problems' (Card et al., 2015, p. 439). Anchor words in Euronews corpus in Table 10 such as *party, right, government, political, coalition, opposition, candidate, minister, vote/-r, prime, member, parliament, policy, democrats, democracy, republican/-s, election, poll, campaign, membership, reform, council* induce frame naming and specific keywords reveal the addressed issues in the context of Russia-Ukraine war such as presidential, parliamentary, or general elections in the USA, France, Belarus, Bulgaria, Estonia, the Czech Republic, Sweden, Italy, etc. ('*Latvia holds general election amid Ukraine war and record-high inflation*'), reforms, migration, refugees, support, the implementation of a European Union-backed 11-point plan to normalise Serbia and Kosovo relationship, EU membership of Moldova and Ukraine.

In Ukrainian corpus, topics address the issues of international war crime punishment based on collected evidence: *tribunal, court, aggression, attack, crime, amnesty, accuse*. ORG entity 'SBU' and PEOPLE entities 'Parnas', 'Kireyev' – financial and intelligence criminals, 'Budanov' – a Ukrainian military leader reinforce the frame and exemplify it with the cases of espionage and financial frauds. Within Policy frame, another issue to be addressed by politicians is exclusion of the Russian Orthodox Church in Ukraine from the Lavra (ORG entities as 'UOC', 'UOC MP',[35] 'Lavra', 'MP', and *church* keyword). Particular attention gained sports in the UA media, with the frequency of the query *sport** 58 hits and only 23 hits in the EU corpus. With assistance of BERTopic, frame on policy prescription and evaluation is specified by the sports domain with the EVENT entities ('Olympics', 5), ('Olympic Games', 3), ('the Paris Olympics', 2), ORG entities 'IOC', 'FIE', 'Dynamo', PEOPLE entities 'Kostyuk', 'Rebrov', keywords of types of sports *fencing*, *athletes*, *football*, general lexicon *club*, *team*, *league*, *compete*, *competition* referring to sports domain, and keywords explaining the issues to be resolved by politicians (*boycott*, *statement*, *decision*, *aid*, *invasion*). Digging deeper into the keyword *sport** in context of Ukrainian media for evaluative components, we see that sports is not a completely neutral sphere. Sports is characterised in media as chaotic (*a chaos in sport*), being *a luxury, not a right*, having *power to change the world* (citing Nelson Mandela), being a battlefield to struggle for justice (*even in sports Ukraine has*

[30] The Ukrainian Orthodox Church.
[31] Ukrainian Orthodox Church (Moscow Patriarchate).
[32] The Security Service of Ukraine.
[33] The International Olympic Committee.
[34] The International Fencing Federation.
[35] the Russian Orthodox Church in Ukraine.

much to fight for/if the Olympics were killings and missile strikes < … >), a mirror that reflects the changes that came with the war (*the situation in Ukrainian sports as a whole is very sad*), and not the most important part of life as claimed by refugees who used to be sportspeople. Policy prescription and evaluation addresses negotiations as well, connecting it to the frame on external regulations by the anchor words *democracy*, *election*, *summit*, functionalisation *president*, *prime*, individualisation by PEOPLE entities 'Fernández', 'Netanyahu', 'Biden', and 'Putin', GPE entities 'Argentina' and 'the United States', LOCATION entity 'America', ORG entities 'White House' and 'Congress', NORP entity 'Republicans'. The frame represents the war through the events and a chain of decisions, such as the reciprocity of Argentina with Kremlin, the White House being engaged in negotiations of weapons delivery to Ukraine, nuclear situation, re-elections to the White House, its opposition to return to oil and gas production, etc., the Israel election win of Benjamin Netanyahu. Here, the value and concept of democracy are crucial, with 172 hits of the query *democra** in the EU corpus and 219 hits in the UA corpus.

In the UA corpus, a complex syntactic structure ADJ + democracy_NOUN, where adjective is combined with a noun, reveals the qualitative characteristics of democracy and a judgement of the current democracy state *(the strength of) real/a successful/(a pro-)Western/American/a proud, strong, and vibrant/genuine/fake/Ukrainian/(an increasingly self-)confident European/(Crimea in the wake of) nationwide, pro-democracy*. The syntactic structure VERB + democracy_NOUN reveals the problems that put at stake the existence of democracy *(Putin's leadership style – the so-called) guided/(international law plainly) humiliates/denigrating (Netanyahu Modi)/(whoever has weapon) limit/(self-)governed democracy (lives under constant threat)*, necessary actions to preserve democratic society *considered/revive/promote/hail (Netanyahu Modi)*, and the benchmark of democracy *(a fully functional self-)governing/(Germany is the) leading democracy (in the West now)*.

Interestingly, in the EU corpus, the definitions are differently accentuated. The syntactic structure ADJ + democracy_NOUN manifests democracy in quantitative terms: *less/(Hungary was a) young democracy*, geopolitical terms *(threaten) Georgian/transnational/Western European*, or political terms *parliamentary democracy/participatory/representative/liberal democracy (had reached its peak of popularity)*. VERB + democracy_NOUN structure reveals the hazards for democracy stemming from political decisions *threaten/(anti-government protests) trying (to) undermine/violate/(President Alejandro Giammattei) eroding* and pursuits to preserve and strengthen it, in particular, through negotiations *(NATO wants to build firmer ties with Japan to) defend/defending/value/believe (in)/survive (as a)/save*. NOUN + democracy_NOUN structure reveals the concepts that vibrate together with democracy. In the EU corpus, these are peace, prosperity, freedom, and values. The judgement of the current state of democracy is that there are *(huge) issues with/threat for/suppression of democracy*, the need for *consolidation of*/support *of/growth in* democracy and price to pay for it. In the UA corpus, there are frequent concepts that accompany democracy, i.e., freedom of speech/free speech, values, freedom, justice, independence, security, rights. The Ukrainian media see democracy as *the antidote to empire*, something that is worth *a fight for*, needs to be protected from *an attack on/the end of*, having *dreams of*, preserving *the strength of* as this is just *the wake of nationwide democracy*.

4. Discussion

Topic Modelling as a primary method for framing analysis uncovered key highlights in the media representation of the Russia-Ukraine war (2022–2023) from both Western and Eastern perspectives. By introducing two models, a generative probabilistic model LDA and a transformer model BERTopic with embedding approach, our study comprehensively analysed media framing in the context of the full-scale Russia-Ukraine war. Even though the objective of this research was to employ the models in a complementary rather than comparative way, they revealed certain aspects in varying proportions. Distribution of topics and frames among articles signifies the greater weight of importance of frames represented by these topics (see Table A.1 in Appendix). In the EU corpus, two models unanimously prescribe remarkable importance to the frames 'Security & Defence: Military actions in the East, South & North of Ukraine' and 'Resources: Financial resources, energy resources' with the respective mean values 26.06 % and 24.91 % of distribution among articles. The LDA model also prioritises topics that are conceptualised into frames on policy prescription and evaluation (22.60 %), whereas BERTopic extracts topics that are summarised into frames on alliances and negotiations for support and global security (19.21 %). In the UA corpus, the significance of frames differs depending on the model used for Topic Modelling. Frames on Security & Defence, Resources, and policies are distributed with mean values of 30.74 %, 13.17 %, and 18.71 % respectivey. Noteworthy is that the BERTopic model for the UA corpus does not prioritise resources frame, but extracts the high distribution of frame on external regulations, in particular, alliances and negotiations for support and security (35.35 %). BERTopic extracted more keywords directed on naming entities such as locations, people, organisations, or political groups. Although there are inconsistencies in the output generated by the two models regarding the distribution of frames among documents, the subtle details begin to reveal a clearer depiction of the narratives within the two corpora.

The KWIC, collocate, frequency, and social actors analysis of certain keywords representative of frames, revealed high prominence of *attack* for frame on security & defence with nearly equal emphasis in both corpora. The UA corpus is characteristic of an emphasis on collectivised social actors to evoke emotional and psychological responses, mobilizing support, or generating empathy. The frame on financial and energy resources with keywords *energy* showed a distinct focus in the EU corpus compared to the UA corpus, with EU media concentrating on *prices* and *crisis*, while Ukrainian media highlighted *energy infrastructure* and *prices*. Similarly, *export* and *import* keywords of the frame on resources & external regulations were more frequently discussed in the EU media but remained significant in both regions. The keyword *weapons* of the frame on external regulations demonstrated a high number of hits, reflecting the media's prioritisation of the topic, in particular, weapon export/import, its types, and bans in the UA media and export of raw materials for weapon production in the EU media, where reference to weapon is often metaphorical (e.g. *Russia is using energy as a tool, as a weapon against Europe*). Notably, support and *alliances* were prevalent in both corpora, underlining the urgency of these issues. The keywords *journalism* and *information* of the frame on public opinion suggested a strategic role of media, especially regarding misinformation, which is often weaponised in conflicts. Finally, the topic of *migration* was disproportionately covered with about 6 times more coverage in the EU corpus than in the UA corpus. Migrants are presented in the EU media in terms of aggregation and water metaphors, emphasizing the growing numbers and policy gaps for migration regulation that leads to radical attitudes and narratives. Migration is also seen as a war strategy. While *sport* garnered limited attention, particularly in EU media, in the UA media it was strategically important to emphasize the policies for participants of sports competitions from aggressor countries. Thus, sports are reconsidered as a mirror reflecting the changes or a battlefield for justice. The Western and Eastern perspectives align on the importance of democracy with almost equal distribution of the query *democra**. The EU media, however, define it in quantitative geopolitical, and political terms bringing into the spotlight the universal concepts of peace, prosperity, freedom, and values. The UA media reveal its qualitative characteristics, bring up the problems, and steps to take to defend democracy. Freedom of speech/free speech, values, freedom, justice, independence, security, and rights are the major concepts in this context. These findings illustrate the differing media priorities and narratives across the two regions.

5. Conclusion

By examining two distinct media outlets with differing perspectives, we have provided a nuanced understanding of the framing strategies employed in shaping public discourse. Through the identification and linguistic analysis of various frames such as security and defence, resources, external regulations, public opinion, health and safety, and policy prescription and evaluation, we have unveiled the intricate narratives woven within the media coverage. These frames offer valuable insights into the socio-political dynamics, economic implications, and humanitarian aspects of the war. The prospects for further research would be to explore deeper specific frames, such as migration, refugees, policies, and economy sectors, from multidisciplinary perspectives encompassing mass communication theory, linguistics, or journalism. By delving further into these areas, scholars can enhance the understanding of how media framing influences public perception, policy formulation, and international relations. Even though, the study was limited to only two specific media outlets, one language, and textual data, its insights underscore the importance of employing advanced computational techniques to navigate and interpret complex narratives in media discourse surrounding global conflicts. Addressing these limitations would lead for future research for more comprehensive understanding of media framing and its impact on public perception and international relations.

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Appendix

Table A.1
The distribution of latent topics with LDA and BERTopic in the corpora across articles and frames

Frame	Distribution/ Euronews/ LDA	%	Distribution/ Euronews/ BERTopic	%	Mean in EU	Distribution/ Kyiv Post/ LDA	%	Distribution/ Kyiv Post/ BERTopic	%	Mean in UA
1. Security & defence: Military actions in the East, South & North of Ukraine	133	23.67	160	28.46	26.06	179	37.44	115	24.05	30.74
2. Resources: Financial resources, energy resources	194	34.52	86	15.30	24.91	83	17.36	43	8.99	13.17
3. Resources & external regulations: Export/import	41	7.30	32	5.69	6.49	25	5.23	21	4.39	4.81
4.1. External regulations: Alliances, negotiations for international support with weapons	0	0.00	41	7.29	3.64	5	1.04	23	4.81	2.92
4.2. External regulations: Alliances, negotiations for international support and global security	52	9.25	108	19.21	14.23	35	7.32	169	35.35	21.33
5. Public opinion: Art & media coverage	11	1.96	41	7.29	4.62	6	1.25	45	9.41	5.33
6. Health & safety: Refugees	4	0.71	54	9.60	5.15	18	3.76	10	2.09	2.92
7. Policy prescription & evaluation	127	22.60	40	7.11	14.85	127	26.56	52	10.87	18.71
	562	100%	562	100%	100%	478	100%	478	100%	100%

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